Abstract—The problems of channel estimation and multiuser detection for direct sequence code division multiple access (DS/CDMA) systems employing long spreading codes are considered. With regard to channel estimation, several procedures are proposed based on the least-squares approach, relying on the transmission of known training symbols but not requiring any timing synchronization. In particular, algorithms suited for the forward and reverse links of a single-rate DS/CDMA cellular system are developed, and the case of a multirate/multicode system, wherein high-rate users are split into multiple virtual low-rate users, is also considered. All of the proposed procedures are recursively implementable with a computational complexity that is quadratic in the processing gain.

With regard to the issue of multiuser detection, an adaptive serial-interference cancellation (SIC) receiver is considered, where the adaptivity stems from the fact that it is built upon the channel estimates provided by the estimation algorithm. Simulation results show that coupling the proposed estimation algorithms with a SIC receiver may yield, with a much lower computational complexity, performance levels close to those of the ideal linear minimum mean square error (MMSE) receiver, which assumes perfect knowledge of the channels for all of the users and which (in a long-code scenario) has a computational complexity per symbol interval proportional to the third power of the processing gain.

Index Terms—CDMA, channel estimation, least-squares, long-code CDMA systems, multiuser detection, serial interference cancellation.

I. INTRODUCTION

The rapidly growing demand for personal communications services, as well as emerging applications such as mobile computing, wireless local area networking, and wireless Internet access, has focused considerable attention on the design of advanced, high-capacity, multiple-access signaling formats capable of supporting such heterogeneous services. Among the several options available for the implementation of the air interface of future multimedia wireless networks, the leading technology is represented by direct-sequence code division multiple access (DS/CDMA), which has emerged as the basic technique for the realization of the physical layer of third-generation (3G) wireless networks, both terrestrial and satellite-based [1]–[3]. When compared with conventional multiple access techniques, such as those based on time and/or frequency division multiplexing, the CDMA technique appears to be quite advantageous. In particular, it is able to achieve higher system capacities, may be implemented with lighter signaling protocols, has higher frequency-reuse capabilities, is characterized by a superior immunity to co-channel interference and multipath distortion, and can easily support the transmission of multirate information streams.

In recent years, increasing attention has been focused on this latter issue of multirate CDMA systems, in which users are allowed to transmit at one out of a set of available data-rates. Indeed, the possibility of transmitting several kinds of data, each with its own bit-rate and required quality-of-service (QoS), is one of the most attractive features of 3G wireless systems. A very simple way to accommodate multiple-rate transmissions is to use a “conventional” single-rate CDMA network, assigning multiple signature waveforms to the high-rate users. That is, in each signaling interval, high-rate users are allowed to simultaneously transmit several bits by modulating as many signatures, so that they are actually split into several “virtual” users. This technique is referred to as multicode (MC), and has been incorporated in the standard proposal for wideband-CDMA (WCDMA).

In the past two decades, there has also been a significant amount of research devoted to both multiuser detection and spread-spectrum signal parameter estimation techniques in multiuser environments [4]–[10], including results for multirate CDMA systems [8]–[10]. Furthermore, motivated by the fact that the radio channel introduces frequency-selective fading on WCDMA signals, another issue that has been widely investigated is the problem of channel estimation and multiuser detection in fading dispersive channels [11]–[15].

It should be noted, however, that one of the key features of the next-generation CDMA-based wireless networks standards is the adoption of long (aperiodic) spreading codes [16]. The use of long codes ensures that all the users achieve “on the average” the same performance, thus avoiding the unpleasant situation that in an asynchronous environment two or more users have highly correlated signature waveforms for several bit intervals. On the other hand, long codes destroy the bit-interval cyclostationarity properties of the CDMA signals and, thus, make ineffective many of the advanced signal processing techniques that have been developed for blind multiuser detection and adaptive channel estimation in short-code DS/CDMA systems [12]–[14], [17]–[18]. As a consequence, the design of intelligent signal processing techniques for both channel estimation and multiuser
detection in DS/CDMA systems with aperiodic spreading codes poses new challenges and is a novel, largely unexplored research topic. Some results in this area include [19], in which both blind and pilot-assisted procedures for channel estimation in a synchronous CDMA system are presented, and [20], in which a blind channel estimation procedure based on array observations is developed. These algorithms, however, have a computational complexity per symbol interval that is proportional to the third power of the processing gain, which makes them poorly suited for real-time implementations. An alternative approach is presented in [21], in which correlation-matching techniques are employed to estimate multipath parameters blindly. In particular, both centralized and decentralized (i.e., single-user) estimation procedures are given, and their performance is assessed in comparison to the subspace method of [19]. However, only the case of a single-rate DS/CDMA system is considered, the propagation delays are assumed to be known, and the resulting algorithms have high computational complexity. The same considerations apply to the work [22], wherein a Toeplitz displacement method for multipath channel estimation is proposed. Finally, the problem of channel acquisition in a single-rate reverse link cellular scenario is considered in [23]. In particular, it is therein assumed that the channel parameters of a single new user need to be estimated while the remaining active users have been already acquired and successfully demodulated. The proposed technique exhibits satisfactory performance and is immune to the near–far effect, but it assumes knowledge of all of the active users spreading codes and is computationally demanding since, due to the use of long codes, it requires a matrix eigendecomposition at each bit interval.

This paper considers the problem of channel estimation and multiuser detection for long-code DS/CDMA systems operating over a frequency-selective fading channel. The main contributions of this paper may be summarized as follows.

- With regard to channel estimation in single-rate CDMA systems, we propose algorithms based on the least-squares criterion, relying on the transmission of known training symbols, but not requiring any prior timing acquisition. In particular, we develop procedures suited for both the uplink and downlink of a cellular system and which are amenable to a recursive implementation with a computational complexity that is quadratic in the processing gain.

- With regard to channel estimation in multirate CDMA systems, we propose an estimation procedure for multirate/MC CDMA systems, which again relies on the transmission of training symbols and that can be recursively implemented with quadratic computational complexity.

- Finally, with regard to the issue of multiuser detection in long-code CDMA systems, we consider an adaptive serial interference cancellation (SIC) detector, which is driven by the channel estimates furnished by our estimation algorithms. In particular, the originality of our work lies in the extension of SIC structures to asynchronous systems operating over fading dispersive channels, and, above all, their coupling with the proposed estimation procedures. The result is, thus, a code-aided adaptive iterative multiuser receiver exhibiting performance levels close to those of the ideal linear minimum mean square error (MMSE) detector but having a computational complexity only quadratic in the processing gain.

