Iterative Multiuser Detection for Coded CDMA Signals in AWGN and Fading Channels

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***Abstract*—In this paper, a new iterative receiver for joint detection and decoding of code division multiple access (CDMA) signals is presented. The new scheme is based on a combination of the minimum mean square error (MMSE) criterion and the turbo processing principle by Hagenauer. The complexity of the new scheme is of polynomial order in the number of users. The new scheme is applicable to two situations: a) when the receiver is capable of decoding the signals from all users and b) when the receiver is only capable of decoding the signals from a subset of users. In the first scenario, we establish that the proposed receiver achieves superior performance to the iterative soft interference cancellation technique (by Alexander *et al.*) under certain conditions. On the other hand, in the second scenario, we argue that the proposed receiver outperforms both the iterative soft interference canceler and the iterative maximum *a posteriori* (MAP) receiver (by Reed *et al.*) because of its superior near–far resistance. For operation over fading channels, the estimation of the complex fading parameters for all users becomes an important ingredient in any multiuser detector. In our scheme, the soft information provided by the decoders is used to enhance this estimation process. Two iterative soft-input channel estimation algorithms are presented: the first is based on the MMSE criterion, and the second is a lower-complexity approximation of the first. The proposed multiuser detection algorithm(s) are suitable for both terrestrial and satellite applications of CDMA.**

***Index Terms*—Fading channels, iterative decoding, multiuser detection, wireless communication.**

I. Introduction

COMBINED multiuser detection and decoding has received considerable attention recently with its potential to improve the performance of a multiuser system to match that of a single user system. In [4], it was shown that the optimum receiver for a code division multiple access (CDMA) system employing forward error control (FEC) coding combines the trellises of both the multiuser detector and the FEC code. The complexity of this receiver is exponential in the product of the number of users and the constraint length of the code. This complexity makes the use of the optimal detector prohibitive for even small systems.

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The impressive performance achieved by iterative decoding of turbo codes has encouraged several researchers to consider applying this iterative architecture in other receiver submodules. In [1], Hagenauer coined the term "turbo processing principle" for this architecture. He also outlined that it can be used to improve the performance of almost all the receiver submodules.

Based on the turbo processing principle, two iterative receivers, for joint detection and decoding of CDMA signals, have been proposed. The first one proposed in [3], [5], and [6] uses the maximum *a posteriori* (MAP) criterion in the design of the iterative multiuser detector. The complexity of this receiver is exponential in the number of users. The second receiver, proposed in [2], is a suboptimal approximation of the MAP detector. This receiver can be viewed as an iterative soft-interference canceler where the reliability values, provided from the previous decoding iteration, are used to generate the soft-cancellation weights. The complexity of this receiver is only a linear function of the number of users. Both techniques were shown through simulation to achieve very close performance to that of the single user system for some range of signal-to-noise ratios (SNR's). This range of SNR depends on the number of users sharing the channel, the cross correlation matrix, and the FEC code constraint length.

The two previously proposed iterative receivers suffer from two major drawbacks. First, the performance of both techniques will be severely degraded in the case where the receiver is only capable of decoding a subset of the total number of users. The reason is that in both receivers, any undecoded user is treated as white Gaussian noise. Hence, similar to the matched filter receiver, both iterative detectors will suffer from a near–far problem from the undecoded users. Second, even when decoding all users, an error floor was observed in the performance of the iterative MAP receiver at moderate to high SNR [5]. While no explanation was given in [5] for this phenomenon, we believe that one possible explanation would be the highly loaded environments and the relatively large cross correlation values between the different users spreading codes. One would also expect the iterative soft interference cancellation receiver to suffer from the same error floor in such scenarios since it is a suboptimal approximation of the MAP receiver.

In this paper, a novel iterative receiver for joint detection and decoding of CDMA signals is presented. It is shown that an iterative receiver where the multiuser detector module is based on the minimum mean square error (MMSE) criterion avoids the limitations of the previously proposed techniques. The new scheme is applicable to two situations: a) when the receiver is capable of decoding the signals from all users and b) when the receiver is only capable of decoding the signals from a subset of users, either due to limited processing power or the unavailability of information about some of the users.

