A New Algorithm for Blind Adaptive Multiuser Detection in Frequency Selective Multipath Fading Channel

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***Abstract*—This paper deals with a modified version of a blind adaptive multiuser detector for direct sequence code-division multiple-access (DS-CDMA) wireless communication systems which is named *precombining blind adaptive multiuser detector* (PBA-MUD). The main properties of this receiver are low complexity, multiple-access interference mitigation and remarkable near–far resistance in time-varying multipath fading scenarios. In particular, the PBA-MUD is based on a blind adaptive algorithm that allows the detector to avoid deep fading impairments and the cancellation of the desired signal due to signature sequence mismatch. Nevertheless, such a receiver experiences a performance degradation in fast fading channels. In order to overcome this problem, a window reprocessing technique (Del Re *et al.* 2001) was introduced which yielded a new blind detection algorithm. It will be shown that this receiver, together with this new algorithm [*precombining reprocessing window blind adaptive multiuser detector* (PWBA-MUD)] allows a high performance without requiring training sequences or the knowledge of the interfering signature waveforms in multipath fast fading channels.**

***Index Terms*—Blind adaptive techniques, CDMA communications, interference suppression, multi-user detection.**

I. Introduction

RECENTLY, code-division multiple-access (CDMA) based on spread spectrum techniques has been recognized as having a significant role in cellular and personal communications. In particular, the DS-CDMA scheme was found to be attractive because of its potential capacity increase and anti-multipath, anti-jamming and soft-handover capabilities. Thanks to these features this technique is to be considered for future 3G wireless standards in order to guarantee a higher transmitting capacity and to satisfy the rising multimedia request for services. As is known, the multiple-access capability of DS-CDMA systems is achieved by assigning a distinct signature waveform for each user from a set of waveforms with low cross-correlation. When different CDMA user signals are simultaneously received on the same frequency, the transmitted information can be recovered by using a filter matched to each user signature sequence (conventional detector). This detection scheme follows a single user strategy according to which each user is detected separately regardless of other users, but despite of its low complexity, two conditions must be satisfied so as to mitigate the multiple-access interference (MAI): 1) all the used signature waveforms should have low cross-correlations for all possible time shifts and 2) power levels of the received users' signals cannot be too much dissimilar. Unfortunately, these conditions are not fulfilled in frequency-selective time-varying channels, e.g., in mobile radio channel, due to the presence of multipath, fading or other type of distortions. Moreover, the conventional detector suffers from a substantial performance loss as the number of the interfering users increases or the signals are received with different power levels (near–far effect).[1]

Multiuser detection (MUD) techniques [15], [23], [24] were proposed in order to cope with the near–far effect and nonorthogonal spreading code scenarios: the matched filter outputs and the parameters of the multiple users are used to jointly perform an optimum detection for each individual signal. MUD is able to mitigate the MAI which is the main limit for a CDMA system capacity as bandwidth is for frequency division multiple-access and time division multiple-access systems. The optimum multiuser detector [14] consists in a bank of matched filters and a Viterbi decoder whose complexity is exponentially related with the number of users and usually results to be excessive in several practical applications. Hence, research has focused on suboptimal detectors which allows a lower implementation complexity [15], [23]. Recently, some attention has been devoted to adaptive blind MUD approaches which avoid the knowledge of the signature waveforms, the timing and the complex amplitudes of the interfering users. These techniques are based on the minimization of the mean square error (MMSE) between the detector output and the transmitted data [16]. Unfortunately, this entails the use of specific training sequences, one for each active user, thus preventing the application of the MMSE receiver in fast time-varying multipath fading environments (transmission of training sequences at short intervals strongly reduces the system efficiency). The use of training sequences was avoided in the blind receiver proposed by Honig *et al.* [1]. This type of receiver is based on the minimization of the output energy (MOE).[2] As for the MMSE scheme, the MOE detector is known to suffer from a strong performance degradation in fast time-varying multipath fading environments due to the mismatch between the received and the nominal spreading sequence of the desired user. It is worth stressing that blind adaptive detec-

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[1]The near–far effect can be avoided by the implementation of a strict power control with a consequent complexity overhead (see IS-95 standard [17]).

[2]It has been demostrated in [1] that the MOE approach is equivalent to the MMSE.

tion in fast fading channels with a moderate complexity is a goal of many recent contributions [30]–[32].

The PBA-MUD proposed in this paper relaxes this drawback and achieves a good performance in both additive white Gaussian noise (AWGN) and multipath-fading environments. The basic idea lies in suppressing MAI in received signals by generating an adaptive vector whose determination takes into account all signal replicas. Each replica of the user of interest is delayed and time aligned before performing a maximal ratio combining. Hence, an adaptive sequence is obtained so that it is orthogonal to this precombined signal. This makes the detector more robust against near–far effects and mitigates mismatch drawbacks. Moreover, in order to counteract the negative effect of the time-varying characteristics of the transmission channel a suitable window reprocessing algorithm [20], [28] is used, so that a notable performance enhancement with a low increase in the implementation complexity is achieved. In particular, the reprocessing technique expounded in this paper is very suitable in the so-called fast fading vehicular channels. Because of its inherent low complexity, the PBA-MUD is of particular interest in reducing MAI effects at the mobile receiving end, taking also into account the interference contributions due to the uncoordinated transmissions in adjacent cells. However, it is important to point out that this may be also effective in applications at the base station receiving end.

The organization of this paper is as follows. In Section II, the system model is described. Section III gives a brief description of the blind detector proposed in [1]. Section IV deals with an extension of the standard blind detector [1] to multipath fading environment and, then, the precombining blind adaptive (PBA) detector is presented. Section V describes the reprocessing window algorithm. Numerical results are reported in Section VI.

II. System Model

Under the assumption of K asynchronous CDMA users sharing the same band in multipath fading channels, the equivalent baseband received signal $y(t)$ can be represented as

$$y(t) = \sum_{i=1}^{L} \sum_{m=-M}^{M} \sum_{k=1}^{K} a_{k,i}^{(m)} w_k b_k^{(m)} \cdot s_k\left(t - mT - \tau_k - \tau_{k,i}^{(m)}\right) + n(t) \quad (1)$$

where

L	number of resolvable paths;
$2M+1$	number of transmitted symbols;
$n(t)$	white Gaussian noise with double side power spectral density $N_o/2$;
T	symbol interval;
w_k	amplitude of the kth user;
τ_k	time delay of the kth user;
$b_k^{(m)}$	mth bit of kth transmission: these are independent identically distributed (i.i.d.) random values in $\{-1, 1\}$ with equal probability 0.5;
$a_{k,i}^{(m)}$ and $\tau_{k,i}^{(m)}$	respectively, the channel coefficient and delay characterizing the ith path of the kth user.

It is worth stressing that, for the sake of simplicity, the time dependency of parameters $a_{k,i}^{(m)}$ and $\tau_{k,i}^{(m)}$ was dropped. Moreover,

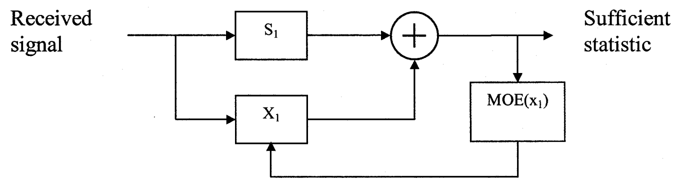

Fig. 1. Blind adaptive multiuser detector basic scheme.

it was supposed that $\tau_{k,j}^{(m)} = \tau_{k,i}$ are perfectly known according to the specifications in [5].

Channel coefficients $a_{k,i}^{(m)}$ are defined as

$$a_{k,i}^{(m)} = A_{k,i}^{(m)} \cdot e^{j\phi_{k,i}^{(m)}} \quad (2)$$

where $A_{k,i}^{(m)}$ are i.i.d. Rayleigh random values and $\phi_{k,i}^{(m)}$ are i.i.d. uniform random values in $[0, 2\pi)$.

User k signature waveform $s_k(t)$ is defined, upon symbol interval, as in the following:

$$s_k(t) = \sum_{n=1}^{N} c_k(n) u(t - nT_c) \quad (3)$$

where $N = T/T_c$ is the processing gain, T_c the chip interval, $c_k(n) \in \{-1, +1\}$ the nth chip of the kth spreading code, and $u(t)$ the chip pulse function.[3] Assuming that the user of interest is the first, the associated bit sequence $\{b_1^{(m)}\}$ has to be demodulated only by means of the signature waveform and timing. No hypothesis is made about interfering users amplitude, timing, and phase offset.