The performance of the proposed estimation/detection algorithms is thoroughly assessed through some analytical considerations and through extensive computer simulation results.

It should be noted that the results presented herein have already been partly reported in the conference paper [24]. For the sake of fairness, the authors would like to acknowledge that estimation algorithms similar to those presented in this paper have independently appeared in [25], which was presented at the same conference as [24].

The rest of the paper is organized as follows. Section II describes the system model for both a single-rate and a multirate/MC DS/CDMA system with aperiodic codes, while Section III presents several channel estimation procedures. The performance of the proposed estimation algorithms is illustrated in Section IV; while in Section V, the adaptive iterative multiuser receiver is presented, and some sample results illustrating its performance are provided and discussed. Finally, in Section VI, concluding remarks are drawn and some open problems are discussed.

**II. System Model**

To begin, let us consider a single-rate asynchronous DS/CDMA system with \( K \) users, employing long spreading codes and operating over a frequency-selective fading channel. The baseband equivalent of the received signal may be written as

\[
r(t) = \sum_{p=0}^{B-1} \sum_{k=0}^{K-1} A_k b_k(p) s_{k,p}(t - T_k - p \Delta t_k) \ast c_k(t) + w(t),
\]

(1)

In the above expression, \( B \) is the transmitted frame or packet length, \( T_k \) is the bit-interval duration, \( A_k \) and \( T_k \geq 0 \) denote the amplitude and timing offset of the \( k \)-th user, \( b_k(p) \in \{+1, -1\} \) is the \( k \)-th user’s information symbol in the \( p \)-th signaling interval, while \( s_{k,p}(t) \) is the \( k \)-th user’s signature waveform in the \( p \)-th signaling interval. Finally, \( c_k(t) \) is the impulse response modeling the channel effects between the receiver and the \( k \)-th user’s transmitter, while \( w(t) \) is the complex envelope of the additive noise term, which is assumed to be a zero-mean, wide-sense stationary (WSS) complex white Gaussian process with power spectral density (PSD) \( 2N_0 \). It is also assumed that the channel coherence time exceeds the packet duration \( BT_k \), so that the channel impulse responses \( c_0(t), \ldots, c_{K-1}(t) \) may be assumed to be time-invariant over each transmitted frame. Notice that the above model is general enough to subsume most cases of relevant interest. In particular, with regard to a downlink (i.e., point-to-multipoint) transmission, the CDMA signals propagate through the same channel, i.e., \( c_0(t) = \ldots = c_{K-1}(t) \), and are synchronously transmitted, i.e., \( T_0 = \ldots = T_{K-1} \). If, instead, the above conditions are not met, then the signal (1) may represent the received waveform in a multipoint-to-point (uplink) transmission.
Denoting by \( h_{k,p}(t) = A_k s_{k,p}(t - \tau_k) \) the effective signature waveform for the \( k \)-th user in the \( p \)-th signaling interval, the signal (1) can be expressed as

\[
r(t) = \sum_{p=0}^{D-1} \sum_{k=0}^{K-1} b_k(p) h_{k,p}(t - pT_b) + w(t).
\]

Notice that the waveform \( h_{k,p}(t) \) is supported in the interval \([\tau_k, \tau_k + T_c + T_m]\), where \( T_m \) denotes the maximum channel multipath delay spread over the \( K \) active users; of course, \( h_{k,p}(t) \) depends explicitly on the symbol index \( p \) since we are considering a DS/CDMA system with aperiodic spreading. In particular, since in a DS system the signature waveform is written as

\[
s_{k,p}(t) = \sum_{n=0}^{N-1} \beta_{k,p}^{(n)} u_{T_c}(t - nT_c)
\]

the waveform \( h_{k,p}(t) \) can also be written as

\[
h_{k,p}(t) = \sum_{n=0}^{N-1} \beta_{k,p}^{(n)} g_k(t - nT_c).
\]

In (3), \( N \) is the processing gain, \( T_c = T_b/N \) is the chip interval, \( \{\beta_{k,p}^{(n)}\}_{n=0}^{N-1} \) is the \( k \)-th user’s spreading sequence in the \( p \)-th signaling interval, \( u_{T_c}(\cdot) \) is a unit-height rectangular waveform of duration \( T_c \), and

\[
g_k(t) = A_k u_{T_c}(t - \tau_k) \ast c_k(t)
\]

is the “effective” chip-pulse at the channel output. From the above equation, it follows easily that the waveform \( g_k(t) \) is supported in the interval \([\tau_k, \tau_k + T_m + T_c]\). Assuming that \( \tau_k + T_m < T_b \), the support of the waveform \( h_{k,p}(t - pT_b) \) is contained in the interval \( [\tau_k, \tau_k + T_b] \), whence the signal \( r(t) \), as observed in the interval \( [\tau_k, \tau_k + T_b] \), can be written as

\[
r_p(t) = \sum_{k=0}^{K-1} b_k(p) h_{k,p}(t - pT_b) + z(t) + w(t)
\]

In the above equation, the term \( z(t) \) denotes the contribution from the bits \( b_k(p) \) and \( b_k(p+1), \forall k \), to the waveform received in the processing window \( [\tau_k, \tau_k + T_b] \). Also, observe that, since for a DS/CDMA communication system \( T_m \) is usually much smaller than the bit interval \( T_b \), the assumption that \( \tau_k + T_m < T_b \) is equivalent to requiring that the initial uncertainty on the propagation delays is approximately on the order of \( T_m \). This is a very mild assumption, in that it may assumed that a coarse timing synchronization has been achieved through the use of a GPS-based common clock, or alternatively, through the aid of higher layer network protocols. Finally, notice that even though it has been assumed that the chip waveform is a rectangular pulse, it is worth pointing out that the following derivations can be extended with very minor modifications to the case that a bandlimited raised-cosine chip waveform is employed, as it occurs in most 3G standard proposals.