The proposed iterative receiver is different from the MMSE receiver in [7] two major aspects. First, in [7], the transmitted symbols are assumed to have a uniform distribution. In the proposed algorithm, this assumption is only valid in the first iteration. In the subsequent iterations, the decoders soft outputs are used to generate the *a priori* probabilities necessary to find the optimum filter coefficients. Second, the MMSE filter in [2] is a feedforward filter. This comes as a result from the uniform distribution assumption. On the other hand, in the proposed algorithm, the filter have both feedforward and feedback coefficients. The feedback connections represent the subtractive interference cancellation part of the receiver.

The direct implementation of the proposed algorithm requires a complexity of polynomial order in the number of users. However, we believe that an adaptive version of the algorithm similar to structures in [8] or [9] can be developed with much less complexity.

One of the major disturbances that affects the transmission of digital information over land-mobile and mobile-satellite links is fading. One of the most challenging tasks is the estimation of the time-varying fading parameters (i.e., fading phase and amplitude). In slow fading channels, the demodulation process can be enhanced by inserting some known symbols in the bit stream and using them at the receiver to estimate the complex fading gains [10]. This scheme is referred to as symbol aided demodulation (SAD).

In this paper, we propose a modification to the SAD technique. This modification allows the channel estimator to use, in addition to the known symbols, the soft information from the previous decoding iteration to obtain better channel estimates. The amplitudes and phases of the user signals thus obtained are used in the multiuser detector module to assist during the interference cancellation. Two iterative soft-input channel estimation algorithms are proposed: the first is based on the MMSE criterion, and the second is a lower-complexity approximation of the first.

The multiuser detection and channel estimation schemes of this paper are suitable for both terrestrial wireless (cellular and PCS) communications as well as for satellite communications. Performance results are presented for both Raleigh fading channels representative of terrestrial wireless environments (and frequently of LEO satellite links) and for Rician fading channels characteristic of most GEO satellite links.

The rest of the paper is organized as follows. Section II contains the system model and a brief review of the iterative receivers available in the literature. The iterative MMSE receiver is developed for the additive white Gaussian noise (AWGN) channel in Section III. The fading channel issues are treated in Section IV. In Section V, numerical results that compare the performance of the iterative MMSE receiver with other techniques are presented. Finally, we present the conclusions of this work in Section VI.

II. System Model

First, the case of the AWGN channel is considered. We assume that K users are sharing the channel. Each one of the K users encodes the binary information sequence using a rate $1/n$ binary convolutional code. Each user independently interleaves the encoded sequence. The necessity of interleaving will be clarified later in this paper. A different spreading sequence of length N-chips is used by each user to modulate the encoded symbols. For simplicity of notations, only the synchronous case is considered. However, it can be easily shown that the extension to slotted asynchronous systems (where synchronization is only performed at the frame level) is straightforward. Using the argument in [7], it is easy to show that a slotted asynchronous system is equivalent to a synchronous system with twice the number of users. The modulation scheme is binary phase shift keying (BPSK), and demodulation is assumed to be done coherently. The baseband output of the chip matched filter bank, in the ith bit duration is given by

$$\underline{r}_i = S\underline{b}_i + \underline{n}_i \tag{1}$$

where

- $\underline{r}_i$ is the $[N \times 1]$ chip matched filter bank output vector;
- $\underline{b}_i$ is the $[K \times 1]$ vector of the transmitted symbols by the K users;
- S is the $[N \times K]$ signature matrix where the kth column is the signature sequence of the kth user;
- $\underline{n}_i$ is a $[N \times 1]$ white Gaussian noise vector.

The different user amplitudes are included in the signature matrix S.

Before we present the new scheme, we will review briefly the two previously proposed iterative receivers. In the MAP receiver [3], without loss of generality, the input to the first decoder at time t is calculated as follows:

$$L_t^{(1)} = \log\left[\frac{E_{b^{(2)},\ldots,b^{(k)}}\left\{p\left(\underline{r}_t \middle| b_t^{(1)} = 1,\, b^{(2)}\,\ldots\, b^{(k)}\right)\right\}}{E_{b^{(2)},\ldots,b^{(k)}}\left\{p\left(\underline{r}_t \middle| b_t^{(1)} = -1,\, b^{(2)}\,\cdots\, b^{(k)}\right)\right\}}\right] \tag{2}$$

where $L_t^{(1)}$ is the log likelihood ratio; $E_{b^{(2)},\ldots,b^{(k)}}$ is the expectation with respect to the transmitted symbols from the other users. The *a priori* probabilities used to evaluate this expectation are obtained from the previous decoding iteration soft outputs [3]. This expectation is the sum of $2^{(K-1)}$ terms corresponding to all combinations of transmitted symbols. Therefore, this receiver suffers from a complexity of exponential order in the number of interfering users ($K-1$).