III. Blind Adaptive Multiuser Detector (BA-MUD)

The well-known BA-MUD [1] is based on the minimization of average output energy subject to a constraint. Since this constraint freezes the contribution of the desired vector to the output, the receiver can only suppress the sum of the noise and interference energies, that is the same quantity minimized by MMSE receivers.[4] The practical implementation of this detector is achieved by means of two orthogonal filters (Fig. 1): one of them is matched to the signature waveform of the desired user, while the other is an adaptive structure that is used to limit the MAI. By considering the impulse response filter coefficients as vectors whose length is equal to the processing gain,[5] a vector $\boldsymbol{x}_1$ has to be added to the desired vector $\boldsymbol{s}_1$ so that the sum vector $\boldsymbol{c}_1 = \boldsymbol{s}_1 + \boldsymbol{x}_1$ is orthogonal step by step to the subspace S_I spanned by the interfering user vectors [Fig. 2(a)]. If we assume that vector $\boldsymbol{x}_1$ is orthogonal to the signature vector $\boldsymbol{s}_1$, the energy of the impulse response $\boldsymbol{c}_1$ of the composed filter is

$$\|\mathbf{c}_1\|^2 = \|\mathbf{s}_1\|^2 + \|\mathbf{x}_1\|^2 = 1 + \chi \quad (4)$$

where χ is the surplus energy of the composed filter due to the adaptive filter. Without loss of generality, all the spreading code energies have been assumed as unitary.

As is shown in Fig. 2(a), the BA-MUD needs a minimum surplus energy $\chi = \chi_I$ in order to have the vector $\boldsymbol{s}_1 + \boldsymbol{x}_1$ orthogonal to the interfering space S_I. In real communication

[3] For simplicity, a rectangular pulse shaping is considered herein.

[4] It is important to stress that this goal is achieved without using a training sequence.

[5] This assumes a chip waveform matched filter prior to MF and blind adaptive filters.

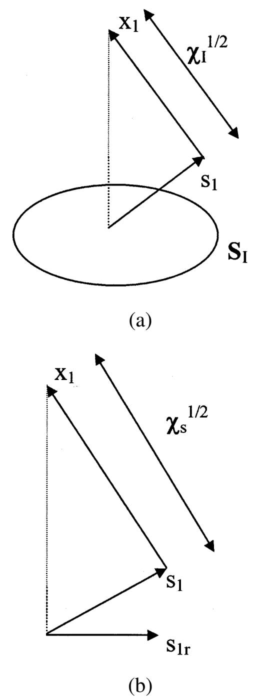

Fig. 2. Surplus energy χ of adaptive filter x_1 that gives a total interference cancellation. (b) Surplus energy χ of adaptive filter x_1 that gives a total desired signal cancellation.

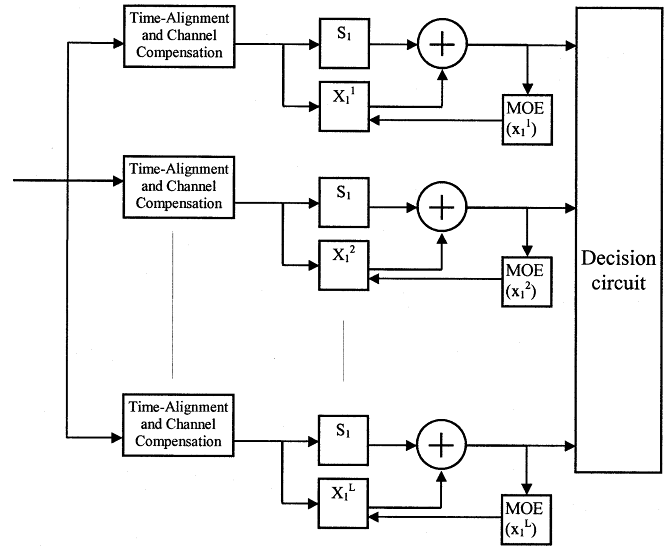

Fig. 3. A possible scheme for a first extension of the blind adaptive MOE detector (BA-MUD) of [1] to a multipath fading environment. This structure was named RAKE blind adaptive multiuser detector (RBA-MUD).

systems, the detector does not exactly know the spreading waveform of interest because of signal distortion introduced by the wireless-fading channel. In fact, it is not possible to assume the original spreading waveform knowledge for the signal despreading since the actual received waveform may include additional multipath components or other channel distortions. This phenomenon is known as a mismatch and can prevent the adaptive blind algorithm from correct convergence. Mismatch could cause the desired signal cancellation if the surplus energy increases uncontrollably; hence, χ has to lie below a specified threshold value χ_s [Fig. 2(b)]. Moreover, it is straightforward to note that the following condition must be fulfilled:

$$\chi_1 \ll \chi_s \tag{5}$$

otherwise, the detector is not able to limit MAI without cancellation of the informative signal.

If we denote with $\langle \bullet, \bullet \rangle$ the inner product, i.e., $\langle p, q \rangle = \int_{mT}^{(m+1)T} p(t)q(t)dt$ in the mth observation interval, the minimum output energy detector aims at determining the vector $\boldsymbol{x}_1$ that minimizes the strictly convex cost function

$$\mathrm{MOE}(\mathbf{x}_1) = E[(\langle \mathbf{y}, \mathbf{s}_1 + \mathbf{x}_1 \rangle)^2] \tag{6}$$

and satisfies the constraint

or equivalently

$$\langle \mathbf{s}_1, \mathbf{x}_1 \rangle = 0 \tag{7}$$

$$\langle \mathbf{c}_1, \mathbf{s}_1 \rangle = 1. \tag{8}$$

By the application of the stochastic gradient algorithm in order to find the minimum point for the output energy, the adaptation rule results in [1]

$$\begin{aligned}\mathbf{x}_1(i) = {} & [1 - \mu\nu_1]\,\mathbf{x}_1(i-1) - \mu \\ & \cdot \langle \mathbf{y}(i), \mathbf{s}_1 + \mathbf{x}_1(i-1) \rangle \,[\mathbf{y}(i) - \langle \mathbf{y}(i), \mathbf{s}_1 \rangle \mathbf{s}_1]\end{aligned} \tag{9}$$

where ν_1 is the Lagrangian multiplier that assures the constraint on surplus energy $\|\boldsymbol{x}_1\|^2$. This algorithm converges to the MMSE solution regardless of initial condition if step μ decrease as $1/i$, where index i represents the iteration number [3]. In the case of synchronous users, the optimum MOE solution was derived in [1] and it is equal to

$$c_1 = \nu_2 \left(\mathbf{A} + \gamma \cdot \mathbf{I}_N\right)^{-1} \mathbf{s}_1 \tag{10}$$

where

$$\mathbf{A} = \sum_{k=1}^{K} A_k^2 \mathbf{s}_k \mathbf{s}_k^T \tag{11}$$

$$\gamma = \nu_1 + \sigma^2 \tag{12}$$

$$\nu_2 = \left[\mathbf{s}_1^T \left(\mathbf{A} + \gamma \cdot \mathbf{I}_N\right)^{-1} \mathbf{s}_1\right]^{-1} \tag{13}$$

and ν_2 is the Lagrangian multiplier to assure $\langle \boldsymbol{x}_1, \boldsymbol{s}_1 \rangle = 0$.

IV. Precombining Blind Adaptive Multiuser Detector

The BA-MUD [1] was proved to be effective in static environments, while its performance rapidly degrades in the case of a time-varying environment. This section proposes a modified BA-MUD in order to relax this drawback. We focus on a time-varying multipath fading channel with amplitudes and phases with Rayleigh and uniform statistics, respectively. In particular, we have adopted a channel model consistent with the GSM specifications [5] for a suburban environment. In this case a possible approach is to insert a single BA-MUD in each finger of a RAKE structure (Fig. 3) in order to counteract the MAI effect in each desired signal significant path [25]–[27]. This detector was called "RAKE" BA-MUD (RBA-MUD).

In this scheme, each detector has its own independent MOE convergence process matched to a specific replica of the desired signal, by considering other informative replicas as interference to be eliminated. The main shortcomings of this scheme are the following:

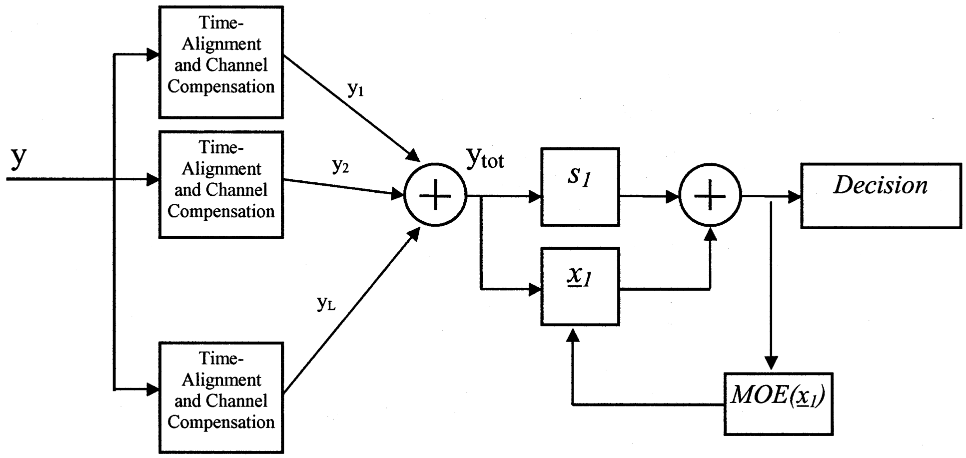

Fig. 4. PBA-MUD.