Before proceeding to the illustration of the proposed channel estimation algorithms, let us now briefly discuss the system model for a multirate DS/CDMA system implemented with the MC access technique. It is assumed here that there is an available data-rates, all of which are integer multiples of the basic data-rate \( T_b \). Accordingly, if, for instance, a given user wants to transmit at rate \( G/T_b \), then it will be assigned \( G \) different signature waveforms. Assuming, with no loss of generality, that these signatures are numbered by the indices \( 0, \ldots, G-1 \), the model in (1) still applies, with the understanding that \( K \) denotes now the number of virtual users. Again, assuming that \( \tau_0 = \cdots = \tau_{K-1} \) and that \( c_0(t) = \cdots = c_{K-1}(t) \) models the received signal in a downlink communication, while, with regard to the uplink, we just have \( \tau_0 = \cdots = \tau_{G-1} \) and \( c_0(t) = \cdots = c_{G-1}(t) \), since the signatures from the high-rate user undergo the same multipath distortion and are synchronously transmitted.

III. CHANNEL ESTIMATION ALGORITHMS

In order to produce a discrete-time signal for processing, the waveform \( r(t) \) is fed to a low-pass filter whose impulse response is an unit-energy rectangular waveform of duration \( T_c/M \), with \( M \) an integer number; the output of this filter is then sampled at rate \( M/T_c \). Observe that, if \( M = 1 \), this operation amounts to chip-matched filtering and chip-rate sampling; if, instead, \( M > 1 \), this operation corresponds to signal-space oversampling by a factor of \( M \). As discussed in [26], letting \( M > 1 \) enables a more accurate representation of the received signal in an asynchronous system, and, ultimately, leads to receivers with improved performance.

Now, stack the samples corresponding to the waveform \( r(t) \), as observed in the \( p \)-th signaling interval \([pT_b, (p+1)T_b]\), in the following \( NM \)-dimensional vector

\[
\mathbf{r}(p) = [r(MNp), r(MNp+1), \ldots, r(NMp + N - 1)]^T
\]

with \((\cdot)^T\) denoting transposition and where, with a slight notational abuse, the sample \( r(MNp + i) \) is defined as

\[
r(MNp + i) = \int_{(MNp+i)T_c/M}^{(MNp+i+1)T_c/M} r(t) dt
\]

with \( i = 0, \ldots, NM - 1 \). Since, as already highlighted, the waveform \( g_k(t) \) is nonzero in the interval \([\tau_k, \tau_k + T_m + T_c]\), and it has been assumed that \( \tau_k + T_m < T_b \), it follows readily that the samples \( g_k(t) = \int_{(MNp+i)T_c/M}^{(MNp+i+1)T_c/M} g_k(t) dt \) are identically zero for \( t \notin \{0, 1, \ldots, (N+1)M - 1\} \). Now, denote by \( \mathbf{u}(p) \) the
A NM-dimensional vector defined as $r(p)$ in (5), by $g_k$ the following $(N+1)M$-dimensional vector

$$g_k = [g_k(0), g_k(1), \ldots, g_k((N+1)M-1)]^T$$

(7)

and by $C_{k,p}$ the $2NM \times (N+1)M$-dimensional code matrix

$$C_{k,p} = \begin{bmatrix}
\beta_{k,p}^{(0)} & 0 & \cdots & 0 \\
\beta_{k,p}^{(1)} & \beta_{k,p}^{(0)} & \cdots & 0 \\
\vdots & \ddots & \ddots & \cdots & 0 \\
0 & \cdots & 0 & \beta_{k,p}^{(N+1)} \\
0 & 0 & \cdots & \beta_{k,p}^{(N)} \\
0 & 0 & \cdots & 0 & \beta_{k,p}^{(N-1)}
\end{bmatrix} \otimes I_M$$

(8)

with $\otimes$ denoting the Kronecker product [27] and $I_M$ the identity matrix of order $M$. Furthermore, denote by $C_{k,p}^u$ and $C_{k,p}^l$ the $NM \times (N+1)M$-dimensional matrices obtained by retaining the $NM$ uppermost and lowest rows of the matrix $C_{k,p}$. Finally, let

$$h_{k,p} = [h_{k,p}(0), h_{k,p}(1), \ldots, h_{k,p}(2NM-1)]^T$$

(9)

denote a $2NM$-dimensional vector with entries given by $h_{k,p}(\ell) = \int_{T_{\ell}/M}^{(\ell+1)T_{\ell}/M} h_{k,p}(t) \, dt$, and denote by $h_{k,p}^u$ and $h_{k,p}^l$ the $NM$-dimensional vector obtained by retaining the $NM$ uppermost and lowest entries of $h_{k,p}$, respectively.

Based on the above notation, the observable $r(p)$, defined in (5), can be expressed as

$$r(p) = \sum_{k=0}^{K-1} \left( b_k(p-1)h_{k,p}^u + b_k(p)h_{k,p}^l \right) + w(p)$$

$$= \sum_{k=0}^{K-1} \left( b_k(p-1)C_{k,p}^u + b_k(p)C_{k,p}^l \right) g_k + w(p)$$

(10)

wherein the equality follows from the relations

$$h_{k,p}^u = C_{k,p}^u g_k \quad \text{and} \quad h_{k,p}^l = C_{k,p}^l g_k.$$  

Interestingly, the above equations reveal that, even though aperiodic codes are being adopted, the discrete-time signatures of the users are, in fact, the product of a time-varying but known code-matrix times an unknown but time-invariant vector, which carries all information about the unknown channel impulse response and signal timing. Our goal is, thus, to develop algorithms for estimating this vector. Although the discrete-time model (10) is general enough to include all the previously illustrated special cases, a clear exposition of the channel estimation algorithms necessarily requires considering each case separately.

A. Decentralized Channel Estimation

Let us first assume that the receiver is interested in estimating the channel from a given user only, say the $h$-th. For instance, such a situation may occur in an asynchronous uplink CDMA channel, wherein a new user is starting its transmission and its channel and timing are to be acquired by the base station. Alternatively, this situation again occurs in a mobile station receiver, which indeed can rely on the knowledge of its own spreading sequence only. Upon defining the matrices

$$C_{k,p} = \begin{bmatrix} C_{k,p}^u, C_{k,p}^l \end{bmatrix}$$

and

$$B_k(p) = [b_k(p-1) b_k(p)] \otimes I_{(N+1)M}$$

(11)

the vector $r(p)$ can be expressed as

$$r(p) = \sum_{k=0}^{K-1} C_{k,p} B_k(p) g_k + w(p).$$

(12)

We now make the following assumptions.

a) The receiver has an initial uncertainty on the delay $\tau_h$ equal to $T_h - T_m$.

b) The bits $b_k(0), \ldots, b_k(N_p)$, are known to the receiver, with $N_p$ the number of signaling intervals devoted to the transmission of the known pilot symbols.

c) No knowledge is assumed on the interfering signals, namely the number of interfering users, their signatures, delays, and propagation channels.