To solve the complexity problem, the following suboptimal approximation was proposed in [2]

$$L_t^{(1)} = \log\left[\frac{\left\{p\left(\underline{r}_t \middle| b_t^{(1)} = 1,\, E\left(b^{(2)}\right)\cdots E\left(b^{(k)}\right)\right)\right\}}{\left\{p\left(\underline{r}_t \middle| b_t^{(1)} = -1,\, E\left(b^{(2)}\right)\cdots E\left(b^{(k)}\right)\right)\right\}}\right] \tag{3}$$

where

$$E\left(b_t^{(k)}\right) = \frac{e^{L_t^{(k)}} - 1}{e^{L_t^{(k)}} + 1} \tag{4}$$

$L_t^{(k)}$ is the previous iteration soft output, in the log domain, of the kth decoder at time t. Note also that (4) was evaluated using the *a priori* probability obtained from the previous decoding iteration. Based on the fact that the chip matched filter bank output vector has a multivariate Gaussian distribution, each iteration can be viewed as a soft interference cancellation operation. The previous iteration soft outputs are used to calculate estimates of the transmitted symbols. These estimates are then remodulated by the corresponding spreading codes and subtracted from the chip matched filter bank output vector to form the next decoding iteration input vector. The complexity of this algorithm is a linear function of the number of interfering users. Compared with the conventional decision feedback multiuser detector, the iterative soft interference cancellation receiver attempts to reduce the probability of error propagations by feeding back soft information instead of hard decisions.

III. The Iterative MMSE Multiuser Receiver for AWGN Channels

The main difference in the proposed scheme, compared with the previously proposed iterative receivers, is the design of the multiuser detection module based on the MMSE criterion. After each decoding iteration, the soft outputs are used to update the *a priori* probabilities of the transmitted symbols. These updated probabilities are then used to calculate the MMSE filter feedforward and feedback weights. Two scenarios will be considered in this section. First, we consider the scenario where joint decoding of all users is possible. Then, we outline the necessary modifications for the case of joint decoding of only a subset of users.

A. Joint Decoding of all Users

Without loss of generality, we will derive a set of equations describing the filter coefficients used for demodulating the ith transmitted binary symbol from the kth user. The input $y_i^{(k)}$ to the kth user decoder at time i is given by

$$y_i^{(k)} = \underline{c}_{fi}^{(k)^T} \underline{r}_i + \underline{c}_{bi}^{(k)^T} \underline{\hat{b}}^{(K/k)} \tag{5}$$

where $\underline{c}_{fi}^{(k)}$ is the $[N \times 1]$ optimized feedforward coefficients vector; $\underline{c}_{bi}^{(k)}$, $\underline{\hat{b}}^{(K/k)}$ are the $[K-1 \times 1]$ vectors of the optimized soft feedback weights and hard decisions, respectively. Note that since the feedback coefficients appear only through their sum, we can assume, without loss of degrees of freedom, that

$$c_{bi}^{(k)} = \underline{c}_{bi}^{(k)^T} \underline{\hat{b}}^{(K/k)} \tag{6}$$

where $c_{bi}^{(k)}$ is a single coefficient that represents the sum of the feedback terms. $\underline{c}_{fi}^{(k)}$, $c_{bi}^{(k)}$ are obtained through minimizing the mean square value of the error (e) between the data symbol and its estimate, given by

$$\begin{aligned} e &= E\left[\left(y_i^{(k)} - b_i^{(k)}\right)^2\right] \\ &= E\left[\left(\underline{c}_{fi}^{(k)^T} \underline{r}_i + c_{bi}^{(k)} - b_i^{(k)}\right)^2\right] \\ &= E\left[\left(\underline{c}_{fi}^{(k)^T} \left\{\underline{S}^{(k)} b_i^{(k)} + S^{(K/k)} \underline{b}_i^{(K/k)} + \underline{n}_i\right\}\right.\right. \\ &\qquad \left.\left. + \; c_{bi}^{(k)} - b_i^{(k)}\right)^2\right] \end{aligned} \tag{7}$$

where

$\underline{S}^{(k)}$ is the $[N \times 1]$ signature vector of the kth user;
$S^{(K/k)}$ is the $[N \times K-1]$ matrix composed of the signature vectors of the other $K-1$ users;
$\underline{b}_i^{(K/k)}$ is the $[K-1 \times 1]$ transmitted data vector form the other $K-1$ users.

