Blind Multiuser Detection Over Highly Dispersive CDMA Channels

Francesco Bandiera, *Member, IEEE*, Giuseppe Ricci, *Member, IEEE*, and Mahesh K. Varanasi, *Senior Member, IEEE*

***Abstract*—This paper addresses blind multiuser detection in a direct-sequence code-division multiple-access (DS-CDMA) network in presence of both multiple-access interference and intersymbol interference. In particular, it considers a DS-CDMA system where K out of $\overline{N}$ users are transmitting; the $\overline{N}$ admissible spreading codes are known, and so is the code of the user to be demodulated. The number of interferers, the signatures of a certain number, possibly all, of the interferers, and the channel impulse response of each active user are unknown. The spreading codes of the unknown interferers are determined via a procedure that exploits the knowledge of the set of admissible transmitted codes and of the known active codes. The procedure applies to both single and multiple receiving antennas. The performance assessment of a blind decorrelating detector, implemented by resorting to the proposed identification procedure, shows that it outperforms a plain subspace-based blind decorrelator for small sizes of the estimation sample.**

***Index Terms*—Code-division multiple access (CDMA), interference identification, intersymbol interference (ISI), multiple receiving antennas, multiuser detection.**

I. Introduction

The code-division multiple-access (CDMA) technique, implemented with the direct-sequence (DS) modulation format, can offer superior performance with respect to the conventional frequency- and/or time-division multiple-access systems when coupled with the adoption of advanced multiuser receivers at the demultiplexing stage [1].

In fact, in a nonorthogonal CDMA system, the conventional correlation receivers suffer from the so-called near–far problem, namely, the situation where a strong nearby user prevents detection of users that are farther away, and hence, are received with low power.

One way to overcome the near–far problem is to resort to multiuser receivers [2], namely, to detection strategies which account for the presence of other interferers in the channel (without or with power control). In a seminal paper [3], it was shown that it is the thermal noise and not the multiple-access interference (MAI) which determines the ultimate performance levels attainable in a CDMA communication system. Moreover, it has been shown that linear structures, i.e., the decorrelating and the minimum mean-square error (MMSE) detectors, achieve optimum resistance against the near–far problem and guarantee low computational requirements, albeit at the price of an increase over the bit-error rate (BER) of the optimum multiuser receiver.

The implementation of the above detectors would require knowledge of the signatures of all the active users, which is not realistic in most situations of practical interest. It is, thus, of primary concern to obtain blind implementations of those multiuser detectors, i.e., to design detectors capable of being implemented with as limited prior knowledge on the interference structure as possible, and also of achieving performance close to that of their nonblind counterparts for small sizes of the estimation sample.

Several papers have focused on blind and adaptive multiuser detection. For example, blind and adaptive implementations of linear multiuser receivers, based upon the so-called minimum mean output energy (MOE) criterion, and, more generally, on a framework that relies on the theory of stochastic approximation, have been proposed for CDMA systems operating over nonfading channels [4]–[6]. The extension of the MOE to work in presence of multipath fading and intersymbol interference (ISI) has been addressed in [7]–[9]. However, those receivers still require exact timing information for the user to be demodulated. The blind linear MMSE receiver proposed in [10], instead, can operate over dispersive ISI channels without explicit channel estimation. A further fully blind multiuser detector has been recently proposed in [11]; one of the advantages of the proposed algorithm, based upon the generalized minimum MOE criterion, is that it lends itself to low-complexity adaptive implementations. Finally, we cite [12], wherein a two-stage adaptive detector is proposed; it is shown that a first predecision stage can be used to train a second one, thus providing better signal-to-interference-plus-noise ratio (SINR) performance.

Increasing attention has also been focused on the problem of blind multipath channel estimation as a first step toward the implementation of blind multiuser receivers; for instance, in [13] and [14], different strategies have been conceived in order to blindly estimate the propagation channel. The former paper focuses on the problem of estimating the propagation delay of each user's signal, assuming a white Gaussian noise channel; several estimators are proposed, one relying on the subspace method. The observation space is first partitioned into a signal

Paper approved by A. Ahlen, the Editor for Modulation and Signal Design of the IEEE Communications Society. Manuscript received November 15, 2002; revised August 15, 2003 and December 15, 2003. This work was supported in part by the Italian CNR under the Short-Term Mobility Programme 2001, in part by the National Science Foundation under Grant CCR-0112977, and in part by the SHINES Italian National Research Project. This paper was presented in part at the 36th Annual Conference on Information Sciences and Systems, Princeton, NJ, March 20–22, 2002 and in part at the 36th Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, CA, November 3–6, 2002.

F. Bandiera and G. Ricci are with the Dipartimento di Ingegneria dell'Innovazione, Università degli Studi di Lecce, 73100 Lecce, Italy (e-mail: giuseppe.ricci@unile.it; francesco.bandiera@unile.it).

M. K. Varanasi is with the Electrical and Computer Engineering Department, University of Colorado at Boulder, Boulder, CO 80309 USA (e-mail: Varanasi@colorado.edu).

Digital Object Identifier 10.1109/TCOMM.2004.833021

subspace and a noise subspace, without prior knowledge of the unknown parameters; then, an estimator of the delay of each user is conceived, based on the observation that the contribution of that user to the useful received signal is orthogonal to the noise subspace. Similarly, in [14], the coefficients and the delays of a given user's channel are determined by resorting to an iterative procedure, aimed at minimizing the Euclidean norm of the projections of received spreading waveforms onto the estimated noise subspace. The subspace method is also used in [15] to obtain blind adaptive implementations of both the decorrelating and the MMSE detector for both synchronous and asynchronous systems. In particular, for asynchronous systems, [15] proposes a blind receiver which estimates the initial delay by taking advantage of the knowledge of the channel delay spread. Those results have been extended to nonorthogonal multipulse modulation and fast frequency-selective fading in [16]. On the other hand, for a synchronous system, adopting short spreading codes, the *a priori* knowledge of the N *admissible* signatures and of the common channel impulse response of active users can be exploited to identify the actual interferers, as shown in [17]. Therein, the received spreading codes of the $K-1$ interferers are identified from among the $N-1$ potential ones as the $K-1$ codes whose projections onto the estimated noise subspace possess the smallest Euclidean norms.

In this paper, we show that the procedure proposed in [17] can be generalized to deal with an unknown propagation environment, for both synchronous and asynchronous systems, and assuming single or multiple antennas at the receiver. More precisely, we show that knowledge of the set of admissible codes can be exploited to identify the actual interferers, provided that the channel impulse responses of the active users do not vary over the processing interval. As a matter of fact, the main advantage of the proposed procedure, with respect to the subspace-based technique proposed in [15], is that the former can be effective over processing intervals much shorter than those necessary to make the latter work. In other words, the proposed technique can be employed, albeit at a price of additional computational complexity, over a wider range of channels since it requires shorter data records.

The paper is organized as follows. Section II introduces the system model. In particular, the so-called multiple-input multiple-output (MIMO) signal model is reviewed, together with the structure of the decorrelating detector. Section III contains the derivation of the new technique for the identification of the active users. The performance assessment of a blind decorrelating detector implemented by resorting to the proposed identification procedure, and a comparison with its nonblind counterpart and a plain subspace-based blind receiver, are the goal of Section IV. Finally, some concluding remarks are reported in Section V.

II. Problem Formulation

Consider a DS-CDMA asynchronous system wherein K users simultaneously transmit a binary phase-shift keying (BPSK) signal. Each user is assigned a different pseudonoise (PN) waveform or signature, which directly modulates the source signal.

Denote by N the number of chips per information bit. Moreover, denote by $\overline{N}$ an integer greater than or equal to N, and by $\mathcal{K}$ a subset of $\{1,\ldots,\overline{N}\}$ of cardinality K, with $K \leqslant N$. Hereafter, the elements of $\mathcal{K}$ will be used to index the active user to be taken into account at the design stage; the interplay between $\mathcal{K}$ and $\{1,\ldots,\overline{N}\}$ will be clarified in Section III.

The baseband equivalent of the signal transmitted by the kth user, $k \in \mathcal{K}$, is given by

$$x_k(t) = a_k \sum_{i=-\infty}^{+\infty} b_k(i) s_k(t - iT - \tau_k)$$

where T is the information symbol interval and a_k, $\{b_k(i)\}_{i=-\infty}^{+\infty}$, and τ_k denote the (complex) amplitude, the symbol stream, and the delay of the kth user, respectively. In the DS spread-spectrum format, the signaling waveforms of the users are given by

$$s_k(t) = \sum_{j=0}^{N-1} c_k(j)\psi(t - jT_c), \quad 0 \leqslant t \leqslant T, \quad k \in \mathcal{K}$$

where $\{c_k(j)\}_{j=0}^{N-1}$, $c_k(j) \in \{-1,1\}$, is the signature sequence of the kth user, $\psi(t)$ is a unit-energy chip waveform whose support belongs to the chip interval $[0, T_c)$, and $T = NT_c$.