1) if only one of the information replicas is received during a deep fade situation, the symbol transmitted cannot be successfully reconstructed;
2) the larger the mismatch between locally generated spreading waveform and the received waveform, the smaller the surplus energy χ_s which gives the desired signal cancellation, with the result that the condition $\chi_I \ll \chi_s$ may not be obeyed;
3) each finger has its own independent adaptive vector $x_1^l (l = 1 \cdots L)$, so that one of these may not reach the stability region with impairments in the replica combining process.

All these problems give rise to a loss of performance. In the proposed PBA multiuser detector (PBA-MUD) the vector x_1 is forced to be orthogonal not to the nominal spreading vector s_1, but to the space spanned by its path directions in order to cope with the problem caused by mismatch phenomena. Therefore, the vector x_1 is forced to be orthogonal to the space spanned by all replicas carrying the desired information. Since the received informative signal vector must lie in this space, the risk of cancellation of the desired signal is avoided. Hence, surplus energy constraint could be neglected. In practice, a surplus energy constraint must be maintained in multipath fading channels because of high variability of channel characteristics and nonexact estimation of channel parameters.

In order to face fading and stability issues, a unique adaptive vector $\underline{x}_1$ is generated, aiming to suppress MAI from all precombined replicas of the desired signal at the same time, instead of a set of L independent adaptive vectors $\{x_1^l\}_{l=1 \cdots L}$ (Fig. 4). In this way, a single receiver has been implemented after the RAKE recombination structure, thus yielding a remarkable complexity reduction.

Thanks to the precombining approach, a convergence situation is more easily obtained for the whole received signal of the user of interest. In particular, the weaker received replicas, e.g., those corresponding to deep fading propagation, are considered as a part of the overall signal and not as a single informative signal, thus yielding a more reliable decision variable and a more robust convergence procedure.

The received continuous-time signal is assumed to be sampled at the rate N/T and to be passed through a multipath combiner[6] before approaching the detection filter (Fig. 4). Hence, the vector at the input of the composed filter $\boldsymbol{s}_1 + \underline{\boldsymbol{x}}_1$, in a single observation interval, is

$$\begin{aligned}\mathbf{y}_{\rm tot}^{(m)} &= \sum_{j=1}^{L} \hat{a}_{1,j}^{*(m)} \mathbf{y}_j^{(m)} \\ &= \sum_{j=1}^{L}\sum_{i=1}^{L}\sum_{k=1}^{K} a_{k,i}^{(d)} \hat{a}_{1,i}^{*(m)} w_k b_k^{(d)} \mathbf{s}_{k,i-j}^{(d)} + \mathbf{n}^{(m)} \\ &\text{for} \quad d = m-1, m, m+1 \end{aligned} \tag{14}$$

where the vector $\boldsymbol{n}$ is the AWGN vector, the coefficients $\hat{a}_{1,i}^{*(m)}$ are the estimated channel coefficients associated with each received replica of the user of interest, and $\mathbf{s}_{k,i-j}^{(d)} = s_k^{(d)}(t - mT - \tau_k - \tau_{k,i} + \tau_{k,j})\big|_{t=N/T}$ represents the part of the ith replica of kth spreading waveform, after its time alignment to jth replica[7] (as in a RAKE structure), that modulates the dth bit falling in the decision interval $[mT, (m+1)T]$. For simplicity we assume, without loss of generality, that $\tau_1 = 0$.The detector output can be written as

$$\begin{aligned}&\langle \mathbf{y}_{\rm tot}, \mathbf{s}_1 + \underline{\mathbf{x}}_1 \rangle = \\ &\underbrace{w_1 b_1^{(m)} \sum_{i=1}^{L} a_{1,i}^{(m)} \hat{a}_{1,i}^{*(m)} \langle \mathbf{s}_1, \mathbf{s}_1 + \underline{\mathbf{x}}_1 \rangle}_{\rm desired} \\ &+ \underbrace{\sum_{d=m-1}^{m+1} \sum_{j=1}^{L} \sum_{\substack{i=1 \\ i \neq j}}^{L} a_{1,i}^{(d)} \hat{a}_{1,j}^{*(d)} w_1 b_1^{(d)} \left\langle \mathbf{s}_{1,i-j}^{(d)}, \mathbf{s}_1 + \underline{\mathbf{x}}_1 \right\rangle}_{\rm self-interference} \\ &+ \underbrace{\sum_{d=m-1}^{m+1} \sum_{j=1}^{L} \sum_{k=2}^{K} \sum_{i=1}^{L} a_{k,i}^{(d)} \hat{a}_{1,i}^{*(m)} w_k b_k^{(d)} \left\langle \mathbf{s}_{k,i-j}^{(d)}, \mathbf{s}_1 + \underline{\mathbf{x}}_1 \right\rangle}_{\rm MAI} + \mathbf{n}'. \end{aligned} \tag{15}$$

The first term is the desired decision variable, the second term is the self-interference due to the disarranged replicas of the

[6]A Maximal Ratio Combiner is supposed herein.

[7]In practice, the anticipated-time $\tau_{k,j}$ should be replaced by $\tau_T - \tau_{k,j}$ because only time-delays are admitted by real devices. In that case, the decision time is delayed of one bit, i.e., at bit time n the receiver decides on bit $n-1$.

desired signal in the mth symbol interval, the third term is the MAI, and the last term represents the noise contribution at the detector output.

A modified steepest descent stochastic gradient algorithm is proposed herein to update $\underline{\boldsymbol{x}}_1$

$$\underline{\mathbf{x}}_1(i) = \underline{\mathbf{x}}_1(i-1) - \mu\langle \mathbf{y}_{\mathrm{tot}}(i), \mathbf{s}_1 + \underline{\mathbf{x}}_1(i-1)\rangle \cdot[\mathbf{y}_{\mathrm{tot}}(i) - \langle \mathbf{y}_{\mathrm{tot}}(i), \tilde{\mathbf{s}}_{1\mathrm{tot}}\rangle \tilde{\mathbf{s}}_{1\mathrm{tot}}] \quad (16)$$

where

$$\tilde{\mathbf{s}}_{1\mathrm{tot}} = \frac{\mathbf{s}_{1\mathrm{tot}}}{\|\mathbf{s}_{1\mathrm{tot}}\|} \quad (16a)$$

and

$$\mathbf{s}_{1\mathrm{tot}} = \sum_{i=1}^{L}\sum_{j=1}^{L} \hat{a}_{1,i}^{*}\mathbf{s}_{1,i-j}^{(d)}. \quad (16b)$$

As can be seen in (15), the blind filtering is performed with the nominal spreading sequence of the desired user $\boldsymbol{s}_1$, but the updating algorithm (16) of the adaptive part of the blind filter $\underline{\boldsymbol{x}}_1$ was modified by forcing it to be orthogonal to the desired signature "combined" vector $\boldsymbol{s}_{1\mathrm{tot}}$. This modification assures that the vector $\underline{\boldsymbol{x}}_1$ was orthogonal to the desired user spreading waveform as well as to each replica created by the channel, thus limiting the negative effects of the self-interference [the second term in (15)] on the decision variable.[8].

If we denote Γ_d as the subspace spanned by the basis vectors associated with the orthonormal signals constructed by means of the Gram-Schmidt procedure (see Appendix A), by starting from the significant paths of the desired signal after multipath recombination, $\underline{\boldsymbol{x}}_1$ is constrained to be orthogonal to Γ_d. Let $\mathbf{P}_d \in \Re^{N\times N}$ be the projection matrix onto the subspace orthogonal to Γ_d, the component of $\boldsymbol{y}$ orthogonal to Γ_d can be taken into account by simply replacing $\boldsymbol{y}$ with $\mathbf{P}_d \cdot \mathbf{y}$ (see (A1) in the Appendix). Analytically, this modification implies that the Lagrangian multiplier ν_2 in (13) now must assure condition $\langle \tilde{\mathbf{s}}_{l\mathrm{tot}}, \underline{\mathbf{x}}_1\rangle = 0$ (see Appendix B).

As can be seen in (16), there is a unique adaptive sequence $\underline{\boldsymbol{x}}_1$ for all the desired signal replicas which affords the minimum value of the total output energy function. As a consequence, the precombined approach allows to obtain the convergence for the whole received signal of the user of interest: in particular, weaker received replicas, e.g., the replicas corresponding to deep fading propagation, are considered as a part of the overall signal and not as an individual informative stream, thus yielding a more reliable decision variable and a more robust convergence procedure. Moreover, precombining of different replicas allows the derivation of one adaptive sequence for multipath signals with a low complexity even in real channels.

It was observed that using the PBA-MUD scheme, the final decision variable is completely impaired when two/three replicas (not just one) of the received signal of interest are received during a deep fade situation. Moreover, due to the orthogonal imposition between $\underline{\boldsymbol{x}}_1$ and $\tilde{\mathbf{s}}_{l\mathrm{tot}}$, i.e., constraint $\underline{\boldsymbol{x}}_1 \perp \Gamma_d$, the bad influence of the self-interference terms in (15) on symbol decision can be limited, which is caused by the partial autocorrelations of the signature waveform of interest.