Using standard minimization techniques, it is easily shown that the MMSE solutions for $\underline{c}_{fi}^{(k)}$ and $c_{bi}^{(k)}$ have to satisfy the following relations:

$$E\left[\underline{b}_i^{(K/k)}\right]^T S^{(K/k)^T} \underline{c}_{fi}^{(k)} + c_{bi}^{(k)} = 0 \tag{8}$$

$$\begin{aligned} &\left\{\underline{S}^{(k)} \underline{S}^{(k)^T} + S^{(K/k)} E\left[\underline{b}_i^{(K/k)} \underline{b}_i^{(K/k)^T}\right] S^{(K/k)^T}\right. \\ &\qquad \left. + E\left[\underline{n}_i \underline{n}_i^T\right]\right\} \underline{c}_{fi}^{(k)} + S^{(K/k)} E\left[\underline{b}_i^{(K/k)}\right] c_{bi}^{(k)} = \underline{S}^{(k)} \end{aligned} \tag{9}$$

where

$$E\left[\underline{n}_i \underline{n}_i^T\right] = \sigma_n^2 I_{N \times N} \tag{10}$$

$$E\left[\underline{b}_i^{(K/k)}\right] = \underline{E}_b^{(K/k)} \tag{11}$$

$$\begin{aligned} E\left[\underline{b}_i^{(K/k)} \underline{b}_i^{(K/k)^T}\right] &= I_{(K-1)\times(K-1)} \\ &\quad - \mathrm{Diag}\left(\underline{E}_b^{(K/k)} \underline{E}_b^{(K/k)^T}\right) \\ &\quad + \underline{E}_b^{(K/k)} \underline{E}_b^{(K/k)^T} \end{aligned} \tag{12}$$

σ_n^2 white noise variance;
$I_{[N \times N]}$ identity matrix of order N;
$\underline{E}_b^{(K/k)}$ $[K-1 \times 1]$ vector of the expected values of the transmitted symbols from the other $K-1$ users.

The *a priori* probabilities used to evaluate the expectations are obtained from the previous decoding iteration soft outputs, through the following component-wise relation:

$$P\left(b_t^{(k)} = 1\right) = 1 - P\left(b_t^{(k)} = -1\right) = \frac{e^{L_t^{(k)}}}{1 + e^{L_t^{(k)}}}. \tag{13}$$

Note that (12) is obtained by assuming that the different users soft outputs are independent. This assumption is justified through the different, and independent, interleaving used by each user. To simplify notation, we define the following:

$$A = \underline{S}^{(k)} \underline{S}^{(k)^T} \tag{14}$$

$$\begin{aligned} B = S^{(K/k)} &\left[I_{(K-1)\times(K-1)}\right. \\ &\quad - \mathrm{Diag}\left(\underline{E}_b^{(K/k)} \underline{E}_b^{(K/k)^T}\right) \\ &\quad \left. + \underline{E}_b^{(K/k)} \underline{E}_b^{(K/k)^T}\right] S^{(K/k)^T} \end{aligned} \tag{15}$$

$$F = S^{(K/k)} \underline{E}_b^{(K/k)} \tag{16}$$

$$R_n = \sigma_n^2 I_{N \times N}. \tag{17}$$

Solving (8) and (9), we obtain the following results for the optimum filter feedforward and feedback coefficients:

$$\underline{c}_{fi}^{(k)} = \left(A + B + R_n - FF^T\right)^{-1} \underline{S}^{(k)} \tag{18}$$

$$c_{bi}^{(k)} = -F^T \underline{c}_{fi}^{(k)}. \tag{19}$$

In the first decoding iteration, we assume that the transmitted symbols have a uniform distribution, and hence, $\underline{E}_b^{(K/k)} = \underline{0}$.