Signals propagate through dispersive channels. Assume, for the moment, a single antenna at the receiver, and denote by $g_k(\tau)$ the baseband equivalent of the impulse response of the channel associated with the kth user, $k \in \mathcal{K}$. The contribution to the received signal due to the kth user is thus given by

$$y_k(t) = a_k \sum_{i=-\infty}^{+\infty} b_k(i) \sum_{j=0}^{N-1} c_k(j)\overline{g}_k(t - iT - jT_c) \quad (1)$$

where

$$\overline{g}_k(t) = \int_{-\infty}^{+\infty} \psi(t-u) g_k(u - \tau_k) du. \quad (2)$$

Thus, the received signal is given by the superposition of the data signals of the K users (not necessarily belonging to the same cell) plus additive white Gaussian noise (AWGN), i.e.,

$$r(t) = \sum_{k \in \mathcal{K}} y_k(t) + v(t)$$

where $v(t)$ is a realization of a zero-mean complex white Gaussian noise with unknown power spectral density σ^2.

Such a model applies both to the uplink (i.e., mobile to base station) and (as a special case) to the downlink (i.e., base station to mobile) of a CDMA network. As to the uplink, it may be reasonable to assume that the base station knows the spreading codes of active in-cell users. With regard to the downlink, instead, it is reasonable to assume that each user does not know other active users' spreading codes; it is also customary to consider the situation where all K users transmit synchronously and the corresponding signals propagate through one and the same channel. Note, though, that such hypotheses are no longer true when taking into account the out-of-cell interference.

A. Discrete-Time MIMO Model

Assume that the K (possibly different) functions $\overline{g}_k(\tau)$, are zero outside $[0, (L_k-1)T]$ where L_k is an integer. The received signal $r(t)$ is fed to a filter matched to $\psi(t)$, and the corresponding output is sampled at the chip rate.[1]

A dispersive CDMA system can be recast in terms of a MIMO signal model framework, as shown in [15]. For the sake of clarity, the MIMO model is reviewed in the following.

First of all, observe that the sample of the received signal at the nth chip of the lth bit interval is given by

$$\begin{aligned} r_n(l) &= \int_{lT+nT_c}^{lT+(n+1)T_c} r(t)\psi(t-lT-nT_c)dt \\ &= \sum_{k\in\mathcal{K}} y_{nk}(l) + v_n(l) \end{aligned}$$

where

$$\begin{aligned} v_n(l) &= \int_{lT+nT_c}^{lT+(n+1)T_c} v(t)\psi(t-lT-nT_c)dt \\ y_{nk}(l) &= \int_{lT+nT_c}^{lT+(n+1)T_c} y_k(t)\psi(t-lT-nT_c)dt \\ &= a_k \sum_{i=0}^{L_k-1} h_{nk}(i) b_k(l-i) \end{aligned}$$

with

$$h_{nk}(i) = h_k(iN+n), \quad 0 \leqslant n \leqslant N-1, \quad 0 \leqslant i \leqslant L_k-1$$

where, in turn

$$h_k(m) = \begin{cases} \sum_{j=0}^{N-1} c_k(j) f_k(m-j), & 0 \leqslant m \leqslant L_k N-2 \\ 0, & m = L_k N-1 \end{cases} \quad (3)$$

$$f_k(m) = \int_0^{T_c} \overline{g}_k(t+mT_c)\psi(t)dt, \quad 0 \leqslant m \leqslant (L_k-1)N-1. \quad (4)$$

In (3), $\{h_k(m)\}_{m=0}^{L_kN-2}$ is the composite code of the kth user. It is the result of the distortion experienced by the original spreading sequence $\{c_k(m)\}_{m=0}^{N-1}$ through the channel impulse response $\{f_k(m)\}_{m=0}^{(L_k-1)N-1}$. Note that, by (2) and (4), the time delays τ_k are encapsulated into the $f_k(m)$'s. In the following, we set:

$$L = \max_{k\in\mathcal{K}} L_k.$$

Now define the following N-dimensional vectors:

$$\boldsymbol{r}(l) = \begin{pmatrix} r_0(l) \\ \vdots \\ r_{N-1}(l) \end{pmatrix}, \quad \boldsymbol{v}(l) = \begin{pmatrix} v_0(l) \\ \vdots \\ v_{N-1}(l) \end{pmatrix}.$$

[1]Sampling at the chip rate is not optimal in this framework, but *oversampling* of the received signal, a common way to deal with asynchronous systems, would increase the computational complexity and, moreover, slow the rate of convergence of the proposed identification algorithm (a point further addressed later in this paper).

Then, by stacking up the m vectors $\boldsymbol{r}(l), \ldots, \boldsymbol{r}(l+m-1)$ and the m vectors $\boldsymbol{v}(l), \ldots, \boldsymbol{v}(l+m-1)$, we define

$$\boldsymbol{r}_m(l) = \begin{pmatrix} \boldsymbol{r}(l) \\ \vdots \\ \boldsymbol{r}(l+m-1) \end{pmatrix}$$

and

$$\boldsymbol{v}_m(l) = \begin{pmatrix} \boldsymbol{v}(l) \\ \vdots \\ \boldsymbol{v}(l+m-1) \end{pmatrix}$$

respectively. In addition, define the k-user channel vector

$$\boldsymbol{f}_k = \begin{pmatrix} f_k(0) \\ \vdots \\ f_k((L-1)N-1) \\ 0 \end{pmatrix} \quad (5)$$

with $(L-1)N$ nonzero entries at most. Finally, let $\boldsymbol{C}_k$ be the $LN \times [(L-1)N+1]$ matrix

$$\boldsymbol{C}_k = \begin{pmatrix} c_k(0) & 0 & \cdots & \cdots \\ c_k(1) & c_k(0) & 0 & \cdots \\ \vdots & \vdots & \ddots & \\ c_k(N-1) & & & \\ 0 & c_k(N-1) & & \\ \vdots & 0 & \ddots & \\ \vdots & \vdots & & \\ 0 & 0 & & c_k(N-1) \end{pmatrix}$$

and denote by $\boldsymbol{C}_k(i)$ the submatrix of $\boldsymbol{C}_k$ from row $iN+1$ to $(i+1)N$, $i=0,\ldots,L-1$.

It is then not difficult to show that (see Appendix A for more details)

$$\boldsymbol{r}_m(l) = \sum_{k\in\mathcal{K}} a_k \sum_{j=l-L+1}^{l+m-1} \mathcal{C}_k^{(j)} \boldsymbol{f}_k b_k(j) + \boldsymbol{v}_m(l) \quad (6)$$

where $\mathcal{C}_k^{(j)}$ denotes the $Nm \times [(L-1)N+1]$ matrix from column $[j-(l-L+1)]\cdot[(L-1)N+1]+1$ to $[j-(l-L+1)+1]\cdot[(L-1)N+1]$ of the $Nm \times [(L+m-1)((L-1)N+1)]$ matrix $\mathcal{C}_k$ which, in turn, is given by

$$\mathcal{C}_k = \begin{pmatrix} \boldsymbol{C}_k(L-1) & \boldsymbol{C}_k(L-2) & \cdots & \boldsymbol{C}_k(0) & \boldsymbol{0} & \cdots & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{C}_k(L-1) & \ddots & & \ddots & & \\ \vdots & \boldsymbol{0} & \ddots & & & \ddots & \\ \vdots & \vdots & & & & & \\ \boldsymbol{0} & \boldsymbol{0} & & & & & \boldsymbol{C}_k(0) \end{pmatrix}.$$

Observe that (6) is very powerful, because it highlights all the contributions to the received signal. In fact, $\boldsymbol{r}_m(l)$ is a sum of signal vectors, each bearing an information symbol, plus noise; additionally, in (6), the known quantities (the matrices $\mathcal{C}_k^{(j)}$) are separated from the unknown ones (the channel vectors $\boldsymbol{f}_k$).

B. Zero-Forcing (ZF) Detector

Now suppose that we have to demodulate the lth bit of user k_0, $k_0 \in \mathcal{K}$, and, for the moment, that the $\mathcal{C}_k$'s and the $\boldsymbol{f}_k$'s are known quantities. In order to suppress both MAI and ISI, we can project the received vector $\boldsymbol{r}_m(l)$ onto the orthogonal complement of the space $\mathcal{S}$ spanned by the Nm-dimensional vectors $\mathcal{C}_k^{(j)}\boldsymbol{f}_k$, $k \in \mathcal{K} \setminus \{k_0\}$, $j = l-L+1, \dots, l+m-1$ and $\mathcal{C}_{k_0}^{(j)}\boldsymbol{f}_{k_0}$, $j = l-L+1, \dots, l-1, l+1, \dots, l+m-1$.