The timing information on significant paths has been assumed to be perfectly retrieved. If a timing estimation error occurs, the detector is aimed at forming a vector $\mathbf{c}_1 = \mathbf{s}_1 + \mathbf{x}_1$ whose direction is far away from that of the desired vector as well as from that of the interfering vector. Moreover, in a practical scenario, each path of the desired user signal is chip asynchronous and may lead to a signal loss if the filter output is sampled to the chip rate. In this case, an over-sampling technique should be employed. For simplicity, in our simulations all the paths are supposed to be chip synchronous, i.e., we assume that paths delays are an integer multiple of the chip time T_c.

Although it is known [1] that a constant step, which was chosen by taking into account the maximum eigenvalue of the output channel correlation matrix (Appendix C), can assure convergence and stability, we are also interested, in actual environments, in facing the MOE minimum value displacements. Hence, step μ was chosen as [2]

$$\mu = \frac{0.1}{\overline{E}_b \cdot f(i)} \quad (17)$$

where i is the iteration number and $\overline{E}_b$ is the mean output power of the matched filter calculated upon 10-bit epochs interval

$$\bar{E}_b = \frac{1}{10T}\sum_{n=1}^{10}\left(\int_{(n-1)T}^{nT} y_{\mathrm{tot}}(t)s_1(t-nT)dt\right). \quad (17a)$$

This value is used to calculate step μ by (17) for the next ten bit intervals and so on. Index $f(i)$ increases monotonically until it reaches $f_{\max}$, then it restarts from $f_{\max}/2$ and so on[9]

$$f(i) = \left\{\begin{array}{lll} 1, & i=0 & \\ i \bmod f_M, & 1 < i < \frac{f_M}{2} & \\ i \bmod f_M, & k\cdot\frac{f_M}{2} \le i < k\cdot f_M & k=1,2,\ldots \\ f_M, & i = f_M & \end{array}\right\}. \quad (17b)$$

The updating rule of the algorithm (16) starts from the initial condition $\underline{\boldsymbol{x}}_1 = 0$, then it let $\underline{\boldsymbol{x}}_1$ energy grow until threshold χ_I is reached and energy constraint $\|\underline{\boldsymbol{x}}_1\|^2 \le \chi_I$ is applied.

Threshold χ_I is estimated as [1]

$$\chi_I = \frac{K-1}{N-(K-1)} \quad (18)$$

if the users are synchronous and

$$\chi_I = \frac{2(K-1)}{N-2(K-1)} \quad (18a)$$

if the users are asynchronous. The term K is the number of active users in the cell and N is the processing gain. This threshold is derived by taking into account relation between χ_I and the near–far resistance η [4]

$$\chi_I = \frac{1}{\eta} - 1. \quad (19)$$

[8]It could be objected that the "optimum" filtering is achieved by using $\boldsymbol{s}_{1\mathrm{tot}}$ for both the "constant" part as well as for updating the adaptive part of the blind filter. The problem is that $\boldsymbol{s}_{1\mathrm{tot}}$ is not constant, but it depends on the instantaneous values of the channel coefficients and path timings bit-by-bit. In such a case, it has not been proven yet that it is possible to divide the blind filter in the canonical form (Fig. 1). The proposed scheme is, thus, a tradeoff between the receiver performance and its practical implementation.

[9]Step μ must be small enough to assure algorithm convergence [3], but not so large to prevent from an efficient MOE point tracking in time-varying environments.

An estimation of the mean value of η is

$$E[\eta] = 1 - \frac{E[d_I]}{N} \tag{20}$$

where d_I represents the (random) value of the subspace dimension of the interfering users. Parameter $E[\eta]$ may be limited as

$$1 - \frac{K-1}{N} \leq E[\eta] \leq \left(1 - \frac{K-1}{N}\right) f(K-1) \tag{21}$$

where $f(K-1) = \prod_{i=1}^{K-1}\left[1 - 2^{-(N-i)}\right]$. The estimation of χ_I is obtained by selecting the lower bound in (21) to avoid the desired signal cancellation and substituting it in (19).

In order to adapt this threshold to a more realistic environment, such as multipath fading channels, its value was set to

$$\chi_I = \frac{\alpha(K-1)\cdot L}{N - \alpha(K-1)\cdot L} \tag{22}$$

where K is the number of active users, L is the number of paths, and α is a parameter experimentally optimized for each contest. The optimum value of α increases with the number of interfering users or the power level of the received signals. Hence, we can derive the optimum value of χ_I as

$$\chi_I^{\text{opt}} = \frac{\alpha^{\text{opt}}(K-1)\cdot L}{N - \alpha^{\text{opt}}(K-1)\cdot L}. \tag{23}$$

This represents the comparison term on $\underline{\boldsymbol{x}}_1$ energy to assure energy constraint at each step of gradient algorithm, i.e., if $\|\underline{\boldsymbol{x}}_1\|^2 < \chi_{\text{Iopt}}$, adaptive algorithm is carried on, otherwise the detector imposes a new $\underline{\boldsymbol{x}}_1$ equal to

$$\underline{\mathbf{x}}_1^{new} = \frac{\underline{\mathbf{x}}_1^{old}}{\left\|\underline{\mathbf{x}}_1^{old}\right\|}\cdot\sqrt{\chi_I^{\text{opt}}}. \tag{24}$$

The initial condition value strongly influences the convergence of the stochastic gradient algorithm (Appendix C). This algorithm guarantees a large convergence region, but not a good convergence speed. Due to the fast variation of mobile channel characteristics, the minimum output energy point changes its position with time so that the steepest descent algorithm is not able to track it. In order to relax this drawback, we propose the processing algorithm described in Section V.

V. Reprocessing Window Blind Adaptive Algorithm

A window reprocessing steepest descent strategy is proposed herein to track the minimum output energy point in fast fading environments. The reprocessing window blind algorithm was previously introduced in [20] and [28] for a BA-MUD receiver. In our case, the information data frame is divided in W length subframes; then, each subframe is buffered into the detector and processed more than once (Fig. 5). Each subframe is stored sequentially in different buffers in order not to loose information.

In this case, the nth iteration has the advantage to start from vector $\underline{\boldsymbol{x}}_1$ calculated at previous iteration, so that the new initial condition is close to the convergence region and allows the blind detector to better follow MOE displacements.

The adaptive algorithm procedure at ith iteration [Fig. 5(a)] can be written as

$$\begin{aligned}\underline{\mathbf{x}}_1^{(l+1,n)}(i) =& \underline{\mathbf{x}}_1^{(l,n)}(i) - \mu\left\langle \mathbf{y}_{\text{tot}}^{(l,n)}(i), \mathbf{s}_1 + \underline{\mathbf{x}}_1^{(l,n)}(i)\right\rangle \\ &\cdot\left[\mathbf{y}_{\text{tot}}^{(l,n)}(i) - < \mathbf{y}_{\text{tot}}^{(l,n)}(i), \tilde{\mathbf{s}}_{1\text{tot}}\right]\tilde{\mathbf{s}}_{1\text{tot}} \\ l =& 1\ldots(W-1) \quad \forall i\ \forall n\end{aligned} \tag{25}$$

where l represents the lth bit in the nth subframe of length W. The last bit of iteration i is used as starting condition to calculate the first bit on $(i+1)$th iteration [Fig. 5(b)]

$$\begin{aligned}\underline{\mathbf{x}}_1^{(1,n)}(i+1) =& \underline{\mathbf{x}}_1^{(W,n)}(i) - \mu\left\langle \mathbf{y}_{\text{tot}}^{(W,n)}(i), \mathbf{s}_1 + \underline{\mathbf{x}}_1^{(W,n)}(i)\right\rangle \\ &\cdot\left[\mathbf{y}_{\text{tot}}^{(W,n)}(i) - < \mathbf{y}_{\text{tot}}^{(W,n)}(i), \tilde{\mathbf{s}}_{1\text{tot}}\right]\tilde{\mathbf{s}}_{1\text{tot}} \\ i =& 1\ldots(I_{\max}-1) \quad \forall n\end{aligned} \tag{26}$$

where $I_{\max}$ is the optimum value of the reiterations number in each window.

The first iteration on the first bit in subframe $n+1$ uses the last bit of previous window [Fig. 5(c)]

$$\begin{aligned}\underline{\mathbf{x}}_1^{(1,n+1)}(1) =& \underline{\mathbf{x}}_1^{(W,n)}(1) - \mu\left\langle \mathbf{y}_{\text{tot}}^{(W,n)}(\mathbf{1}), \mathbf{s}_1 + \underline{\mathbf{x}}_1^{(W,n)}(1)\right\rangle \\ &\cdot\left[\mathbf{y}_{\text{tot}}^{(W,n)}(1) - < \mathbf{y}_{\text{tot}}^{(W,n)}(1), \tilde{\mathbf{s}}_{1\text{tot}}\right] \\ &\cdot\tilde{\mathbf{s}}_{1\text{tot}}\forall n.\end{aligned} \tag{27}$$

This yields that the trajectory of the steepest descent procedure is preserved.