The feedforward filter coefficients vector $\underline{c}_{fi}^{(k)}$ in this iteration is given by the MMSE equations derived in [7] and the feedback coefficient $c_{bi}^{(k)} = 0$. After each iteration, $\underline{E}_b^{(K/k)}$ are recalculated using the decoders soft outputs. $\underline{E}_b^{(K/k)}$ are then used to generate the new set of filter coefficients as described. In the asymptotic case when $|\underline{E}_b^{(K/k)}| = \underline{1}$, the receiver is equivalent to the subtractive interference canceler. This is expected, since $|\underline{E}_b^{(K/k)}| = \underline{1}$ means that the previous iteration decisions, for the other users, are error free. Under this assumption, the subtractive interference canceler becomes the optimum solution.

B. Joint Decoding of a Subset of Users

One major drawback of the two previously proposed iterative receivers is the necessary assumption of joint decoding of all users at the receiver. Any undecoded user is treated as white Gaussian noise. This imposes a significant limitation on the receiver performance in the presence of undecoded users with relatively high transmission powers. In the new algorithm, this problem is solved naturally through the use of the MMSE filter as a front-end in the receiver. The MMSE filter asymptotically eliminates the interference coming from the undecoded users through the optimization of the feedforward coefficients [7], [8]. We assume that the receiver has prior knowledge of the undecoded users spreading codes. However, we believe that this assumption can be relaxed through the use of an adaptive architecture similar to [8] or [9].

In this scenario, the feedforward and feedback filter coefficients $\underline{c}_{fi}^{(k)}$ $c_{bi}^{(k)}$ are still given by (18) and (19). However, for the undecoded users, the expected values of the transmitted symbols are $E_b(j) = 0$ and do not change with iterations. In closed form, let K_1 be the number of undecoded users and K_2 be the number of decoded users where $K - 1 = K_1 + K_2$. $S^{(K_1)}$, $S^{(K_2)}$ are the $[N \times K_1]$ and $[N \times K_2]$ signature matrices of the undecoded and decoded users, respectively. Now to calculate the feedforward filter coefficients, B should be evaluated from the following instead of (15):

$$B = S^{(K_1)} S^{(K_1)^T} + S^{(K_2)} \Big[I_{(K_2)\times(K_2)} - \mathrm{Diag}\Big(\underline{E}_b^{(K_2)} \underline{E}_b^{(K_2)^T} \Big) + \underline{E}_b^{(K_2)} \underline{E}_b^{(K_2)^T} \Big] S^{(K_2)^T} \quad (20)$$

and the feedback coefficient can be obtained from

$$c_{bi}^{(k)} = -\underline{E}_b^{(K_2)^T} S^{(K_2)^T} \underline{c}_{fi}^{(k)}. \quad (21)$$

C. Near–Far Resistance

The near–far resistance characterizes the performance of the multiuser detector(s) in the presence of high power interferers. In the case of joint decoding of only a subset of users, the two previously proposed iterative receivers [2], [3] treat the undecoded signals as white Gaussian noise. This means that in such a scenario, the near–far resistance of these receivers is equal to zero, similar to the simple matched filter receiver.

Due to the soft information feedback in this class of receivers, the near–far resistance, as defined in [11] and [12] cannot be obtained in a closed form. However, for the iterative MMSE algorithm, unlike the other two algorithms, a lower bound on the performance can be easily obtained by analyzing the single sweep receiver. It can be easily seen that the single sweep receiver is equivalent to the MMSE receiver in [7]. Therefore, the near–far resistance of this single sweep receiver is equal to the near–far resistance of the decorrelator receiver given in [11] and [12]. It is also clear that this lower bound, on the near–far resistance, holds in the case of joint decoding of only a subset of users. This supports our claim of the iterative MMSE receiver superiority, compared with the other iterative receivers, in the case where only joint decoding of a subset of users is possible. This argument will be validated by the simulation results presented in Section V.

IV. The Iterative MMSE Multiuser Receiver for Fading Channels

In the development of the iterative multiuser detection algorithm for the AWGN channel, we assumed prior knowledge of each signal amplitude and phase. This assumption is not valid in fading channels due to the multiplication of each signal by a complex fading parameter. Accordingly, the iterative algorithm has to be modified to account for the unknown amplitudes and phases. Note also that the two previously proposed iterative receivers [2], [3], [5], [6] were designed for AWGN channels and assumed known amplitudes and phases at the receiver. In the following discussion, we will restrict ourselves to Rayleigh fading channels; the extension to Rician fading channels is straightforward.