Projecting $\boldsymbol{r}_m(l)$ onto the orthogonal complement of $\mathcal{S}$, we get

$$\boldsymbol{z}_m(l) = P_{\mathcal{S}}^{\perp}\boldsymbol{r}_m(l) = P_{\mathcal{S}}^{\perp}\mathcal{C}_{k_0}^{(l)}\boldsymbol{f}_{k_0}a_{k_0}b_{k_0}(l) + P_{\mathcal{S}}^{\perp}\boldsymbol{v}_m(l)$$

where $P_{\mathcal{S}}^{\perp}$ is the projector onto the orthogonal complement of $\mathcal{S}$.

The maximum-likelihood (ML) decision rule based upon the $\boldsymbol{z}_m(l)$'s is given by

$$\widehat{b}_{k_0}(l) = \operatorname{sgn}\left\{\mathcal{R}\left[\boldsymbol{d}_{k_0}^H\boldsymbol{z}_m(l)\right]\right\} = \operatorname{sgn}\left\{\mathcal{R}\left[\boldsymbol{d}_{k_0}^H\boldsymbol{r}_m(l)\right]\right\}$$

where

$$\boldsymbol{d}_{k_0} = P_{\mathcal{S}}^{\perp}\mathcal{C}_{k_0}^{(l)}a_{k_0}\boldsymbol{f}_{k_0} \tag{7}$$

$\mathcal{R}[z]$ is the real part of the complex number z, ^{H} denotes conjugate transpose, and $\operatorname{sgn}(\cdot)$ is the signum function.

If we assume differential encoding of information data,[2] we can also resort to differential demodulation [18], namely to the following decision rule:

$$\widehat{b}_{k_0}(l) = \operatorname{sgn}\left\{\mathcal{R}\left[\left(\boldsymbol{d}_{k_0}^H\boldsymbol{r}_m(l-1)\right)\left(\boldsymbol{d}_{k_0}^H\boldsymbol{r}_m(l)\right)^*\right]\right\} \tag{8}$$

where * denotes complex conjugate. Note that implementation of decision rule (8) does not require knowledge of a_{k_0}; more specifically, the previous rule requires knowledge of $a_{k_0}\boldsymbol{f}_{k_0}$ up to a complex factor only.

III. Identification of the Interferers

A. Single-Antenna Case

The $\mathcal{C}_k^{(j)}\boldsymbol{f}_k$'s, $k \in \mathcal{K}\setminus\{k_0\}$, $j = l-L+1, \dots, l+m-1$, and $\boldsymbol{f}_{k_0}$ are usually unknown quantities which are to be estimated from the observables. As a matter of fact, it is possible to estimate $\boldsymbol{d}_{k_0}$ up to a multiplicative factor based upon the P vectors $\boldsymbol{r}_m(j)$, $j = l-P, \dots, l-1$, as shown in [15].

Here, instead, following the lead of [17], we make the assumption that active codes belong to a larger set of admissible ones, i.e.,

$$\{c_1(j)\}_{j=0}^{N-1}, \dots, \{c_{\overline{N}}(j)\}_{j=0}^{N-1}$$

known at the receiver. Without loss of generality, we assume that the first N codes

$$\{c_1(j)\}_{j=0}^{N-1}, \dots, \{c_N(j)\}_{j=0}^{N-1}$$

are used by in-cell users, while the remaining $\overline{N}-N$ (if $\overline{N} > N$)

$$\{c_{N+1}(j)\}_{j=0}^{N-1}, \dots, \{c_{\overline{N}}(j)\}_{j=0}^{N-1}$$

are used in a certain number of adjacent cells.[3] We will show that knowledge of such a set of admissible codes and of the code of the user to be demodulated can be exploited to identify the spreading codes of the unknown interferers and, eventually, to come up with a blind implementation of the decorrelating detector. As in [17], if the number K of active users is unknown, we can resort to standard techniques, such as the Akaike Information Criterion (AIC) [19] to estimate d and, eventually, K, see Appendix B for more details. Hereafter, the estimate of d is denoted by $\widehat{d}$, and that of K by $\widehat{K}$.

Let us now focus on the identification of the codes of the interferers in asynchronous systems. As already highlighted, it may be reasonable to assume that part of the interference is known at the receiver. As an example, in a typical uplink scenario, the receiver at the base station could know the codes of the active in-cell users; however, it could be beneficial for the obtainable performance to identify and, eventually, suppress possible strong out-of-cell interferers. Let $J-1$ be the number of in-cell interferers whose spreading codes are known at the receiver ($J=1$ means that no *a priori* information is available); then, the problem to be solved is that of identifying the codes of the $K-J$ unknown interferers, and the search has to be restricted among the codes indexed by the elements of the set $\{1, \dots, \overline{N}\} \setminus \mathcal{Q}$, where $\mathcal{Q}$ is the set of indexes of codes that can be discarded (based upon the *a priori* knowledge). As an example, if the receiver actually knows the in-cell interferers, then $\mathcal{Q} = \{1, \dots, N\}$; if, instead, it is assumed that all of the interferers are unknown, then $\mathcal{Q} = \{k_0\}$, where k_0 is the index of the user to be demodulated ($k_0 \in \{1, \dots, N\}$).

In order to identify the active users, we can exploit the fact that if the kth user is active, the $\mathcal{C}_k^{(j)}\boldsymbol{f}_k$'s, $j = l-L+1, \dots, l+m-1$, are orthogonal to the noise subspace, i.e.,

$$k\text{th user is active} \Rightarrow \mathcal{C}_k^{(j)}\boldsymbol{f}_k \in \mathcal{S} \Rightarrow \left\|\boldsymbol{B}^H\mathcal{C}_k^{(j)}\boldsymbol{f}_k\right\| = 0 \tag{9}$$

where the columns of $\boldsymbol{B}$ form an orthonormal basis for the orthogonal complement of the signal space, namely, the space spanned by the $\mathcal{C}_k^{(j)}\boldsymbol{f}_k$'s, $k \in \mathcal{K}$, $j = l-L+1, \dots, l+m-1$, and $\|\cdot\|$ denotes the Euclidean norm of a vector. A crucial assumption here is that, given m, the number of users be not too large; more precisely, the dimension $d = K(L+m-1)$ of the signal subspace must be less than Nm, so that the noise subspace exists.

However, (9) contains the unknown quantities $\boldsymbol{f}_k$ and $\boldsymbol{B}$ that must be estimated from the observables.

- $\boldsymbol{B}$ can be substituted by a matrix, $\widehat{\boldsymbol{B}}$, say, whose column range coincides with the estimated noise subspace. Following the lead of [15], we resort to a matrix whose columns are the unit-norm eigenvectors corresponding to the $Nm-\widehat{d}$ smallest eigenvalues of the correlation matrix of the received signal vectors $\boldsymbol{r}_m(j)$, $j = l-P, \dots, l-1$, which, in turn, is given by

$$\widehat{\boldsymbol{C}} = \frac{1}{P}\sum_{j=l-P}^{l-1}\boldsymbol{r}_m(j)\left(\boldsymbol{r}_m(j)\right)^H.$$

[2] The decision rule is derived by assuming that the modulator transmits a phase shift of π rad if the symbol to be transmitted is -1, and a phase shift of 0 rad if it is $+1$.

[3] Such codes could be obtained by scrambling those used in the cell of interest.

- We identify $\boldsymbol{f}_k$ with the $(L-1)N$-dimensional vector obtained from $\boldsymbol{f}_k$ by striking out its last entry,[4] and assume no *a priori* knowledge about the channels, but for the value of L. Then, we replace $\boldsymbol{f}_k$ in (9) with the unit-norm vector, which minimizes the sum of the squared norms of the vectors $\widehat{\boldsymbol{B}}^H \mathcal{C}_k^{(j)} \boldsymbol{f}_k$, $j = l-L+1, \dots, l+m-1$, i.e.,

$$\widehat{\boldsymbol{f}}_k = \arg \min_{\boldsymbol{v}, \|\boldsymbol{v}\|=1} \sum_{j=l-L+1}^{l+m-1} \left\| \widehat{\boldsymbol{B}}^H \mathcal{C}_k^{(j)} \boldsymbol{v} \right\|^2$$
$$= \arg \min_{\boldsymbol{v}, \|\boldsymbol{v}\|=1} \boldsymbol{v}^H \times \left(\sum_{j=l-L+1}^{l+m-1} \mathcal{C}_k^{(j)H} \widehat{\boldsymbol{B}} \widehat{\boldsymbol{B}}^H \mathcal{C}_k^{(j)} \right)_{(L-1)N(L-1)N} \boldsymbol{v} \quad (10)$$

where $(\mathbf{M})_{n\,n}$ is the matrix obtained from $\mathbf{M}$ [of dimensions $(n+1)$] by striking out its last row and column.