Based on the previous assumptions, the use of a least-squares-based procedure is here proposed, i.e., the estimate, $\hat{g}_h(n)$ say, of the vector $g_h$, available upon transmission of $n$ known training symbols, is obtained as the solution to the following minimization problem

$$\hat{g}_h(n) = \arg \min_{\tilde{g}} \sum_{j=1}^{n} \frac{1}{n} \| r(p) - C_{h,p} B_h(p) \tilde{g}(n) \|^2.$$  

(13)

Solving problem (13) yields the following batch solution

$$\hat{g}_h(n) = \left( \sum_{j=1}^{n} B^H_h(p) C_{h,p}^H \right)^{-1} \sum_{j=1}^{n} B^H_h(p) C_{h,p}^H r(p).$$  

(14)

with $(\cdot)^H$ denoting conjugate transposition. Since the product $B^H_h(p) C_{h,p}^H \tilde{g}_h(p)$ is a square matrix of order $(N+1)M$, the above estimation rule entails a computational complexity equal to $O(((N+1)M)^3)$. This can be an unaffordable computational effort, especially in mobile terminals, or, alternatively, if the transmitting station adopts a separate channel on which training symbols are continuously transmitted, so that the estimate

1Observe that this hypothesis, which is not necessary in CDMA systems employing short codes, is needed here because the receiver has to know which spreading code the desired user will be adopting in each signaling interval, i.e., it has to know that the bit $b_h(p)$ modulates the signature $C_{h,k} g_k$, which is entirely contained in the interval $[\tau_h - T_h/2, \tau_h + T_h/2]$. However, this is a very mild assumption, in that, since usually $T_m \ll T_h$, this assumption corresponds to requiring an initial delay estimate affected by an error contained in the interval $[-T_h/2, T_h/2]$. As already discussed, such an estimate can easily be obtained by resorting, for instance, to a GPS-based common synchronization clock, or, alternatively, can be delivered by higher-layer network protocols.

2This circumstance occurs in many CDMA-based 3G wireless network standard proposals [1], [3].
mate of the vectors $\mathbf{g}$, may be updated on a bit-interval basis. It may, thus, be preferable to resort to the following steepest-descent recursive adaptation rule

$$\hat{\mathbf{g}}_n = \left[ I_{NM+1} - \mu \sum_{j=1}^{n} \frac{1}{n} \mathbf{B}_j^H(p) \mathbf{C}_{\eta_{a,j}} \mathbf{C}_{\eta_{b,j}} \mathbf{B}_j(p) \right]$$

$$\times \hat{\mathbf{g}}_{n-1} + \mu \sum_{j=1}^{n} \frac{1}{n} \mathbf{B}_j^H(p) \mathbf{C}_{\eta_{a,j}} \mathbf{r}(p).$$

(15)

with $\mu$ a suitably chosen step-size. The complexity per bit interval of this rule is now quadratic in the processing gain.

### B. Centralized Channel Estimation

Let us now consider the case that the channels of all active users are to be estimated, thus implying that all the users are transmitting known training symbols. Such a situation may occur in the uplink of an asynchronous CDMA-based packet network, wherein users transmit a data packet (with a known preamble) in a given time-slot with a coarse synchronization so that the signal received at the base station is actually asynchronous. It is here assumed that a) the receiver has an initial uncertainty on the delays $\tau$ equal to $[-T_b/2, T_b/2]^K$ and b) the bits $b_k(0), \ldots, b_k(N_p)$, $\forall k = 0, \ldots, K - 1$ are known to the receiver, with $N_p$ the length in bit intervals of the preamble of each packet.

To begin with, observe that, upon defining

$$\tilde{\mathbf{C}}_p = [\mathbf{C}_{0,p}, \mathbf{C}_{1,p}, \ldots, \mathbf{C}_{K-1,p}],$$

$$\tilde{\mathbf{B}}_p = \mathbf{D}_{\text{avg}}(\tilde{\mathbf{B}}_0(p) \mathbf{B}_1(p) \ldots \mathbf{B}_{K-1}(p)),$$

and

$$\tilde{\mathbf{g}} = [\tilde{\mathbf{g}}_1, \ldots, \tilde{\mathbf{g}}_{K-1}]^T$$

(16)

the vector $\mathbf{r}(p)$ in (12) can be written as

$$\mathbf{r}(p) = \tilde{\mathbf{C}}_p \tilde{\mathbf{B}}_p \tilde{\mathbf{g}} + \mathbf{w}(p).$$

(17)

Accordingly, the estimate, $\hat{\mathbf{g}}(n)$, say, of the $K(N+1)M$-dimensional vector $\tilde{\mathbf{g}}(n)$, available upon observation of the vectors $\mathbf{r}(1), \ldots, \mathbf{r}(n)$, solves the problem

$$\hat{\mathbf{g}}(n) = \arg \min_{\mathbf{g}} \sum_{j=1}^{n} \frac{1}{n} ||\mathbf{r}(p) - \tilde{\mathbf{C}}_p \tilde{\mathbf{B}}_p \mathbf{g}||^2.$$  

(18)

Accordingly, the solution is written as

$$\hat{\mathbf{g}}(n) = \left( \sum_{j=1}^{n} \mathbf{B}_j^H(p) \tilde{\mathbf{C}}_p^H \mathbf{C}_{\eta_{a,j}} \mathbf{B}_j(p) \right)^{-1} \times \left( \sum_{j=1}^{n} \mathbf{B}_j^H(p) \tilde{\mathbf{C}}_p^H \mathbf{r}(p) \right).$$

(19)

It is worth pointing out that, for the case at hand, the least-squares criterion (18) is equivalent to the maximum-likelihood (ML) estimation procedure, whence (19) does represent the ML estimator of the vector $\tilde{\mathbf{g}}$. Additionally, since it is seen from (17) that there exists a linear relationship between the noiseless data and the quantity to be estimated, it can be also shown ([28], Theorem 4.1) that (19) is also the minimum variance unbiased estimator (MVUE) for the vector $\tilde{\mathbf{g}}$.