First, the system model in (1) has to be modified to account for the multiplication by the complex fading amplitudes. The baseband output vector of the chip matched filter bank, in the ith bit duration is now given by

$$\underline{r}_i = SF_i \underline{b}_i + \underline{n}_i \quad (22)$$

where F_i is a $[K \times K]$ diagonal matrix of the complex fading amplitudes [i.e., $F_i(k, g) = f_i(k)\delta_{k-g}$]. The fading process is assumed to be frequency nonselective, and the complex fading amplitude is assumed to remain constant over one symbol interval. The *a priori* fading correlation sequences are organized as the diagonal matrices $\{V(n)\}$: $V(n) = E[\underline{f}_{n_1}^* \underline{f}_{n_1+n}^T]$; $\underline{f}_{n_1}$ is the $[K \times 1]$ complex fading vector at time n_1. It is also assumed that the fading processes of the different users are independent. In Rayleigh fading channels, $\underline{f}_{n_1}$ is a complex Gaussian random vector with zero mean. Consequently, $\underline{r}_i$ is characterized by a multivariate Gaussian distribution, when conditioned on the transmitted data vector. Based on this fact, it is straightforward to develop a soft-input–soft-output MAP multiuser detector similar to the one proposed for the AWGN in [3], [5], and [6]. However, the receiver thus obtained will have a complexity of exponential order in the product of the number of users and the channel estimation filter length. The channel estimation filter length is a design parameter which should be chosen based on the fading bandwidth and the available processing power. The exponential complexity of the MAP approach makes it impractical, and hence, the need arises for lower complexity architectures.

In [13], it was shown that under the assumption of uncorrelated errors in the different users fading parameter estimates, the channel estimation and the multiuser detection can be done

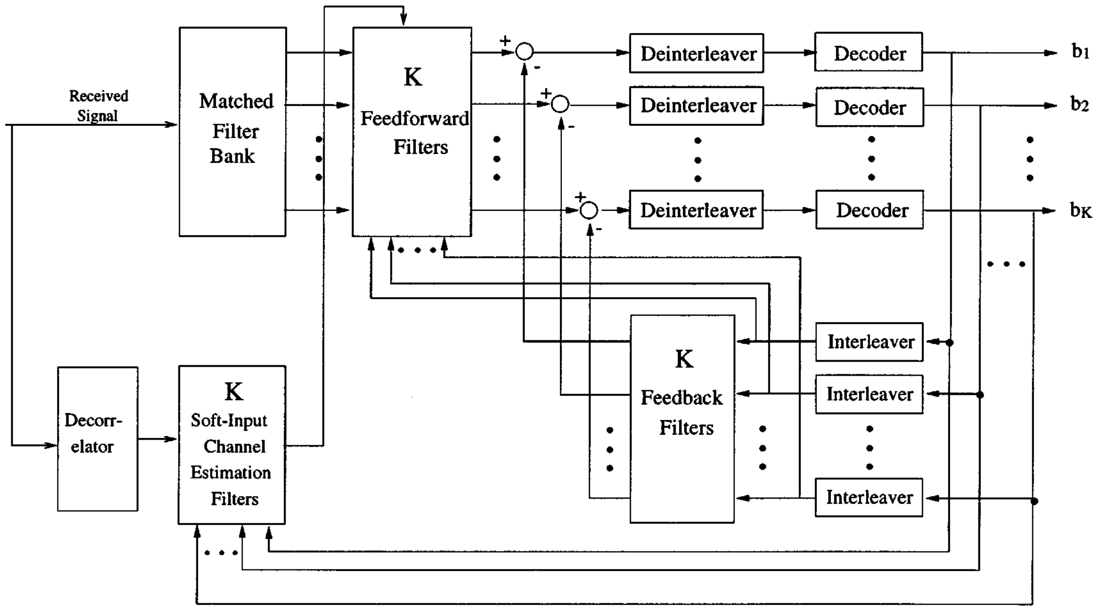

Fig. 1. Block diagram of the proposed multiuser receiver in fading channels.

separately. It was also shown, through simulation and analytical bounds, that this "near-optimum" detector achieves much better performance than the conventional matched filter receiver for uncoded systems. Accordingly, we will restrict ourselves to the canonical receiver architecture shown in Fig. 1. In this architecture, the channel estimation and the multiuser detection operations are performed in different modules. However, the loss in performance due to this separation is minimized through the soft information passing between the different modules and the iterative architecture of the receiver.