It is important to stress that such an estimation technique for the channel vector of the k-user can be adopted only when

$$\sum_{j=l-L+1}^{l+m-1} \left\| \boldsymbol{B}^H \mathcal{C}_k^{(j)} \widehat{\boldsymbol{f}}_k \right\|^2 = 0 \quad (11)$$

admits a unique (up to a multiplicative factor) nontrivial solution. When $m \geq L-1$, we get a unique (up to a multiplicative factor) nontrivial solution if the intersection of the column span of the matrix $\boldsymbol{I} - \boldsymbol{B}\boldsymbol{B}^H$ and that of the matrix obtained from $\mathcal{C}_k^{(l)}$ by striking out its last column is a one-dimensional subspace [15].

On the other hand, it is well known that [20]

$$\min_{\boldsymbol{v}, \|\boldsymbol{v}\|=1} \boldsymbol{v}^H \boldsymbol{M} \boldsymbol{v} = \lambda_1(\boldsymbol{M})$$

where $\lambda_1(\boldsymbol{M})$ denotes the smallest eigenvalue of the Hermitian matrix $\boldsymbol{M}$, and the minimizer is the corresponding unit-norm eigenvector. Otherwise stated, under the hypothesis that the kth user is active, $\widehat{\boldsymbol{f}}_k$ is given by the unit-norm eigenvector corresponding to the smallest eigenvalue of the matrix

$$\mathcal{M}_k = \left(\sum_{j=l-L+1}^{l+m-1} \mathcal{C}_k^{(j)H} \widehat{\boldsymbol{B}} \widehat{\boldsymbol{B}}^H \mathcal{C}_k^{(j)} \right)_{(L-1)N(L-1)N}. \quad (12)$$

We propose to scan the set of admissible codes, choosing the ones corresponding to the $\widehat{K} - J$ smallest values of the $\lambda_1(\mathcal{M}_k)$'s, $k \in \{1, \dots, \overline{N}\} \setminus \mathcal{Q}$. In fact, if the kth code is not used, and the intersection of the column span of $\boldsymbol{I} - \boldsymbol{B}\boldsymbol{B}^H$ and that of the matrix obtained from $\mathcal{C}_k^{(l)}$ by striking out its last column is $\{\boldsymbol{0}\}$, (11) does not admit nonzero solutions.

Summarizing, the above-proposed identification procedure can be a viable means to take into account either in-cell interferers or in-cell plus strong out-of-cell interferers. In the former case, we assume that the set of admissible codes has cardinality N, with N denoting the processing gain of the system. In the latter case, the set of admissible codes includes the ones used in a certain number of adjacent cells (i.e., $\overline{N} > N$). Moreover, we can either assume that in-cell interferers are known at the receiver $(J > 1)$ or that all of the interferers are unknown $(J = 1)$.

Note that the stronger the interferer, the higher its probability of detection; on the other hand, the presence of strong out-of-cell interferers, assuming $\overline{N} = N$, might force the detection of idle in-cell codes.

When out-of-cell interference can be neglected and, hence, $\overline{N} = N$, mobile receivers can also implement a slightly different procedure to identify the interferers, because for this case, all of the channels share one and the same impulse response; hence, the common response $\boldsymbol{f}$ can be determined by exploiting the knowledge of the code of the user to be decoded or, more generally, of J known codes, as proposed in [15]. Denoting by $\mathcal{J}$ the set of integers corresponding to the active codes known at the receiver, $\boldsymbol{f}$ can be determined as

$$\widehat{\boldsymbol{f}} = \arg \min_{\boldsymbol{f}, \|\boldsymbol{f}\|=1} \boldsymbol{f}^H \times \left(\sum_{j=l-L+1}^{l+m-1} \sum_{k \in \mathcal{J}} \mathcal{C}_k^{(j)H} \widehat{\boldsymbol{B}} \widehat{\boldsymbol{B}}^H \mathcal{C}_k^{(j)} \right)_{(L-1)N(L-1)N} \boldsymbol{f}. \quad (13)$$

Then, the remaining $K - J$ active users are identified by scanning the set of admissible codes for the $\widehat{K} - J$ signatures which guarantee the $\widehat{K} - J$ smallest values of

$$\sum_{j=l-L+1}^{l+m-1} \left\| \widehat{\boldsymbol{B}}^H \mathcal{C}_k^{(j)} \widehat{\boldsymbol{f}} \right\|^2, \quad k \in \{1, \dots, N\} \setminus \mathcal{J}. \quad (14)$$

Some remarks are now in order. First of all, it is worth stressing again that the channel impulse responses can be determined only up to multiplicative factors; thus, differential encoding of information data, coupled with differential demodulation, is strictly necessary. Second, note that while $\boldsymbol{B}\boldsymbol{B}^H$ is the projector onto the orthogonal complement of the space spanned by the users' signals, the newly proposed procedure is aimed at identifying the active interferers and, ultimately, to come up with a representation of $P_{\mathcal{S}}^{\perp}$. Third, observe that the channel is completely unknown, as we only assume that the lth bit of the user of interest is somewhere in the interval $[lT, (l+L)T]$, and this assumption makes the proposed receiver *timing free*, in the sense that it is not necessary to assume knowledge or to explicitly estimate the timing information. Finally, if we have some *a priori* knowledge about the channel [for instance, the channel delay spread or the number of propagation paths for a tapped-delay line (TDL)], it is possible to solve (10) or (13) under additional constraints, in order to come up with a better estimate of the channel impulse response [14], [15], [21].

B. Multiple-Antenna Case

Suppose now that the receiver employs N_a antennas, and denote by $\boldsymbol{f}_k^{(i)}$ the vector representing the (discrete time) channel impulse response of the kth user at the ith antenna, $i = 1, \dots, N_a$, $k \in \mathcal{K}$.

[4] Otherwise stated, hereafter $\boldsymbol{f}_k$ denotes both the $[(L-1)N+1]$-dimensional vector defined by (5) and the $(L-1)N$-dimensional one obtained from (5) by neglecting its last (zero) entry.

A way to extend the previously proposed identification procedure, assuming N_a receiving antennas, is to stack the N_a received vectors in one vector and perform a processing similar to that for the single-antenna case. Processing N_aNm-dimensional vectors, the maximum number of users would increase linearly with the number of antennas; however, the number of bit intervals, necessary for a reliable identification of the active users, would increase with the number of antennas as well. In order to circumvent this drawback, we propose a different algorithm that works with a sample size comparable to that fed to a single-antenna algorithm.

To this end, denote the signal vector at the ith antenna by $\boldsymbol{r}_m^{(i)}(l)$; it can be expressed as

$$\boldsymbol{r}_m^{(i)}(l)=\sum_{k\in\mathcal{K}} a_k \sum_{j=l-L+1}^{l+m-1} \mathcal{C}_k^{(j)}\boldsymbol{f}_k^{(i)} b_k(j)+\boldsymbol{v}_m^{(i)}(l), \quad i=1,\dots,N_a \tag{15}$$

where $\boldsymbol{v}_m^{(i)}(l)$ is the corresponding noise term; moreover, assume that the noise is spatially uncorrelated.

If the $\mathcal{C}_k^{(j)}\boldsymbol{f}_k^{(i)}a_k$'s were known, the ML decision rule, based upon the $\boldsymbol{z}_m^{(i)}(l)$'s, $i=1,\dots,N_a$, would be

$$\begin{aligned}\widehat{b}_{k_0}(l) &= \operatorname{sgn}\left\{\sum_{i=1}^{N_a}\mathcal{R}\left[\boldsymbol{d}_{k_0}^{(i)H}\boldsymbol{z}_m^{(i)}(l)\right]\right\}\\ &= \operatorname{sgn}\left\{\sum_{i=1}^{N_a}\mathcal{R}\left[\boldsymbol{d}_{k_0}^{(i)H}\boldsymbol{r}_m^{(i)}(l)\right]\right\}\end{aligned} \tag{16}$$

where $\boldsymbol{d}_{k_0}^{(i)}$ is given by

$$\boldsymbol{d}_{k_0}^{(i)} = P_{\mathcal{S}_i}^{\perp}\mathcal{C}_{k_0}^{(l)} a_{k_0}\boldsymbol{f}_{k_0}^{(i)}, \quad i=1,\dots,N_a \tag{17}$$

and $P_{\mathcal{S}_i}^{\perp}$ is the projector onto the orthogonal complement of $\mathcal{S}_i$, the subspace spanned by the interference (MAI plus ISI) at the ith antenna.