The computational complexity involved in the computation of expression (19) is $O((MK)^3(N + 1)^3)$; and, also in this case, alternative, lower complexity, steepest-descent adaptation rules can be adopted, yielding

$$\hat{\tilde{\mathbf{g}}}(n) = \left[ I_{K(NM+1)} - \mu \sum_{j=1}^{n} \frac{1}{n} \mathbf{B}_j^H(p) \mathbf{C}_{\eta_{a,j}} \mathbf{C}_{\eta_{b,j}} \mathbf{B}_j(p) \right]$$

$$\times \hat{\tilde{\mathbf{g}}}(n-1) + \mu \sum_{j=1}^{n} \frac{1}{n} \mathbf{B}_j^H(p) \mathbf{C}_{\eta_{a,j}} \mathbf{r}(p).$$

(20)

Due to the highly structured shape of the matrix $\mathbf{B}_j^H(p) \mathbf{C}_{\eta_{a,j}} \mathbf{C}_{\eta_{b,j}} \mathbf{B}_j(p)$, it can be shown that implementing the above adaptation rule entails a computational complexity equal to $O((KNM)^3)$.

As a final remark, it is worth pointing out that the proposed strategy may be easily extended to the more realistic case that only one “new” user is sending training bits, while the remaining users are transmitting information bits. One simple way to cope with such a scenario might be to apply the decentralized estimation procedure; however, in the base-station, another choice is to apply the centralized estimation algorithm in a decision-directed mode for the other users. It is reasonable to expect that, for reliable bit estimates, the corresponding modified version of the centralized estimation algorithm should perform better than the decentralized estimation algorithm, which does not exploit knowledge of the spreading codes of the remaining users.

### C. Channel Estimation for Multirate/Multicode Systems

Let us now consider the case of a multirate/multicode DS/CDMA system. Resuming the signal model introduced at the end of the previous section, i.e., assuming that the first $G$ signatures are assigned to one high-rate user, the $NM$-dimensional vector $\mathbf{r}(p)$ is now written as

$$\mathbf{r}(p) = \sum_{k=0}^{G-1} \mathbf{C}_{k,p} \mathbf{B}_k(p) \mathbf{g}_0$$

$$+ \sum_{k=G}^{K-1} \mathbf{C}_{k,p} \mathbf{B}_k(p) \mathbf{g}_k + \mathbf{w}(p)$$

(21)

wherein the fact that $\mathbf{g}_0 = \ldots = \mathbf{g}_{G-1}$ has been used. On letting

$$\mathbf{C}_G(p) = [\mathbf{C}_{0,p}, \mathbf{C}_{1,p}, \ldots, \mathbf{C}_{G-1,p}]$$

and

$$\mathbf{B}_G(p) = [b_0(p) b_1(p) \ldots b_{G-1}(p)]^T \otimes \mathbf{I}_{(N+1)M}$$

(22)

and assuming that the high-rate user is in a training mode, i.e., it is transmitting known symbols by linearly modulating all of its $G$ signatures, the estimate, $\hat{\mathbf{g}}_0(n)$, say, of the vector $\mathbf{g}_0$, obtained upon observation of the vectors $\mathbf{r}(1), \ldots, \mathbf{r}(n)$, is the solution to the following minimization problem

$$\hat{\mathbf{g}}_0(n) = \arg \min_{\mathbf{g}_0} \frac{1}{n} \sum_{j=1}^{n} ||\mathbf{r}(p) - \mathbf{C}_G(p) \mathbf{B}_G(p) \mathbf{g}_0||^2.$$  

(23)
Skipping the mathematical details, the batch solution to the above problem and its recursive implementation may be written respectively as

\[ \hat{\mathbf{g}}_b(n) = \left( \frac{1}{n} \sum_{j=1}^{n} \mathbf{B}_G^H(p) \mathbf{C}_G^H(p) \mathbf{C}_G(p) \mathbf{B}_G(p) \right)^{-1} \times \left( \frac{1}{n} \sum_{j=1}^{n} \mathbf{B}_G^H(p) \mathbf{C}_G^H(p) \mathbf{r}(p) \right) \]

and

\[ \hat{\mathbf{g}}_b(n) = \left[ \mathbf{I}_{(N+1)M} - \mu \sum_{j=1}^{n} \frac{1}{n} \mathbf{B}_G^H(p) \mathbf{C}_G^H(p) \mathbf{C}_G(p) \mathbf{B}_G(p) \right] \times \hat{\mathbf{g}}_b(n-1) + \mu \sum_{j=1}^{n} \frac{1}{n} \mathbf{B}_G^H(p) \mathbf{C}_G^H(p) \mathbf{r}(p). \]  

Again, it can be easily shown that the computational complexity of the recursive adaptation rule is quadratic in the product \( N M \). Obviously, if we let \( G = 1 \) the rules (24) and (25) reduce to the decentralized estimation rules (14) and (15), respectively.

As a final remark, notice that, if pilot symbols are continuously transmitted (as in the downlink, the proposed algorithms may be also used in fast-fading environments to track the channel impulse response variations. In this case, however, in order to ensure the algorithm tracking capabilities, it is advisable to use an exponential forgetting factor (i.e., \( \lambda^{n-p} \)) in place of the factor \( 1/n \) (with \( \lambda \) a positive constant slightly smaller than unity) in the penalty functions (13), (18) and (23). The corresponding solutions, minimizing these modified penalty functions can be straightforwardly obtained along the same lines that led to the above adaptation rules. Further details on this issue are omitted for the sake of brevity.

IV. PERFORMANCE ANALYSIS

Some results on the convergence properties of the adaptive rules (14), (19), (24), and of their recursive counterparts (15), (20) and (25) can be easily proven. In particular, the following results hold.

1) Assuming that the bits \( b_{h}(0), \ldots, b_{h}(n) \) are nonrandom parameters, while the bits \( b_{hl}(0), \ldots, b_{hl}(n), \forall h' \neq h \), are zero-mean random binary variates, the estimation rule (14) is unbiased \( \forall h \) and asymptotically (i.e., for increasingly large \( n \)) consistent.