The window length must be chosen as

$$W < \frac{\Delta t_c}{T} \tag{28}$$

where $\Delta t_c/T$ is the coherence time of the channel and signaling interval ratio. At the same time, W should not be too large in order to efficiently pursuit MOE point dislocations caused by the nonstationary environment.

The optimum value of the reiterations $I_{\max}$ has to be empirically determined as a trade-off between two different sides. The number of reiterations has to be high enough to assure the convergence of the algorithm and to face the impairments caused by time-varying channel features. On the contrary, $I_{\max}$ cannot be indefinitely high in order to avoid the introduction of correlation properties among the bits. In that case, the equivalence between MMSE and MOE detectors would not be verified and a performance degradation would be introduced.

Although the advanced blind algorithm obtains a significant increase in performance in the uplink channel, where each user undergoes independent fading, a high number of reiterations per subframe is needed, thus yielding a bit decision delay near the present implementation limit. However, precombining reprocessing window BA-MUD (PWBA-MUD) has its main application in mobile terminal and in the downlink where only few reiterations are requested.

Although the proposed reprocessing window algorithm yields a more robust detection in rapid fading channels, this benefit is counterbalanced by a computational complexity increase. As to PWBA-MUD, it can be noted that, in the same hypothesis, the following operations must be performed for each bit

$$\frac{5NW+2N}{W}\cdot I_{\text{MAX}} \cong 5\cdot I_{\text{MAX}}\cdot N \quad \text{additions} \tag{29}$$

$$\frac{6NW+2N}{W}\cdot I_{\text{MAX}} \cong 6\cdot I_{\text{MAX}}\cdot N \quad \text{multiplications.} \tag{30}$$

The computational load is nearly equal to BA-MUD complexity times the number of iteration upon the buffered stream so that an adequate processing speed has to be provided. Even if the computational complexity increase is apparent, it is worth stressing that the implementation complexity is not related to the number

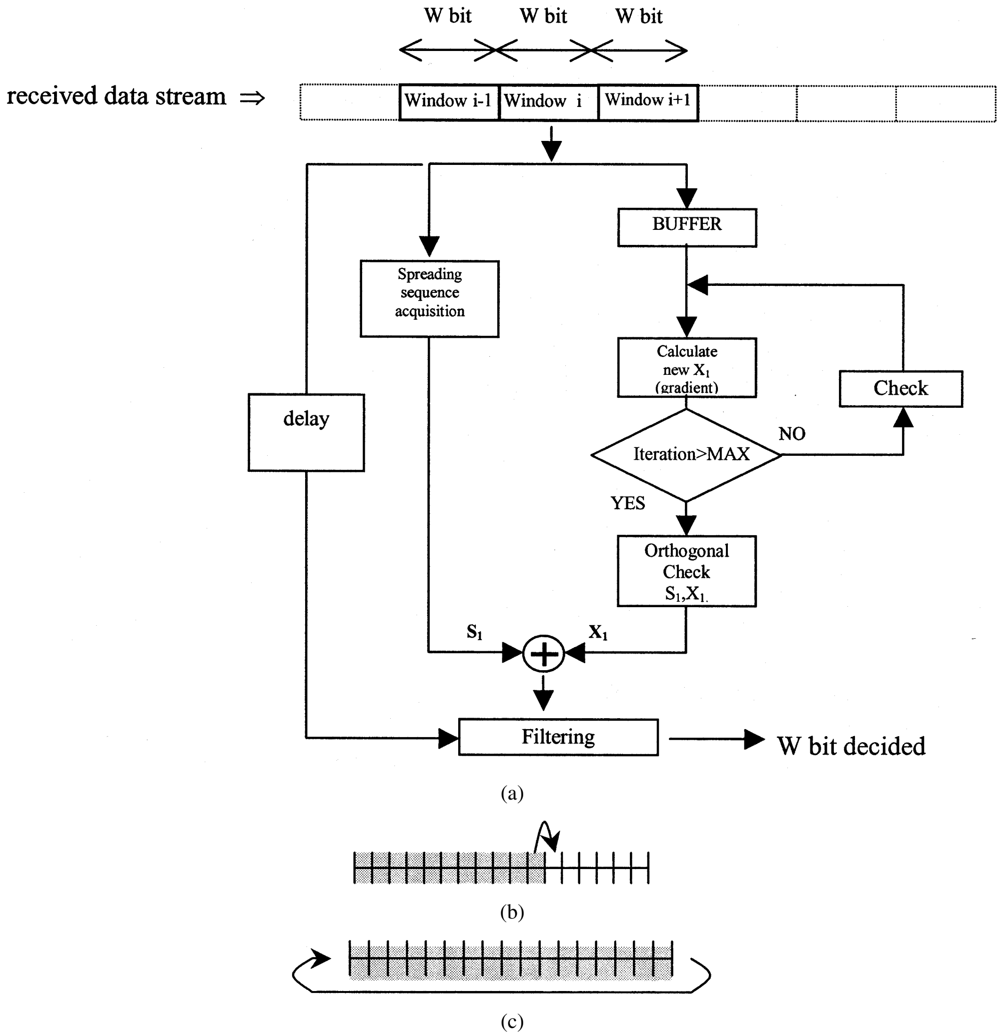

Fig. 5. Flow chart of the advanced blind adaptive algorithm. (a) The steepest descent algorithm is run through the stored bits in each subframe. (b) The adaptive algorithm is run more times in each subframes. (c) When all the reiterations have been performed in one subframe, those bits can be decided and the following subframe is taken into account by the reprocessing procedure.

of active users. Conversely, this linearly grows with the number of active users in the case of classical MUD methods.

VI. Numerical Results

We have focused here on both up and down links in wireless terrestrial and satellite suburban channels according to specifications [5] and [6]. A BPSK transmission scheme was considered with the following main parameters.

- Symbol rate equal to 31.496 Ksymb/s.
- Gold spreading sequences of length 127 (therefore, the processing gain is $N = 127$).
- Number of channel paths (L): six for the terrestrial and three for the satellite channels.
- Channel bandwidth equal to 4 MHz.
- Rayleigh classical Doppler spectrum is assumed with Doppler spread $B_d = 100$ Hz for the terrestrial scenario

$$S(f) = \frac{A}{\sqrt{1-\left(\frac{f}{B_d}\right)^2}} \quad \text{for } |f| \leq B_d. \tag{31}$$

- Rice (relative to direct path)—Rayleigh (relative to echoes) Doppler spectrum with Doppler spread $B_d =$ 100 Hz and $f_{\mathrm{dsat}} = 40$ Hz is assumed for the LEO satellite scenario (it is worth noting that an automatic frequency compensator is supposed which performs the compensation of the Doppler shift due to the satellite deterministic movement)

$$S_{\mathrm{Rice}}(f) = \frac{C'}{\sqrt{1-\left(\frac{f-f_{\mathrm{dsat}}}{B_d}\right)^2}} + \delta(f - f_{\mathrm{dsat}}) \tag{32}$$

$$S_{\mathrm{Rayleigh}}(f) = \frac{C}{\sqrt{1-\left(\frac{f-f_{\mathrm{dsat}}}{B_d}\right)^2}}. \tag{33}$$

- Length of reprocessing window (W): 40 bits.
- Number of reiterations per window ($I_{\max}$): 25 in the uplink; 2 in the downlink channels.
- Perfect tracking of the phase and delay of the significant paths of the desired signal.

The PBA-MUD performance is compared, in terms of bit error probability (P_e), with conventional RAKE detector (CRD) and RAKE version of BA-MUD (RBA-MUD), with a different MAI level, i.e., a different number of interfering users and a different received power ratios between interfering signals and

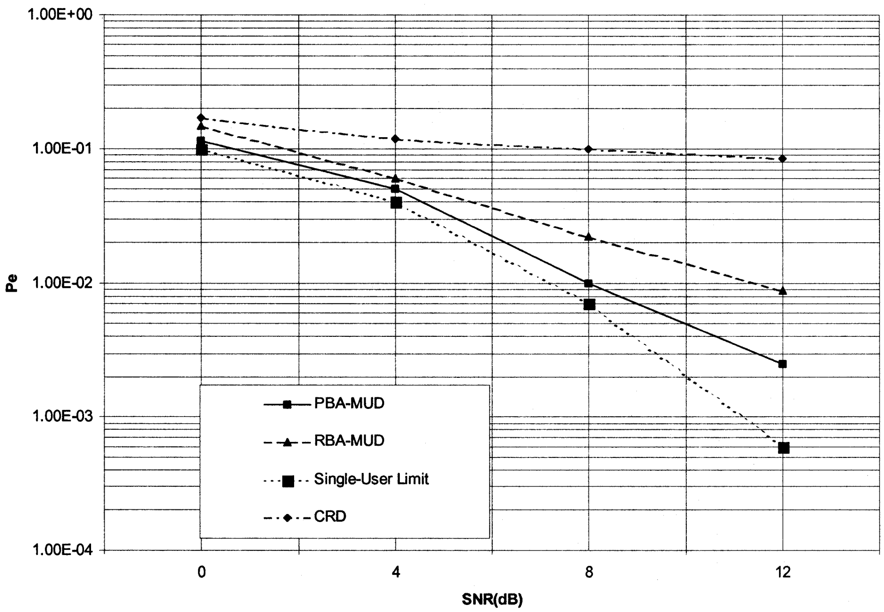

Fig. 6. Error probability comparison between PBA-MUD, RBA-MUD, CRD and single user bound in the uplink GSM suburban channel (see Table I for parameters) with four 10 dB stronger asynchronous interfering users.