In the case of differential encoding and differential demodulation, the following (suboptimal) decision rule can be adopted:

$$\widehat{b}_{k_0}(l) = \operatorname{sgn}\left\{\sum_{i=1}^{N_a}\mathcal{R}\left[\left(\boldsymbol{d}_{k_0}^{(i)H}\boldsymbol{r}_m^{(i)}(l-1)\right)\left(\boldsymbol{d}_{k_0}^{(i)H}\boldsymbol{r}_m^{(i)}(l)\right)^*\right]\right\}. \tag{18}$$

In order to obtain a blind implementation of (18), we first estimate $d=K(L+m-1)$. Due to the fact that it is the common dimension of the signal subspace of the $\boldsymbol{r}_m^{(i)}$'s, we evaluate such value as

$$\widehat{d} = \text{round}\left(\frac{1}{N_a}\sum_{i=1}^{N_a}\widehat{d}_i\right) \tag{19}$$

where $\widehat{d}_i$, given by (25), is the estimated dimension of the signal subspace, based upon the signal impinging on the ith antenna, and round (x) is the integer closest to x. Then, it is necessary to identify the active users and the channel impulse responses $\boldsymbol{f}_k^{(i)}$'s, as discussed in the previous section. To this end, define the N_a analogs of matrix $\mathcal{M}_k$, i.e.,

$$\mathcal{M}_k^{(i)} = \left(\sum_{j=l-L+1}^{l+m-1}\mathcal{C}_k^{(j)H}\widehat{\boldsymbol{B}}_i\widehat{\boldsymbol{B}}_i^H\mathcal{C}_k^{(j)}\right)_{(L-1)N(L-1)N}, \quad i=1,\dots,N_a, \quad k=1,\dots,\overline{N} \tag{20}$$

where the columns of $\widehat{\boldsymbol{B}}_i$ form an orthonormal basis for the estimated noise subspace at the ith antenna. Now the users' identification procedure is tantamount to choosing the $\widehat{K}-J$ admissible codes with the smallest values of the quantities

$$\sum_{i=1}^{N_a}\lambda_1\left(\mathcal{M}_k^{(i)}\right), \quad k\in\{1,\dots,\overline{N}\}\setminus\mathcal{Q} \tag{21}$$

where again, $\lambda_1(\mathcal{M}_k^{(i)})$ is the smallest eigenvalue of the matrix $\mathcal{M}_k^{(i)}$. Observe that the rule based on (21) coincides with that relying on (12) for $N_a=1$. Then, we construct the projector $P_{\mathcal{S}_i}^{\perp}$, $i=1,\dots,N_a$, by replacing the unknown channel of each interferer with the unit-norm eigenvector associated to the corresponding eigenvalue $\lambda_1(\mathcal{M}_k^{(i)})$, and finally implement decision rule (18).

In a synchronous channel, when neglecting out-of-cell interference, all the users share one and the same channel impulse response at the ith antenna, $\boldsymbol{f}^{(i)}$, say, that can be estimated by resorting to a straightforward modification of (13), namely, to

$$\widehat{\boldsymbol{f}}^{(i)} = \arg\min_{\boldsymbol{f},\|\boldsymbol{f}\|=1}\boldsymbol{f}^H \times\left(\sum_{j=l-L+1}^{l+m-1}\sum_{k\in\mathcal{J}}\mathcal{C}_k^{(j)H}\widehat{\boldsymbol{B}}_i\widehat{\boldsymbol{B}}_i^H\mathcal{C}_k^{(j)}\right)_{(L-1)N(L-1)N}\boldsymbol{f}, \quad i=1,\dots,N_a. \tag{22}$$

Then, the remaining users can be selected as the ones with the smallest values of

$$\sum_{i=1}^{N_a}\sum_{j=l-L+1}^{l+m-1}\left\|\widehat{\boldsymbol{B}}_i^H\mathcal{C}_k^{(j)}\widehat{\boldsymbol{f}}^{(i)}\right\|^2, \quad k\in\{1,\dots,N\}\setminus\mathcal{J}. \tag{23}$$

C. A Blind Decorrelating Detector

Identification of the active interferers and of the corresponding channel impulse responses can be used to obtain an adaptive implementation of a decorrelating detector. The corresponding blind algorithms are summarized in Tables I and II for the synchronous and the asynchronous case, respectively.

IV. Performance Assessment

The blind detectors of Tables I and II are simulated by resorting to standard Monte Carlo counting techniques. More precisely, in order to evaluate the BERs, we resort to a number of independent trials which produces the occurrence of 100 errors. The dispersive channels are modeled in terms of TDLs with the same number of paths, N_p, say, for each user. For the case of diversity reception, we assume a calibrated uniform linear array, with a $\lambda/2$ distance between antenna elements, where λ is the carrier wavelength. Under these assumptions, the channel impulse response of the kth user at the ith antenna can be expressed as

$$g_k^{(i)}(\tau-\tau_k)=\sum_{\ell=0}^{N_p-1}\alpha_{k,\ell}^{(i)}\delta(\tau-\tau_{k,\ell}), \quad k\in\mathcal{K}, \quad i=1,\dots,N_a$$

and, given antenna 1 as a reference, the fading coefficients $\alpha_{k,\ell}^{(i)}$ are given by

$$\alpha_{k,\ell}^{(i)}=\alpha_{k,\ell}^{(1)}e^{j\pi(i-1)\sin\theta_{k,\ell}}, \quad i=1,\dots,N_a$$

TABLE I
PROPOSED BLIND DECORRELATING DETECTOR: SYNCHRONOUS CASE WITH $J = 1$

1. construct the sample correlation matrix of the received signal vectors $\boldsymbol{r}_m^{(i)}(j)$, $j = l-P,\ldots,l-1$:
$$\widehat{\boldsymbol{C}}^{(i)} = \frac{1}{P}\sum_{j=l-P}^{l-1} \boldsymbol{r}_m^{(i)}(j)\left(\boldsymbol{r}_m^{(i)}(j)\right)^H, \quad i = 1,\ldots,N_a;$$
2. estimate $d = K(m+L-1)$ by resorting to the AIC and, eventually, K (equations (25) and (26) in Appendix B);
3. determine $\widehat{\boldsymbol{B}}_i$ as the matrix whose columns are the unit-norm eigenvectors of the sample correlation matrix $\widehat{\boldsymbol{C}}^{(i)}$ corresponding to its $Nm - \widehat{d}$ smallest eigenvalues, $i = 1,\ldots,N_a$;
4. determine $\widehat{\boldsymbol{f}}^{(i)}$ by choosing the unit-norm eigenvector corresponding to the smallest eigenvalue of the matrix
$$\mathcal{M}_{k_0}^{(i)} = \left(\sum_{j=l-L+1}^{l+m-1} \mathcal{C}_{k_0}^{(j)H}\widehat{\boldsymbol{B}}_i\widehat{\boldsymbol{B}}_i^H\mathcal{C}_{k_0}^{(j)}\right)_{(L-1)N\ (L-1)N}, \quad i = 1\ldots N_a;$$
5. identify the $K-1$ remaining active users by scanning for the admissible codes which guarantee the $\widehat{K}-1$ smallest values of
$$\sum_{i=1}^{N_a}\sum_{j=l-L+1}^{l+m-1}\left\|\widehat{\boldsymbol{B}}_i^H\mathcal{C}_k^{(j)}\widehat{\boldsymbol{f}}^{(i)}\right\|^2, \quad k \in \{1,\ldots,N\}\setminus\{k_0\};$$
6. estimate $\widehat{b}_{k_0}(l)$ as
$$\widehat{b}_{k_0}(l) = \text{sgn}\left\{\sum_{i=1}^{N_a}\mathcal{R}\left[\left(\boldsymbol{d}_{k_0}^{(i)H}\boldsymbol{r}_m^{(i)}(l-1)\right)\left(\boldsymbol{d}_{k_0}^{(i)H}\boldsymbol{r}_m^{(i)}(l)\right)^*\right]\right\}$$
where $\boldsymbol{d}_{k_0}^{(i)}$ is given by (17) with the unknown quantities $P_{\mathcal{S}_i}^{\perp}$ and $a_{k_0}\boldsymbol{f}_{k_0}^{(i)}$ substituted by the corresponding estimates.