2) Assuming that the bits \( b_{h}(0), \ldots, b_{h}(n), \forall h = 0, \ldots, K-1 \) are nonrandom parameters, the estimation rule (19) is unbiased \( \forall h \) and asymptotically (i.e., for increasingly large \( n \)) consistent. Additionally, it achieves the Cramer–Rao bound \( \forall h \).

3) Assuming that the bits \( b_{h}(0), \ldots, b_{h}(n), \forall h = 0, \ldots, G-1 \) are nonrandom parameters, while the bits \( b_{hl}(0), \ldots, b_{hl}(n), \forall h' = G, \ldots, K-1 \), are zero-mean random binary variates, the estimation rule (24) is unbiased \( \forall h \) and asymptotically (i.e., for increasingly large \( n \)) consistent.

4) Under the same assumptions made in 1., let \( \lambda_{\text{max}}(n) \) denote the largest eigenvalue of the matrix

\[ \frac{1}{n} \sum_{j=1}^{n} \mathbf{B}_h^H(p) \mathbf{C}_h^H(p) \mathbf{C}_h(p) \mathbf{B}_h(p). \]

The recursive rule (15) is asymptotically unbiased if the step size \( \mu \) satisfies the condition \( 0 < \mu < (2/\lambda_{\text{max}}(n)), \forall h \).

5) Under the same assumptions made in 2., let \( \lambda_{\text{max}}(n) \) denote the largest eigenvalue of the matrix

\[ \frac{1}{n} \sum_{j=1}^{n} \mathbf{B}_h^H(p) \mathbf{C}_h^H(p) \mathbf{C}_h(p) \mathbf{B}_h(p). \]

The recursive rule (20) is asymptotically unbiased if the step size \( \mu \) satisfies the condition \( 0 < \mu < (2/\lambda_{\text{max}}(n)), \forall h \).

6) Under the same assumptions made in 3., let \( \lambda_{\text{max}}(n) \) denote the largest eigenvalue of the matrix

\[ \sum_{j=1}^{n} \frac{1}{n} \mathbf{B}_h^H(p) \mathbf{C}_h^H(p) \mathbf{C}_h(p) \mathbf{B}_h(p). \]

The recursive rule (25) is asymptotically unbiased if the step size \( \mu \) satisfies the condition \( 0 < \mu < (2/\lambda_{\text{max}}(n)), \forall h \).

The proofs of the above results are based on standard techniques employed in the analysis of adaptive algorithms [29] and are omitted for the sake of brevity. However, in order to corroborate the effectiveness of the proposed estimation algorithms in what follows, some computer simulation results are provided. The considered performance measure is the normalized correlation coefficient between the estimated effective received signature waveforms and their actual values, i.e.

\[ \rho(n) = \frac{1}{Q} \sum_{k=0}^{Q-1} \frac{\mathbf{b}_{hk}^H(p) \mathbf{C}_{hk}(n) \hat{\mathbf{g}}_b(n)}{||\mathbf{b}_{hk}|| ||\mathbf{C}_{hk}(n)||} \]

wherein \( || . || \) denotes the usual Euclidean norm in \( \mathbb{C}^{NM} \) (\( C \) denotes the complex field), while \( Q \) is equal to \( 1, K \) or \( G \) for the decentralized, centralized, and multirate/MC estimation algorithms, respectively. The simulations consider a CDMA system with processing gain \( N = 15 \), and oversampling factor \( M = 2 \). The average received energy contrast \( E_{bl}/N_0 \) is 13 dB. The long spreading sequences have been randomly generated, and the results given are an average over 1000 independent simulation trials; in each trial, the propagation channel has been assumed to have the following three-path impulse response

\[ c_k(t) = \sum_{l=0}^{L} \alpha_{k,l} \delta(t - \tau_{k,l}), \quad \forall k = 0, \ldots, K-1 \]

with the fading coefficients \( \alpha_{k,l} \) and the delays \( \tau_{k,l} \) randomly generated.
Fig. 1 shows the parameter $\rho(n)$ (for the decentralized steepest-descent rule (15)) versus the number of iterations for single-rate systems with $K = 4$ and $K = 9$. More precisely, for each value of $K$, Fig. 1 shows two curves, corresponding to the cases that the interfering users signals have 3 dB and 10 dB advantage over the signal of the user of interest. In order to compare the performance of the recursive, lower complexity, adaptation rule (15) with that of the batch estimation procedure (14), Fig. 2 shows the normalized correlation $\rho(n)$ for both rules. In particular, it is therein considered a single-rate system with $K = 5$ users and three different values of the interfering signals' power advantage (referred to in the captions through the acronym ISR) over the signal of interest. In Fig. 3, instead, we show the performance of the adaptation rule (25) in an actual multirate scenario with $K = 10$; in particular, this figure shows the normalized correlation $\rho(n)$ for several values of $G$. The interfering users are chosen to have a power advantage of 10 dB over the $G$ users of interest. Overall, these results confirm that the proposed technique is effective, even though, for increasing values of the ISR, some performance degradation is observed. Additionally, it is seen from Fig. 2 that the recursive, lower-complexity, rule is capable of closely tracking the convergence dynamics of the batch estimation procedure, while Fig. 3 reveals that, for increasing $G$, the acquisition performance noticeably improves. This implies that, in a time-multiplexed pilot scenario, a high-rate user should send training bits in a parallel fashion on all of the $G$ available signatures so that its channel can be rapidly acquired.

V. ADAPTIVE ITERATIVE INTERFERENCE CANCELLATION

Once reliable estimates of the channel impulse responses have been obtained, the receiver is then faced with the problem of detecting the transmitted information bits. It is worth noting that the problem of multiuser detection for CDMA systems with long codes is not trivial, since, due to the aperiodicity of the spreading codes, the well-known adaptive implementations of the linear MMSE detector, based, e.g., on the RLS algorithm and on the subspace approach [18], [30], are not effective in this context. Likewise, implementing the nonadaptive version of the MMSE receiver requires a matrix inversion at each bit interval, thus entailing a computational complexity proportional to the third power of the processing gain.