TABLE I
MAIN PARAMETERS OF THE GSM SUBURBAN CHANNEL MODEL

Number of path	Attenuation (dB)	Delay (μsec)
1	-3.0	0
2	0	0.2
3	-2.0	0.5
4	-6.0	1.6
5	-8.0	2.3
6	-10.0	5.0

the desired signal (assuming that the interference-to-signal-ratio (ISR) is equal to 0, 10, or 20 dB, this means that the interfering signals are received with a power level 0, 10, or 20 dB higher than the desired signal). Moreover, in order to take into account, in the downlink case the adjacent cells interference scenario, an equivalent asynchronous interfering signal with received power level 15 dB[10] higher than that of the desired user signal[11] is introduced. For each case under examination, an optimization procedure is adopted to obtain the α_{opt} value that minimizes the probability of bit error [12].

It is worth stressing that the curves of the probability of error (P_e) of the blind receiver are calculated by considering also the errors coming from the training period before the blind algorithm convergence. Therefore, they have to be considered as a worst case.

Fig. 6 shows the better performance of the PBA-MUD with respect to the RBA-MUD (in particularly in uplink communications with bad near–far level (ISR=10 dB) and in downlink communications with a nonnegligible intercell interference level). Fig. 7 highlights that the performance of this detector is just lightly impaired as the number of interfering users increases, i.e., a P_e level is achieved which assures a good symbol demodulation. Fig. 8 shows that our detector exhibits a high performance independently of intercell interfering signal delay, while the CRD has a lower performance strongly dependent on the received intercell interfering signal delay. The same is true for the uplink communications. This demonstrates that the detector performance is independent of the delays oif the other users and, hence, it is effective even in the case of asynchronous users. Since the mobile terminal cannot know all spreading codes of active users, the PBA-MUD appears to be an attractive solution in terms of MAI mitigation and complexity because it needs only one filter with respect to the L filters needed by the RBA-MUD.

In Fig. 9, the performance of the reprocessing window algorithm for the precombining BA-MUD (PWBA-MUD) and the RAKE BA-MUD (RWBA-MUD) in terms of bit error rate as a function of the signal-to-noise ratio in the uplink suburban multipath fading channel is reported. The performance of the PBA-MUD, RBA-MUD and classical RAKE detector is also reported in the same figures for comparison purposes. All the blind receivers are just lightly impaired by the power level increase of the interfering users, i.e., they exhibit remarkable near–far resistance, but it is still evident that the PBA-MUD has a better performance than the RBA-MUD. Moreover, the reprocessing window technique coupled with the proposed precombining scheme is able to gain 3 dB in terms of performance compared to the PBA-MUD, thus allowing a significant

[10]This value is chosen to simulate transmission from base-station to mobiles near the edge of the cell (worst case of interference).

[11]Higher values of equivalent intercell interference signal imply a soft-handover procedure start.

[12]It is worth to stress that no other coding techniques are considered in simulations, e.g., no interleaving, no channel coding, and so on. In this case, the goal for the Pe level is normally fixed to 10^{-2}.

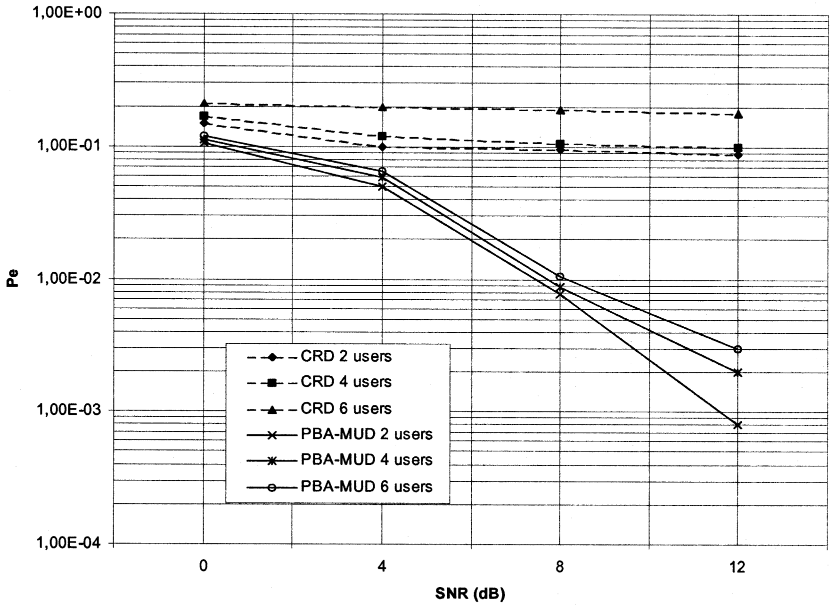

Fig. 7. Error probability comparison between PBA-MUD and CRD in the uplink GSM suburban channel with 10 dB stronger two-four-six asynchronous interfering users.

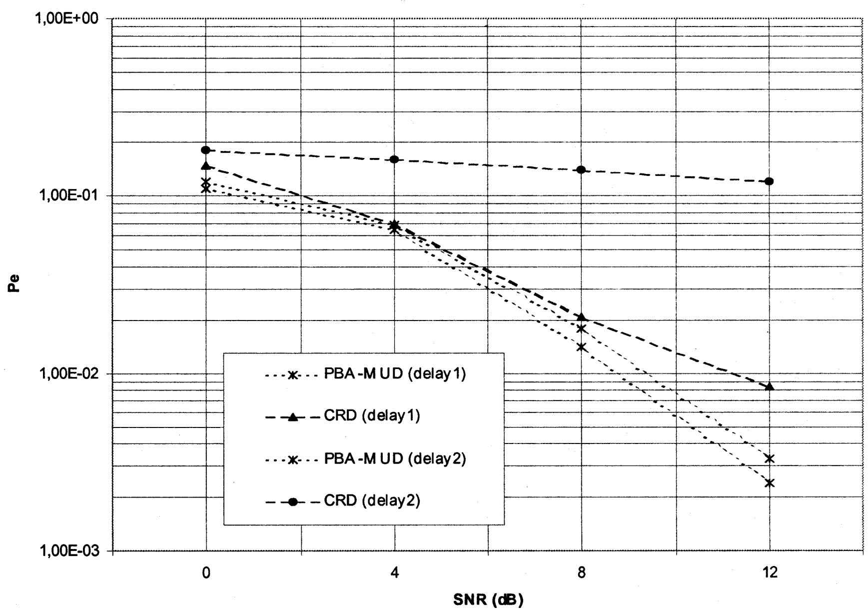

Fig. 8. Error probability comparison between PBA-MUD and CRD in the downlink GSM suburban channel with ten interfering users plus an intercell asynchronous interfering signal with different time delays (delay1 $>$ delay2).

improvement in CDMA wireless systems capacity. Even in the downlink connection the reprocessing window algorithm affords a performance improvement when the intercell interference is present (Fig. 10).

In Fig. 11 the performance of the above receivers are reported for the satellite LEO communication system scenario. The better performance of the proposed PBA-MUD is maintained with respect to the RBA-MUD, but in this case the reprocessing window technique does not yield an appreciable performance gain due to the "slower" variability of the satellite channel. Anyway, these results are of special interest for the implementation of the on-board demodulation method foreseen in the ESA report [12]. The performance of a single-user RAKE receiver (*lower bound*) is also reported in all these figures for comparison purposes.