TABLE II
PROPOSED BLIND DECORRELATING DETECTOR: ASYNCHRONOUS CASE

1. construct the sample correlation matrix of the received signal vectors $\boldsymbol{r}_m^{(i)}(j)$, $j = l-P,\ldots,l-1$:
$$\widehat{\boldsymbol{C}}^{(i)} = \frac{1}{P}\sum_{j=l-P}^{l-1} \boldsymbol{r}_m^{(i)}(j)\left(\boldsymbol{r}_m^{(i)}(j)\right)^H, \quad i = 1,\ldots,N_a;$$
2. estimate $d = K(m+L-1)$ by resorting to the AIC and, eventually, K (equations (25) and (26) in Appendix B);
3. determine $\widehat{\boldsymbol{B}}_i$ as the matrix whose columns are the unit-norm eigenvectors of the sample correlation matrix $\widehat{\boldsymbol{C}}^{(i)}$ corresponding to its $Nm - \widehat{d}$ smallest eigenvalues, $i = 1,\ldots,N_a$;
4. identify the $K-J$ remaining active users by scanning for the admissible codes which guarantee the $\widehat{K}-J$ smallest values of
$$\sum_{i=1}^{N_a}\lambda_1\left(\mathcal{M}_k^{(i)}\right), \quad k \in \{1,\ldots,\overline{N}\}\setminus\mathcal{Q},$$
where $\mathcal{M}_k^{(i)}$ is given by
$$\mathcal{M}_k^{(i)} = \left(\sum_{j=l-L+1}^{l+m-1} \mathcal{C}_k^{(j)H}\widehat{\boldsymbol{B}}_i\widehat{\boldsymbol{B}}_i^H\mathcal{C}_k^{(j)}\right)_{(L-1)N\ (L-1)N}, \quad \begin{array}{l} i = 1,\ldots,N_a, \\ k = 1,\ldots,\overline{N}; \end{array}$$
5. determine the impulse response $\widehat{\boldsymbol{f}}_k^{(i)}$ of each active user as the unit-norm eigenvector associated with $\lambda_1\left(\mathcal{M}_k^{(i)}\right)$, $i = 1,\ldots,N_a$;
6. estimate $\widehat{b}_{k_0}(l)$ as
$$\widehat{b}_{k_0}(l) = \text{sgn}\left\{\sum_{i=1}^{N_a}\mathcal{R}\left[\left(\boldsymbol{d}_{k_0}^{(i)H}\boldsymbol{r}_m^{(i)}(l-1)\right)\left(\boldsymbol{d}_{k_0}^{(i)H}\boldsymbol{r}_m^{(i)}(l)\right)^*\right]\right\}$$
where $\boldsymbol{d}_{k_0}^{(i)}$ is given by (17) with the unknown quantities $P_{\mathcal{S}_i}^{\perp}$ and $a_{k_0}\boldsymbol{f}_{k_0}^{(i)}$ substituted by the corresponding estimates.

where $\theta_{k,\ell}$ is the angle of arrival of the ℓth path of the kth user, which is assumed to be uniformly distributed in $[0, 2\pi]$. Observe that, due to the correlation between the impinging signals, the considered model is a sort of worst case on the attainable gain in presence of diversity [22]. All of the simulations assume TDLs with $N_p = 3$ and $L = 2$. Moreover:

- the $\alpha_{k,\ell}^{(1)}$, $\ell = 0,\ldots,2$, are complex, zero-mean, Gaussian random variables (rvs) with mean-square values given by $E[|\alpha_{k,0}^{(1)}|^2] = 0.5$, $E[|\alpha_{k,1}^{(1)}|^2] = 0.3$, and $E[|\alpha_{k,2}^{(1)}|^2] = 0.2$, respectively;
- coefficients associated with different paths (or different channels for the asynchronous case) are independent of each other;
- the $\tau_{k,\ell}$'s are independent rvs uniformly distributed in $[0, (N-1)T_c]$.

The spreading codes are m-sequences with processing gain $N = 15$. All of the figures assume users with the same power, $m = 3$, the sample size P and, possibly, the number of antennas N_a as parameters. The results are obtained by averaging the BERs over all random quantities; otherwise stated, the angles of arrival of the plane waves impinging on the array of antennas and the gains and the delays of the TDLs are randomly generated at each trial of the Monte Carlo simulation.

Figs. 1–3 refer to a synchronous system (with $J = 1$), whereas Figs. 4–6 assume an asynchronous one. We plot the BERs of the proposed receivers versus the signal-to-noise ratio (SNR), defined as
$$\text{SNR} = \frac{\mathcal{E}_b}{\sigma^2}$$
where $\mathcal{E}_b = |a_{k_0}|^2 N$ denotes the energy per bit of the baseband equivalent of the received signal associated with each user's information stream (remember that all of the users possess one and the same value of the power). All of the figures assume $k_0 = 1$, $\overline{N} = N$ ($\mathcal{Q} = \{k_0\}$), and $K = 5$ active users, but for Fig. 6, where performances refer to $\overline{N} = 3N$ ($\mathcal{Q} = \{1,\ldots,N\}$) and $K = 6$ active users.

For comparison purposes, we also plot the performance of the decorrelating detector (DEC-D) given by (18), i.e., the one which assumes knowledge of the signatures of the active users and of the corresponding channel impulse responses, and that of the subspace-based blind decorrelating detector (B-DEC-D) proposed in [15], possibly extended to the multiple-antenna case. The performance of an ideal single-user system (which, after zero-forcing the ISI, performs coherent detection and, for

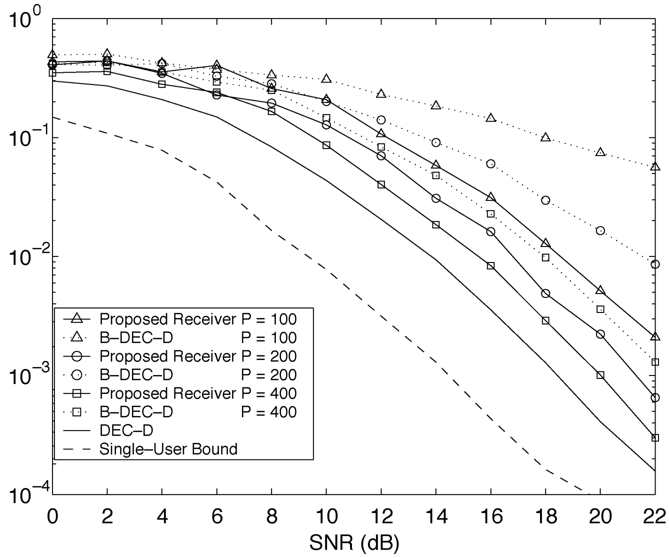


Fig. 1. BER versus SNR in a synchronous system for the proposed receiver, the B-DEC-D, the DEC-D, and the single-user bound, $K = 5$, $N_a = 1$, and P as a parameter.

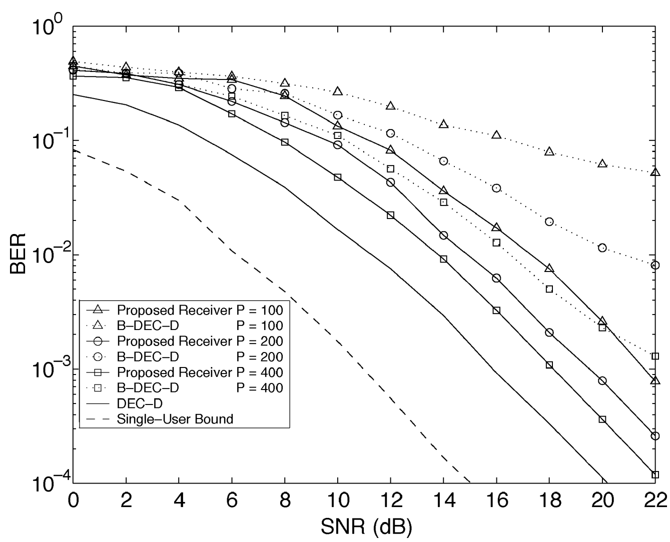


Fig. 2. BER versus SNR in a synchronous system for the proposed receiver, the B-DEC-D, the DEC-D, and the single-user bound, $K = 5$, $N_a = 2$, and P as a parameter.

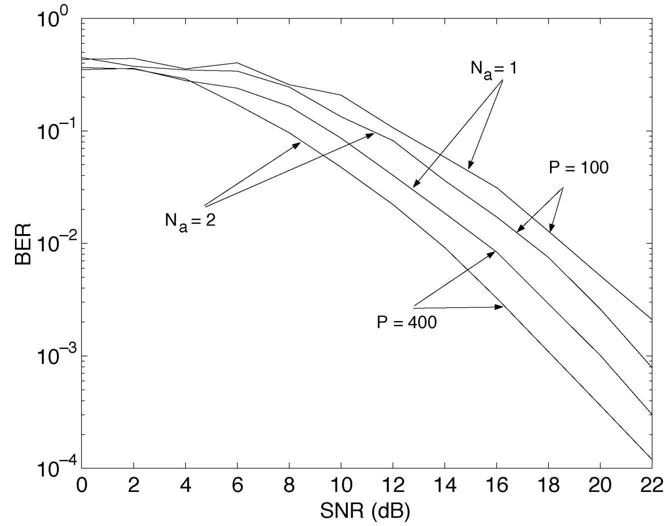


Fig. 3. BER versus SNR in a synchronous system for the proposed receiver, $K = 5$, N_a, and P as parameters.

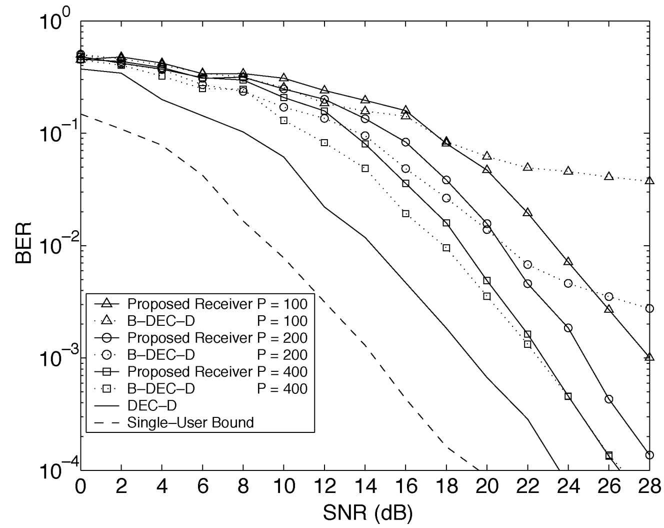


Fig. 4. BER versus SNR in an asynchronous system for the proposed receiver, the B-DEC-D, the DEC-D, and the single-user bound, $K = 5$, $N_a = 1$, and P as a parameter.

the case of multiple antennas, ideal diversity combining) is plotted too.