This section focuses on the problem of multiuser detection in DS/CDMA systems with long-codes. In particular, an uplink channel is considered, i.e., it is here assumed that the receiver is interested in demodulating the information transmitted by all of the active users, based on the knowledge of their spreading codes and on the estimates of their propagation channels. In order to obtain a multiuser detector with quadratic complexity, we resort here to the concept of linear iterative SIC, which has been shown to be able to provide performance levels close to those of the MMSE receiver but with a lower complexity [31]–[33]. Previously, SIC receivers have been mostly considered with reference to synchronous CDMA systems operating over nonfading channels and assuming perfect knowledge of the signals' amplitudes. The contribution of this section is, thus, the application of SIC structures to the asynchronous,
Fig. 2. Performance of the decentralized batch rule (14) and decentralized recursive adaptation rule (15) for a single-rate system with $K = 5$ users and several values of ISR. System parameters: $E_b/N_0 = 13$ dB, $M = 2$.

Fig. 3. Performance of the recursive algorithm (25) for a multirate system with $K = 10$ and several values of $G$. System parameters: $E_b/N_0 = 13$ dB, $M = 2$, ISR = 10 dB.
fading-dispersive scenario, and, mostly important, their coupling with our previously outlined estimation procedure. The result is an adaptive iterative SIC receiver, which does not require knowledge of the received signal parameters to be implemented. In the following, the structure of the linear SIC receiver is first briefly reviewed, and then some simulation results illustrating the performance of the proposed adaptive iterative SIC receiver are discussed.

In order to demodulate the information bits with index \( i \), it is convenient to consider the waveform \( r_2(t) \) observed in the interval \( T_p = [jiI_1, (p + 2)I_1] \) [see (4)]. Discretizing the signal received in such an interval gives thus the following 2NM-dimensional vector

\[
\mathbf{r}_2(p) = \sum_{k=0}^{K-1} \left( b_k(p-1)\mathbf{c}_{k, p}^i + b_k(p)\mathbf{c}_{k, p} \right) + b_k(p+1)\mathbf{c}_{k, p+1}^i \mathbf{g}_k + \mathbf{w}_2(p)
\]

(26)

wherein \( \mathbf{w}_2(p) \) represents the thermal noise contribution and the matrices \( \mathbf{c}_{k, p}^i \) and \( \mathbf{c}_{k, p} \) are defined as

\[
\mathbf{c}_{k, p}^i = \begin{bmatrix} \mathbf{c}_{k, p}^{i-1} \\ \mathbf{O} \end{bmatrix}
\]

and

\[
\mathbf{c}_{k, p} = \begin{bmatrix} \mathbf{O} \\ \mathbf{c}_{k, p+1} \end{bmatrix}
\]

(27)

with \( \mathbf{O} \) an all-zero \( NM \times (N+1)M \)-dimensional matrix. Any linear receiver takes a decision on the \( h \)-th user bit \( b_h(p) \) according to the following rule

\[
b_h(p) = \text{sign} \left\{ \Re \left[ \mathbf{d}_h^H(p) \mathbf{r}_2(p) \right] \right\}
\]

(28)

wherein \( \text{sign}(\cdot) \) and \( \Re(\cdot) \) denote signum and real part, respectively, while \( \mathbf{d}_h(p) \) is a vector to be designed according to some optimization criterion. If, for instance, linear MMSE detection is considered, we have

\[
\mathbf{d}_h(p) = \mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p)\mathbf{c}_{h,p}^i \mathbf{g}_h = (\mathbf{H}(p)\mathbf{H}(p)^H + 2N_0\mathbf{I}_{2NM})^{-1} \mathbf{h}_{h,p}
\]

(29)

wherein \( \mathbf{H}(p) \) is the \( 2NM \times 3K \)-dimensional signature matrix defined as

\[
\mathbf{H}(p) = \begin{bmatrix} \mathbf{c}_{0,p-1}^i \mathbf{g}_0 \cdots \mathbf{c}_{0,p}^i \mathbf{g}_0 \cdots \\ \mathbf{c}_{K-1,p-1}^i \mathbf{g}_{K-1} \cdots \mathbf{c}_{K-1,p}^i \mathbf{g}_{K-1} \cdots \\ \mathbf{c}_{0,p}^i \mathbf{g}_0 \cdots \mathbf{c}_{K-1,p}^i \mathbf{g}_{K-1} \cdots \end{bmatrix}
\]

(30)

Based on (29) and (30), it is clear that the linear MMSE receiver can be made adaptive by replacing the vectors \( \mathbf{g}_0 \cdots \mathbf{g}_{K-1} \) in the matrix \( \mathbf{H}(p) \) with their estimates \( \hat{\mathbf{g}}_0(\cdot) \cdots \hat{\mathbf{g}}_{K-1}(\cdot) \), and the vector \( \mathbf{h}_{h,p} \) in (29) with its estimate \( \hat{\mathbf{c}}_{h,p}^i(\cdot) \). Furthermore, in order to avoid the computationally demanding batch inversion of the matrix \( \mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p) \), we can resort to the iterative Gauss–Seidel procedure [34], [35]. More precisely, since the test statistic in (28) is given by \( \mathbf{h}_{h}^H(p)\mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p)\mathbf{r}_2(p) \), the vector \( \mathbf{y}(p) = \mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p)\mathbf{r}_2(p) \) can be regarded as the solution to the linear system

\[
\mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p)\mathbf{y}(p) = \mathbf{r}_2(p).
\]

This system can be solved through the Gauss–Seidel iterative technique so as to avoid the computationally demanding batch matrix inversion. On decomposing

\[
\mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p)\mathbf{y}(p) = \mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p)\mathbf{r}_2(p) + \mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p)\mathbf{y}^{(m-1)}(p)
\]

with \( \mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p), \mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p) \) and \( \mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p) \) denoting the upper triangular, lower triangular, and diagonal part of the matrix \( \mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p) \), the algorithm output at the \( m \)-th iteration is, thus, written as [34]

\[
\mathbf{y}^{(m)}(p) = \mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p)\mathbf{r}_2(p) + \mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p)\mathbf{y}^{(m-1)}(p)
\]

(31)

Notice that each iteration can be accomplished with \( \mathcal{O}((NM)^2) \) computational complexity, while the estimate, at the \( m \)-th iteration, of the bit \( b_h(p) \), is given by

\[
b_h^{(m)}(p) = \text{sign} \left\{ \Re \left[ \mathbf{g}_h^H(\cdot)\mathbf{c}_{h,p}^i(\cdot)\mathbf{y}^{(m)}(p) \right] \right\}.
\]

(32)

As is well known under a “multiuser detection” perspective, applying the Gauss–Seidel algorithm is equivalent to considering a linearly weighted SIC receiver [31]. Since the matrix \( \mathbf{R}^{-1}_{\mathbf{r}_2\mathbf{r}_2}(p) \) is positive definite, the adaptation rule (31) is guaranteed to converge for any starting point \( \mathbf{y}^{(0)} \) ([34], Th. 10.1.2, p. 512).