VII. Conclusion

In this paper a blind adaptive multiuser detector for DS-CDMA wireless communication systems has been discussed. It has been demonstrated by means of computer simulations that this receiver is capable of mitigating the problems which affect the standard blind detector [1], in particular in the case of a time-varying environment. A blind

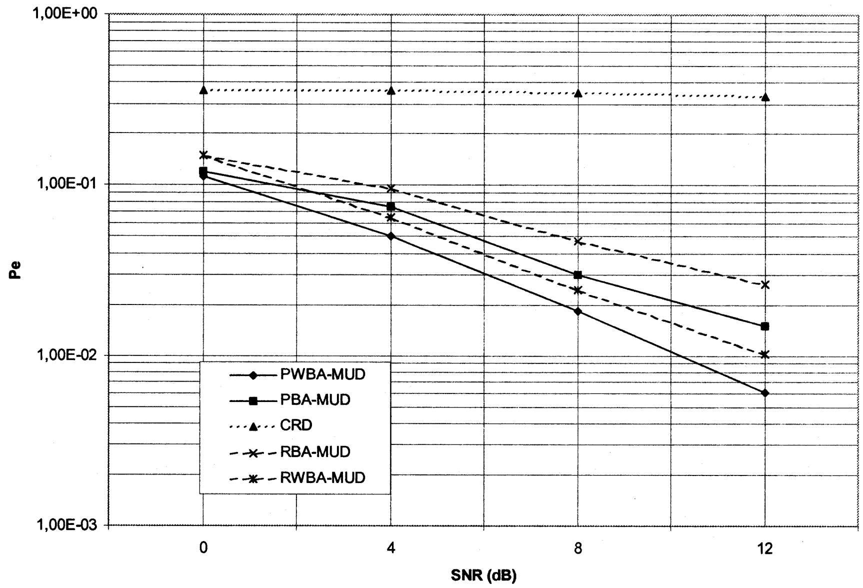

Fig. 9. Error probability comparison between PBA-MUD, PWBA-MUD, RBA-MUD, RWBA-MUD and CRD in the uplink GSM suburban channel with four 20 dB stronger asynchronous interfering users.

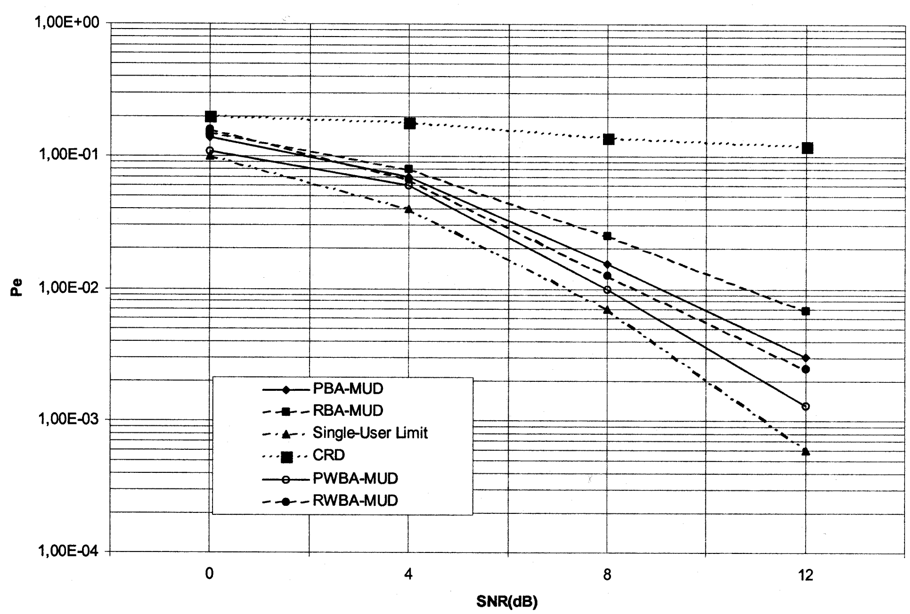

Fig. 10. Error probability comparison between PBA-MUD, PWBA-MUD, RBA-MUD, RWBA-MUD, CRD, and single-user bound in the downlink GSM suburban channel with ten interfering users plus an intercell asynchronous interfering signal.

algorithm based on a reprocessing window technique and on a projection constraint approach, was introduced in order to achieve a better near–far resistance and convergence rapidity in fast fading channels. The numerical results presented in this paper clearly demonstrates that such an approach outperforms different alternatives already published in the literature on the same subject.

Appendix A
Space Γ_d Generation

For the sake of simplicity, let us consider the case of two resolvable paths. The received vector of interest, in a single observation interval, is $\mathbf{r} = A_{1,1}\mathbf{s}_1 + A_{1,2}\mathbf{s}_{1,2}$ where we have supposed that first path delay is equal to zero. Thus, after RAKE combination, the received vector is equal to $\mathbf{r}_{\rm tot} = A_{1,1}\mathbf{s}_1 + A_{1,2}\mathbf{s}_{1,2}^{(1)} + A_{1,1}\mathbf{s}_{1,1}^{(2)} + A_{1,2}\mathbf{s}_1$ where the apex indicates which kind of replica the detector has time aligned.

The space spanned by the replicas $\{\boldsymbol{s}_1\boldsymbol{s}_{1,1}^{(2)}\mathbf{s}_{1,2}^{(1)}\}$ can be calculated with Gram-Schmidt procedure: taking $\boldsymbol{s}_{1,1}^{(2)}$ and normalizing it $\tilde{\mathbf{s}}_{1,1}^2 = \mathbf{s}_{1,1}^2/||\mathbf{s}_{1,1}^2||$, the part of $\boldsymbol{s}_{1,2}^{(1)}$ orthonormal to $\tilde{\mathbf{s}}_{1,1}^{(2)}$ is: $\tilde{\mathbf{s}}_{1,2}^{(1)} = \mathbf{s}_{1,2}^{(1)} - \langle\tilde{\mathbf{s}}_{1,1}^{(2)}, \mathbf{s}_{1,2}^{(1)}\rangle\mathbf{s}_{1,2}^{(1)} / \left\|\mathbf{s}_{1,2}^{(1)} - \langle\tilde{\mathbf{s}}_{1,1}^{(2)}, \mathbf{s}_{1,2}^{(1)}\rangle\mathbf{s}_{1,2}^{(1)}\right\|$. In the same way, the part of $\boldsymbol{s}_1$ orthonormal to the previous two vectors is equal to: $\tilde{s}_1 = s_1 - \langle\tilde{s}_{1,1}^{(2)} s_1\rangle s_1 - \langle\tilde{s}_{1,2}^{(1)} s_1\rangle s_1/$

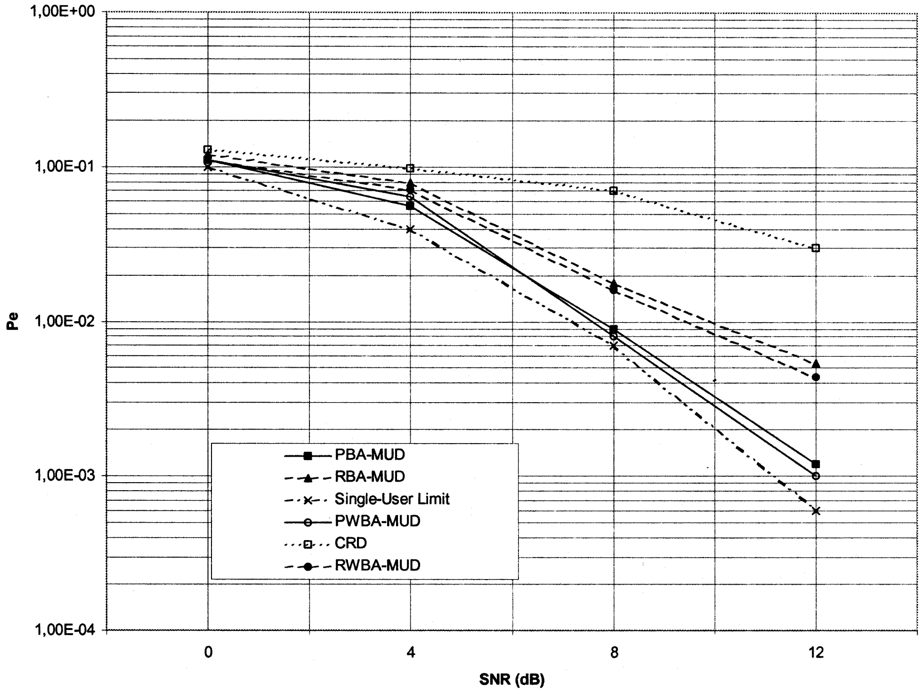

Fig. 11. Error probability comparison between PBA-MUD, PWBA-MUD, RBA-MUD, RWBA-MUD, CRD, and single user bound in the uplink satellite LEO suburban channel (see Table II for parameters) with four asynchronous interfering users.

TABLE II
MAIN PARAMETERS OF THE LEO SUBURBAN CHANNEL MODEL

Number of path	Attenuation (dB)	Doppler Spectrum	Delay (nsec)
1	9.7 (LOS) -7.3 (NLOS)	Rice Rayleigh	0
2	-23.6	Rayleigh	100
3	-28.1	Rayleigh	180

$\left\| s_1 - \langle \tilde{s}^{(2)}_{1,1} s_1 \rangle s_1 - \langle \tilde{s}^{(1)}_{1,2}, s_1 \rangle s_1 \right\|$. Hence, Γ_d is the space spanned by the following orthonormal column vectors $\{\tilde{\mathbf{s}}_1 \quad \tilde{\mathbf{s}}^{(2)}_{1,1} \quad \tilde{\mathbf{s}}^{(1)}_{1,2}\}$.