For the synchronous case, the comparison between the newly proposed blind receiver and the B-DEC-D shows that the former outperforms the latter for all considered values of P and N_a. Obviously, as P becomes increasingly large, as a consequence of the unbiasedness and consistency of the adopted identification procedures, both receivers converge to the DEC-D. Fig. 3 highlights the diversity gain obtained by increasing the number of antennas.

Similar considerations apply to the asynchronous case. More precisely, Figs. 4 and 5 show that the proposed receiver outperforms the B-DEC-D for $P = 100$ and $P = 200$, and also for $P = 400$ in the case of $N_a = 3$ receiving antennas.

Finally, in Fig. 6, we plot the performance of the proposed asynchronous receiver for $\overline{N} = 3N$, $K = 6$ active users, and $N_a = 3$ receiving antennas. The considered scenario is the following. There are two in-cell $(J - 1 = 2)$ and three out-of-cell interferers; moreover, the proposed detector and the B-DEC-D know the codes of the in-cell interferers, while those of the out-of-cell interferers are to be identified among the remaining $\overline{N} - N = 2N$ ones. The set of admissible codes is obtained by random scrambling of the N codes to be used by users connected to the base station under consideration. All of the channel impulse responses are unknown. The figure shows that the proposed approach is still a viable means to identify the interferers and, eventually, to combat MAI and ISI. Obviously, identification of the active users requires scanning a larger set of potential codes than for previous scenarios.

It is thus apparent that the proposed identification procedure can help the system to adapt to time-varying scenarios more rapidly than previously proposed adaptive detectors. Reliable identification of the interferers, based upon short data records,

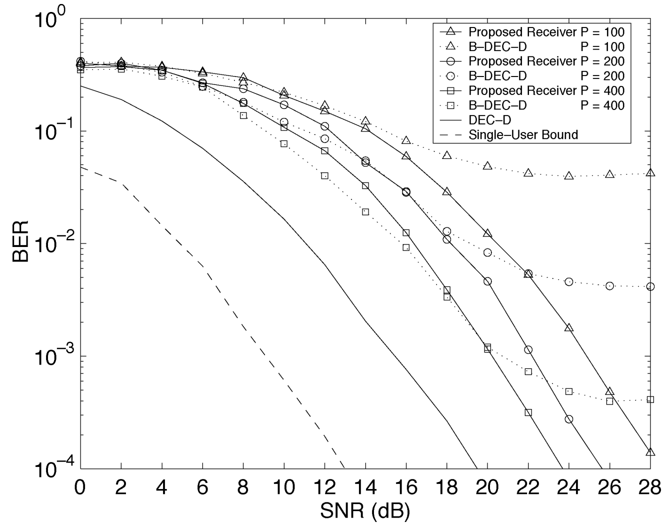


Fig. 5. BER versus SNR in an asynchronous system for the proposed receiver, the B-DEC-D, the DEC-D, and the single-user bound, $K = 5$, $N_a = 3$, and P as a parameter.

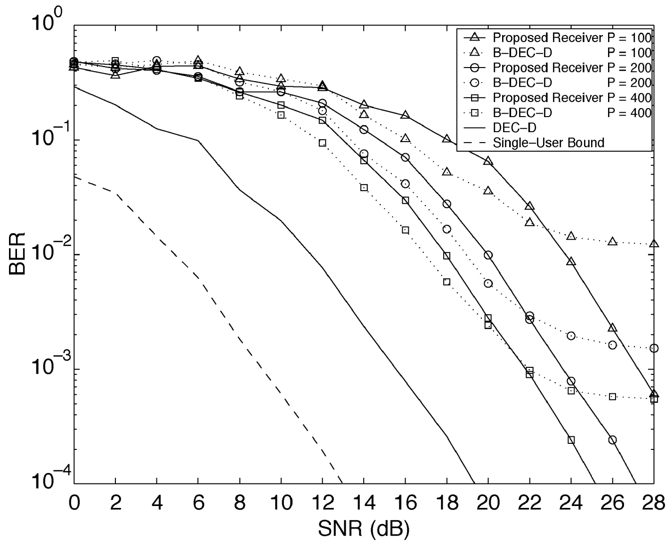


Fig. 6. BER versus SNR in an asynchronous system for the proposed receiver, the B-DEC-D, the DEC-D, and the single-user bound, $K = 6$, $N_a = 3$, and P as a parameter.

also makes the receiver capable of promptly adapting to a dynamic load and, eventually, of increasing the system capacity.

V. Conclusions

In this paper, the problem of interference identification over dispersive CDMA channels in the presence of both MAI and ISI has been addressed. We have exploited the fact that the K spreading codes of the active users belong to a known set of admissible ones. The number of interferers, the signatures of a certain number (possibly all) of the interferers, and the channel impulse response of each active user are unknown. The procedure applies to both single and multiple receiving antennas.

Simulation examples have shown that the proposed algorithm, when coupled with a decorrelating detector, allows outperforming a plain subspace-based detector, for small sizes of the estimation sample.

Finally, it must be emphasized that the advantage of the proposed receiver with respect to the B-DEC-D is to be traded for an increase of the computational complexity, and that such an increase of the complexity appears only partly mitigated by resorting to recursive algorithms.

Appendix A
Derivation of the Discrete-Time Representation of the Received Signal

First of all, remember that the sample of the received signal at the nth chip of the lth bit interval is given by

$$r_n(l) = \sum_{k\in\mathcal{K}} y_{nk}(l) + v_n(l) = \sum_{k\in\mathcal{K}} a_k \sum_{i=0}^{L-1} h_{nk}(i) b_k(l-i) + v_n(l).$$

It follows that

$$\boldsymbol{r}_m(l) = \begin{pmatrix} \boldsymbol{r}(l) \\ \vdots \\ \boldsymbol{r}(l+m-1) \end{pmatrix} = \begin{pmatrix} r_0(l) \\ \vdots \\ r_{N-1}(l) \\ \vdots \\ r_0(l+m-1) \\ \vdots \\ r_{N-1}(l+m-1) \end{pmatrix}.$$

Now define the following N-dimensional column vector:

$$\boldsymbol{h}_k(l) \triangleq [h_{0k}(l) \cdots h_{N-1\ k}(l)]^T$$

it follows that

$$\begin{aligned} \boldsymbol{r}_m(l) = \sum_{k\in\mathcal{K}} a_k & \\ \times & \begin{pmatrix} \boldsymbol{h}_k(L-1) & \boldsymbol{h}_k(L-2) & \cdots & \boldsymbol{h}_k(0) & & & \\ & \ddots & & & \ddots & & \\ & & \boldsymbol{h}_k(L-1) & \boldsymbol{h}_k(L-2) & \cdots & \boldsymbol{h}_k(0) \end{pmatrix} \\ \times & \begin{pmatrix} b_k(l-L+1) \\ \vdots \\ b_k(l+m-1) \end{pmatrix} + \boldsymbol{v}_m(l) \end{aligned} \tag{24}$$

where the right-hand side matrix containing the $\boldsymbol{h}_k(l)$ terms is $Nm \times (L+m-1)$-dimensional. Note that the represented one refers to $m > L$.