### A. Computer Simulation Examples

In order to assess the performance of the proposed adaptive receiver, a single-rate DS/CDMA system with processing gain \( N = 15 \) and with \( K = 6 \) users is considered. The oversampling factor \( M \) is set equal to 2. In Fig. 4, the performance of the proposed adaptive SIC receiver is reported versus the average received energy contrast \( E_p/N_0 \), expressed in dB. It is assumed that the centralized estimation algorithm (20) is adopted by processing a training sequence of 50 and 150 bits, for the plot on the left and on the right, respectively. The channel impulse responses have the same structure as in the previous simulations, and the curves represent the average performance corresponding to 100 different random realizations of the propagation channels and users’ delays. All of the users have the same average power (the instantaneous powers are random due to the different channel realizations). The initial point \( \mathbf{y}^{(0)} \) of the iterative procedure is set equal to the all-zero vector. Fig. 5, moreover, considers the same scenario as Fig. 4 but with the difference that the users’ average powers are randomly distributed so that the maximum allowable average power disparity is 15 dB. For comparison purposes, it is also reported on the same plots the performance of the adaptive (in the sense that it is built upon the channel estimates for the several users) conventional matched filter receiver, and that of the ideal linear MMSE receiver, corresponding to expression (29). As expected, it is seen that the proposed system achieves better performance in the power-controlled scenario than in that with power disparities. Additionally, the performance also improves if longer training intervals are considered. Also, for any \( m \), the SIC receiver outperforms
Fig. 4. Performance of the adaptive SIC receiver for a single-rate system with $K = 6$ and several values of $m$. Power-controlled scenario. System parameters: $M = 2$, ISR = 10 dB. In the plot on the left (right) 50 (150) bits have been employed to train the estimation algorithm.

Fig. 5. Performance of the adaptive SIC receiver for a single-rate system with $K = 6$ and several values of $m$. Power-disparities up to 15dB. System parameters: $M = 2$, ISR = 10 dB. In the plot on the left (right) 50 (150) bits have been employed to train the estimation algorithm.
the conventional matched filter (whose performance is badly degraded by ISI and MAI) and the larger the \( m \), the better the receiver performance. Interestingly, it is seen that even with low values of \( m \) (e.g., \( m = 4,5 \)) the iterative receiver achieves a fairly minimal loss with respect to the ideal MMSE receiver, especially for the case that 150 training symbols are used for channel estimation. However, in any case, for \( m \geq 4 \) the receiver performance at 20 dB is close to \( 10^{-3} \), and since here the effects of coding and interleaving are not considered, this should be a satisfactory result.

As a final remark, we notice that the proposed system may be amenable to some improvements and/or modifications. Indeed, instead of considering a linear SIC receiver, one could resort to nonlinear interference cancellation, which is well known to bring some performance improvement with respect to linear structures [36], [37]. Additionally, in order to save bandwidth and improve performance, the length of the training preamble might be reduced, and one might let the channel estimation algorithm work in decision-directed mode, i.e., based on the symbol estimates furnished by the iterative SIC receiver. The thorough exploration of the pros and cons of such strategies is, for the sake of brevity, beyond the scope of this paper and is a possible topic for future study.

VI. CONCLUSION

In this paper, the problem of channel estimation and multiuser detection for long-code DS/CDMA systems operating over frequency-selective fading channels has been considered. This is an important research issue since long codes have been included in the majority of 3G standards, while most previously developed estimation techniques assume the use of short (periodic) spreading codes. With regard to channel estimation, the solution that has been proposed in this paper assumes that known training symbols are transmitted and makes use of the least-squares criterion. It is based on the crucial fact that, even if aperiodic codes are employed, the received effective signature waveform can be written as the product of a known time-varying code matrix times an unknown time-invariant (as long as the fading is slow) vector, that contains the needed information on the propagation delay and channel impulse response. Estimation algorithms suited for both the uplink and downlink of a cellular system have been given, and the case of a multirate/MC CDMA system has been considered as well. All the proposed algorithms may be implemented with a computational complexity that is quadratic in the processing gain. With regard to multiuser detection, an uplink single-rate scenario has been considered, and it has been shown that the estimates furnished by the proposed procedure may be fed to an “adaptive” linear SIC receiver which may achieve performance levels not far from those of the ideal linear MMSE receiver.

Beyond the results presented here, there are several relevant open and challenging problems on CDMA systems with long codes. In particular, some issues that are worth investigating include the following.

- The development of quadratic complexity, possibly blind, and near-far resistant signal parameter estimation algorithms. Indeed, it should be noted that the proposed estimation procedures have been shown to be sensitive to the near–far problem, thus implying that they need power-control in order to achieve satisfactory performance. On the other hand, any linear near–far resistant receiver needs to orthogonalize to the interference subspace, and, in a long-code framework, this operation entails a computational complexity which is more than quadratic. Accordingly, while quadratic complexity estimation algorithms that do not require the use of training bits and that are near–far resistant are the common practice in short-code systems (see, e.g., [13]), they are still missing for long-code systems.

- The development of blind adaptive multiuser detection algorithms. Indeed, recall that the proposed adaptive SIC receiver is suited for centralized detection in that it requires prior knowledge of the spreading codes from all of the active users. In short-code systems, the bit-interval cyclostationarity of the CDMA signals enables the application of well-known adaptive filtering algorithms that are capable of estimating from the received signal the (near–far resistant) linear MMSE receiver, based on the knowledge of the spreading code of the user of interest and with a quadratic (or less than quadratic) computational burden [18], [30]. As a result, it is theoretically possible to achieve, in mobile receivers, performance levels very similar to those of the centralized multiuser receivers. Conversely, for long-code systems, high-performance decentralized adaptive implementations of any multiuser receiver are not yet developed.

REFERENCES


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