In general, by denoting with $\Xi \in \Re^{N \times L(L-1)+1}$ the matrix whose columns are the orthonormal vectors of the space Γ_d, we can express the projection matrix $\boldsymbol{P}_d$ as

$$\mathbf{P}_d = \mathbf{I} - \Xi\Xi^T \tag{A1}$$

APPENDIX B
OPTIMUM SOLUTION

An analytical form of the proposed blind algorithm can be achieved by solving the minimum of

$$E\left\{ (\langle \mathbf{y}, \mathbf{s}_1 + \underline{\mathbf{x}}_1 \rangle)^2 \right\} \tag{B1}$$

conditioned to the following two conditions:

$$\|\underline{\mathbf{x}}_1\|^2 = \chi_I^{\mathrm{opt}} \tag{B2}$$

$$\langle \tilde{\mathbf{s}}_{1\mathrm{tot}}, \underline{\mathbf{x}}_1 \rangle = 0. \tag{B3}$$

The latter condition can be rewritten as

$$\left\langle \frac{\sum_{j=1}^{L}\sum_{i=1}^{L} \mathbf{s}_{1,i-j}}{\left\| \sum_{j=1}^{L}\sum_{i=1}^{L} \mathbf{s}_{1,i-j} \right\|}, \underline{\mathbf{x}}_1 \right\rangle = 0 \tag{B4}$$

where each $\mathbf{s}^{(d)}_{1,i-j} = s^{(d)}_1 (t - mT - \tau_{1,i} + \tau_{1,j}) \big|_{t=N/T}$ *with* $d = m-1, m, m+1$ represents a received path direction of the desired signature waveform at the output of RAKE combining, i.e., they represent all the carrying information waveforms, time aligned (if $i = j$) and not (if $i \neq j$), at the input of the blind receiver. Thus, the adaptive vector $\underline{\boldsymbol{x}}_1$ is constrained to be orthogonal to the space spanned by the received replicas of the desired signal. For the sake of simplicity, we consider the case of K synchronous users. By introducing two Lagrangian multipliers to guarantee the condition on surplus energy and on orthogonal projection onto the orthonormal space Γ_d spanned by $\{\mathbf{s}_{1,i-j}\}$, the constrained MOE is calculated by taking the derivative respect to $\mathbf{c}_1 = \mathbf{s}_1 + \underline{\mathbf{x}}_1$ of the associated Lagrangian. In fact, it can be demonstrated [2] that, except for a scaling factor, the gradient vector $\nabla(J)$ of a cost function $J = J(\mathbf{c}_1)$ is equal to $\nabla(J) = \partial J / \partial \mathbf{c}_1^*$, where $(*)$ denotes the complex conjugate and $(^H)$ the complex conjugate transpose. Hence, by taking as cost function the constraint MOE function

$$\begin{aligned} J = J(\mathbf{c}_1) &= E\left\{ \left(\mathbf{y}^T \mathbf{c}_1\right) \cdot \left(\mathbf{y}^T \mathbf{c}_1\right)^* \right\} \\ &+ \nu_1 \left[\left(\mathbf{c}_1^H \cdot \mathbf{c}_1\right) - 1 - \chi_I^{\mathrm{opt}} \right] \\ &+ \nu_2 \left[\tilde{\mathbf{s}}_{1\mathrm{tot}}^T \mathbf{s}_1 - \tilde{\mathbf{s}}_{1\mathrm{tot}}^T \mathbf{c}_1 \right] \end{aligned} \tag{B5}$$

results, noting that $\mathbf{c}_1^* = \mathbf{c}_1$

$$E\left\{ \mathbf{y}^T \mathbf{c}_1 \cdot \mathbf{y} \right\} + \nu_1 \mathbf{c}_1 - \nu_2 \tilde{\mathbf{s}}_{1\mathrm{tot}} = 0. \tag{B6}$$

Then the optimum solution is

$$\mathbf{c}_{1\text{opt}} = (\mathbf{R}_y + \nu_1 \mathbf{I}_N)^{-1} \cdot [\nu_2 \tilde{\mathbf{s}}_{1\text{tot}}] \tag{B7}$$

where $\mathbf{R}_y = E\{\mathbf{y}\mathbf{y}^T\}$ is the output channel autocorrelation matrix and ν_1, ν_2 are the Lagrangian multipliers to assure the conditions $(\underline{\mathbf{x}}_1^H \underline{\mathbf{x}}_1) = \chi_I^{\text{opt}}$ and $(\tilde{\mathbf{s}}_{1\text{tot}}^T \underline{\mathbf{x}}_1) = 0$ respectively.

Thus, the Lagrangian multiplier ν_2 can be calculated from (B7) by taking into account the condition $(\tilde{\mathbf{s}}_{1\text{tot}}^T \underline{\mathbf{x}}_1) = 0$

$$\nu_2 = \left(\tilde{\mathbf{s}}_{1\text{tot}}^T \left[\tilde{\mathbf{s}}_{1\text{tot}}^T [\mathbf{R}_y + \nu_1 \mathbf{I}_N]^{-1} \tilde{\mathbf{s}}_{1\text{tot}} \right]^{-1} \mathbf{s}_1 \right)^{-1}. \tag{B8}$$

Appendix C
Convergence Analysis

We can compute the trajectory of the mean tap vector $E\{\boldsymbol{c}_1(i)\}$ in the modified algorithm

$$\mathbf{c}_1(i) = \mathbf{c}_1(i-1) - \mu [(\langle \mathbf{y}(i), \mathbf{c}_1(i-1) \rangle) (\mathbf{P}_d \mathbf{y})] \tag{C1}$$

where we have defined with $\boldsymbol{P}_d$ the orthogonal projection matrix onto the subspace Γ_d spanned by the desired signal main paths directions.

Equation (C1) can be rewritten as

$$\mathbf{c}_1(i) = (\mathbf{I} - \mu \mathbf{P}_d \mathbf{y}\mathbf{y}^T) \mathbf{c}_1(i-1). \tag{C2}$$

Hence, the mean tap error vector is

$$\mathbf{e}(i) = \mathbf{c}_1(i) - \mathbf{c}_{1\text{opt}} \tag{C3}$$

where $\boldsymbol{c}_{1\text{opt}}$ is the filter tap after convergence.

By writing equation (C1) in terms of $\boldsymbol{e}(i)$, we have

$$\begin{aligned} \mathbf{e}(i) &= (\mathbf{I} - \mu \mathbf{P}_d \mathbf{y}\mathbf{y}^T) \mathbf{e}(i-1) \\ &\quad + (\mathbf{I} - \mu \mathbf{P}_d \mathbf{y}\mathbf{y}^T) \mathbf{c}_{1\text{opt}} - \mathbf{c}_{1\text{opt}} \\ &= (\mathbf{I} - \mu \mathbf{P}_d \mathbf{y}\mathbf{y}^T) \mathbf{e}(i-1) - (\mu \mathbf{P}_d \mathbf{y}\mathbf{y}^T) \mathbf{c}_{1\text{opt}}. \end{aligned} \tag{C4}$$

By supposing there is no constraint on the surplus energy, if we take expectation of both sides in (C4)

$$\begin{aligned} E\{\mathbf{e}(i)\} &= (\mathbf{I} - \mu \mathbf{P}_d E\{\mathbf{y}\mathbf{y}^T\}) E\{\mathbf{e}(i-1)\} \\ &= (\mathbf{I} - \mu \mathbf{P}_d \mathbf{R}_y) E\{\mathbf{e}(i-1)\} \end{aligned} \tag{C5}$$

where we have used the relation $\boldsymbol{R}_y \boldsymbol{c}_{1\text{opt}} = 0$.

We can observe that $\boldsymbol{c}_1(i)$ converges asymptotically along N modes and decays exponentially with $(1 - \mu\lambda_k)$, where $\{\lambda_k\}_{k=1\cdots k}$ are the eigenvalues of the matrix $(\mathbf{P}_d \mathbf{R}_y)$ [2].

Thus, the following condition must be guaranteed for stability

$$0 \le \mu \le \frac{2}{\max_k \{|\lambda_k|\}}. \tag{C6}$$

Moreover, taking into account the following condition:

$$\left| \max_k \{\lambda_k\} \cdot (\mathbf{P}_d \mathbf{R}_y) \right| \le \max_k \{\lambda_k\} \cdot \mathbf{R}_y \tag{C7}$$

we can deduce that this algorithm is closer to the minimum of the output energy cost function. This implies to be closer to determinate the optimum coefficients of the detection filter, or, in other words, to obtain a faster convergence of this algorithm. The relation (C7) can be simply demonstrated by observing that the matrix $\boldsymbol{P}_d$ has been created from an orthonormal base of column vectors: the projection of $\boldsymbol{R}_y$ onto $\boldsymbol{P}_d$ is necessarily lower (in terms of modulus) than the output channel correlation matrix $\boldsymbol{R}_y$.

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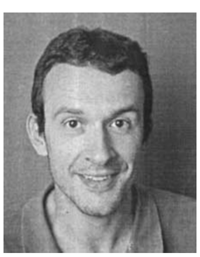

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