On the other hand, it is also true that

$$\boldsymbol{C}_k \boldsymbol{f}_k = \begin{pmatrix} h_k(0) \\ \vdots \\ h_k(LN-1) \end{pmatrix}$$

and, hence, that

$$\boldsymbol{C}_k(i)\boldsymbol{f}_k = \begin{pmatrix} h_k(iN) \\ \vdots \\ h_k(iN+N-1) \end{pmatrix} = \begin{pmatrix} h_{0,k}(i) \\ \vdots \\ h_{N-1,k}(i) \end{pmatrix} = \boldsymbol{h}_k(i).$$

It follows that (24) can be rewritten as shown in the equation at the top of the next page.

$$\boldsymbol{r}_m(l)=\sum_{k\in\mathcal{K}} a_k \begin{pmatrix} \boldsymbol{C}_k(L-1)\boldsymbol{f}_k & \boldsymbol{C}_k(L-2)\boldsymbol{f}_k & \cdots & \boldsymbol{C}_k(0)\boldsymbol{f}_k & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \boldsymbol{C}_k(L-1)\boldsymbol{f}_k & \ddots & & \ddots & & \\ \vdots & \mathbf{0} & \ddots & & & \ddots & \\ \vdots & \vdots & & & & & \\ \mathbf{0} & \mathbf{0} & & & & & \boldsymbol{C}_k(0)\boldsymbol{f}_k \end{pmatrix} \begin{pmatrix} b_k(l-L+1) \\ \vdots \\ b_k(l+m-1) \end{pmatrix} + \boldsymbol{v}_m(l)$$

APPENDIX B
ESTIMATION OF THE DIMENSION OF THE SIGNAL SUBSPACE

The aim of this appendix is to show how the AIC [19] is used to estimate the rank of the signal subspace, namely, the term $d=K(L+m-1)$. To this end, let $\widehat{\boldsymbol{C}}$ be the sample correlation matrix of the received signal vectors $\boldsymbol{r}_m(l)$, evaluated over P consecutive symbol intervals

$$\widehat{\boldsymbol{C}}=\frac{1}{P}\sum_{j=l-P}^{l-1}\boldsymbol{r}_m(j)\left(\boldsymbol{r}_m(j)\right)^H$$

and let $\widehat{\lambda}_1,\ldots,\widehat{\lambda}_{Nm}$ be the eigenvalues of $\widehat{\boldsymbol{C}}$ arranged in nonincreasing order. The estimate of d is thus given by [15], [19]

$$\widehat{d}=\arg\min_{k\in\{0,\ldots,Nm-1\}}\Phi(k) \tag{25}$$

where

$$\Phi(k)=P(Nm-k)\ln\gamma(k)+k(2Nm-k)$$

and

$$\gamma(k)=\frac{\frac{\left(\sum_{i=k+1}^{Nm}\widehat{\lambda}_i\right)}{(Nm-k)}}{\left(\prod_{i=k+1}^{Nm}\widehat{\lambda}_i\right)^{\frac{1}{(Nm-k)}}}.$$

Finally, the estimated value of the number of the active users, $\widehat{K}$, say, can be obtained from $\widehat{d}$ as follows (remember that m and L are known quantities):

$$\widehat{K}=\text{round}\left(\frac{\widehat{d}}{L+m-1}\right) \tag{26}$$

where round (x) is the integer closest to x.

REFERENCES

[1] M. K. Varanasi and T. Guess, "Bandwidth-efficient multiple-access (BEMA): A new strategy based on signal design under quality service constraints for successive-decoding-type multiuser receivers," *IEEE Trans. Commun.*, vol. 49, pp. 844–854, May 2001.

[2] S. Verdú, *Multiuser Detection*. Cambridge, U.K.: Cambridge Univ. Press, 1998.

[3] ——, "Minimum probability of error for asynchronous Gaussian multiple-access channels," *IEEE Trans. Inform. Theory*, vol. IT-32, pp. 85–96, Jan. 1986.

[4] M. Honig, U. Madhow, and S. Verdú, "Blind adaptive multiuser detection," *IEEE Trans. Inform. Theory*, vol. 41, pp. 944–960, July 1995.

[5] D. Das and M. K. Varanasi, "Blind adaptive multiuser detection for cellular systems using stochastic approximation with averaging," *IEEE J. Select. Areas Commun.*, vol. 20, pp. 310–319, Feb. 2002.

[6] A. Kapur, M. K. Varanasi, and D. Das, "Noncoherent MMSE multiuser receivers and their blind adaptive implementations," *IEEE Trans. Commun.*, vol. 50, pp. 503–513, Mar. 2002.

[7] M. K. Tsatsanis, "Inverse filtering criteria for CDMA systems," *IEEE Trans. Signal Processing*, vol. 45, pp. 102–112, Jan. 1997.

[8] M. K. Tsatsanis and Z. Xu, "Performance analysis of minimum variance CDMA receivers," *IEEE Trans. Signal Processing*, vol. 46, pp. 3014–3022, Nov. 1998.

[9] Z. Xu and M. K. Tsatsanis, "Blind adaptive algorithms for minimum variance CDMA receivers," *IEEE Trans. Commun.*, vol. 49, pp. 180–194, Jan. 2001.

[10] D. Gesbert, J. Sorelius, P. Stoica, and A. Paulraj, "Blind multiuser MMSE detector for CDMA signals in ISI channels," *IEEE Commun. Lett.*, vol. 3, pp. 233–235, Aug. 1999.

[11] S. Buzzi, M. Lops, and H. V. Poor, "Blind adaptive joint multiuser detection and equalization in dispersive differentially encoded CDMA channels," *IEEE Trans. Signal Processing*, vol. 51, pp. 1880–1893, July 2003.

[12] G. Caire, "Two-stage nondata-aided adaptive linear receivers for DS-CDMA," *IEEE Trans. Commun.*, vol. 48, pp. 1712–1724, Oct. 2000.

[13] E. G. Ström, S. Parkvall, S. L. Miller, and B. E. Ottersten, "Propagation delay estimation in asynchronous direct-sequence code-division multiple-access systems," *IEEE Trans. Commun.*, vol. 44, pp. 84–93, Jan. 1996.

[14] S. E. Bensley and B. Aazhang, "Subspace-based channel estimation for code-division multiple-access communication systems," *IEEE Trans. Commun.*, vol. 44, pp. 1009–1020, Aug. 1996.

[15] X. W. Wang and H. V. Poor, "Blind equalization and multiuser detection in dispersive CDMA channels," *IEEE Trans. Commun.*, vol. 46, pp. 91–103, Jan. 1998.

[16] M. L. McCloud and L. L. Scharf, "Interference estimation with applications to blind multiple-access communication over fading channels," *IEEE Trans. Inform. Theory*, vol. 46, pp. 947–961, May 2000.

[17] G. Ricci, M. K. Varanasi, and A. De Maio, "Blind multiuser detection via interference identification," *IEEE Trans. Commun.*, vol. 50, pp. 1172–1181, July 2002.

[18] M. K. Varanasi, "Noncoherent detection in asynchronous multiuser channels," *IEEE Trans. Inform. Theory*, vol. 39, pp. 157–176, Jan. 1993.

[19] M. Wax and T. Kailath, "Detection of signals by information theoretic criteria," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. ASSP-33, pp. 387–393, Apr. 1985.

[20] R. Horn and C. Johnson, *Matrix Analysis*. Cambridge, U.K.: Cambridge Univ. Press, 1985.

[21] F. Bandiera, G. Ricci, and M. K. Varanasi, "Subspace-based interference identification over highly-dispersive CDMA channels," in *Proc. 36th Annu. Conf. Information Sciences and Systems*, Princeton, NJ, Mar. 20–22, 2002.

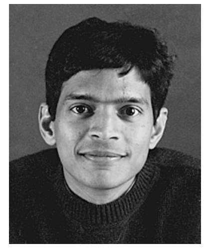
[22] C. Papadias and H. Huang, "Linear space-time multiuser detection for multipath CDMA channels," *IEEE J. Select. Areas Commun.*, vol. 19, pp. 254–265, Feb. 2001.

Francesco Bandiera (M'01) was born in Maglie (LE), Italy, on March 9, 1974. He received the Dr. Eng. degree in computer engineering in 2001 from the University of Lecce, Lecce, Italy, where he is currently working toward the Ph.D. degree.

From July 2001 to February 2002, he was engaged in a research project at the University of Sannio, Benevento, Italy. From September 2003 to March 2004, he was a Visiting Scholar at the Electrical and Computer Engineering Department of the University of Colorado at Boulder. His main interests are in the area of statistical signal processing with emphasis on CDMA systems and radar detection.

Giuseppe Ricci (M'01) was born in Naples, Italy, on February 15, 1964. He received the Dr. Eng. Degree and the Ph. D. degree, both in electronic engineering, from the University of Naples Federico II, Naples, Italy, in 1990 and 1994, respectively.

Since 1995 he has been with the University of Lecce, Lecce, Italy, where he is currently Professor of Electrical Communications. He has held visiting positions at the University of Colorado at Boulder in 1997–1998 and in April/May 2001, and at the Colorado State University, Fort Collins, in July/September 2003. His research interests are in the field of statistical signal processing with emphasis on radar processing and CDMA systems.



Mahesh K. Varanasi (S'87–M'89–SM'95) received the B.E. degree in electronics and communications engineering from Osmania University, Hyderabad, India, in 1984, and the MS. and Ph.D. degrees in electrical engineering from Rice University, Houston, TX, in 1987 and 1989, respectively.

He joined the faculty of College of Engineering and Applied Sciences, University of Colorado, Boulder, in 1989, where he is currently a Professor of Electrical and Computer Engineering. His teaching and research interests are in the areas of communication and information theory, coding, and signal processing. His current research contributions have been in wireless communications, including the areas of multi-user detection, resource allocation via signal design and power control for multiple-user channels, blind receivers, stochastic power control, the information theory of single- and multiuser, multiantenna fading channels, and space–time coding.