A. Channel Estimation Module

We first examine closely the channel estimator proposed in [13]. This will allow for valuable insights that will help later in developing the iterative soft-input estimator. In [13], it was assumed that the decision process is sequential. Hence, only past hard decisions were used to successively improve the fading parameter estimates. It was also assumed that the decision process is error free. Based on that, the $[K \times 1]$ estimated fading parameters vector in the ith symbol interval is given by [13]

$$\underline{\hat{f}}_i^* = \nu^H \left[V + \sigma_n^2 \hat{B}\hat{A}^{-1}\hat{B}\right]^{-1} \hat{B}\hat{A}^{-1}\hat{\boldsymbol{S}}\underline{r} \tag{23}$$

where

- $\underline{r} = [\underline{r}_0^T \cdots \underline{r}_{i-1}^T]^T$ is the chip matched filter bank output vector through the $(i-1)$th bit interval;
- $\hat{B}$ is the $[iK \times iK]$ block diagonal matrix of past decisions;
- $\hat{A}$ is a $[iK \times iK]$ block diagonal matrix whose lth diagonal block is $S^T S$;
- $\hat{\boldsymbol{S}}$ is the $[iK \times iK]$ matched filter block diagonal matrix whose lth element is S^T;
- ν, V are the fading correlation matrices as given by (15) in [13].

The complexity of this estimator is polynomial in the product of the number of users and the length of the horizon. The straightforward modification of this estimator to accept soft inputs is to calculate the expected value of $\underline{\hat{f}}_i^*$ over all possible combinations of $\hat{B}$ using the soft information in a fashion similar to (2). However, this approach suffers from exponential complexity similar to the MAP approach. Hence, we need to find a different, and more efficient approach in terms of the performance complexity tradeoff.

The first observation on the estimator in (23) is has composed of a decorrelator front-end given by $\hat{A}^{-1}\hat{\boldsymbol{S}}\underline{r}$. The decorrelator output vector is then multiplied by the past decisions $\hat{B}$ to remove the data modulation effect from the samples. This results in interference free samples of the different fading processes at past times. These samples are used by the joint MMSE estimation filter $[\nu^H(V + \sigma_n^2\hat{B}\hat{A}^{-1}\hat{B})^{-1}]$ to obtain estimates of the different fading parameters in the ith bit interval. The joint optimization of the channel estimation filter is required because of the correlation between the noise samples affecting the different entries of the decorrelator output vector. This leads to the second observation. If the nondiagonal elements of $\hat{B}\hat{A}^{-1}\hat{B}$ are assumed to be zero, which is equivalent to assuming uncorrelated noise samples in the decorrelator output vector, the optimum joint channel estimation filter will reduce to K individual MMSE estimation filters. These two critical observations are the basis of our design for the soft-input channel estimator.

1) Soft Input MMSE Channel Estimator: The channel estimation filter given by (23) has two drawbacks. First, the joint optimization process results in complexity of polynomial order in the product of the number of users and the estimation filter length. This complexity becomes prohibitive for some practical applications. The approach that will be followed to reduce this complexity is to perform the channel estimation process for each user separately. The second drawback is that the estimator uses previous hard decisions to improve the fading parameter estimates at each time instant. The use of hard decisions makes the estimator vulnerable to error propagations. The probability of error propagation is reduced in the proposed scheme through the feedback of soft information instead of hard decisions.

In the proposed scheme, a decorrelator is used as a front-end to allow for an independent estimation process for each fading channel. The decorrelator output vector is given by

$$\underline{a}_i = \left(S^T S\right)^{-1} S^T \underline{r}_i. \tag{24}$$

Without loss of generality, only the estimator for the kth user is considered. The kth user's fading parameter estimate at time i is

$$\hat{f}_i^{(k)} = \underline{c}_{ei}^{(k)^T} \underline{a}^{(k)} \tag{25}$$

where $\underline{c}_{ei}^{(k)^T}$ is the kth user filter coefficient vector; $\underline{a}^{(k)}$ is defined as

$$\underline{a}^{(k)} = [a_{i-l}(k), \ldots, a_j(k), \ldots, a_{i+l}(k)]^T. \tag{26}$$

Note that the samples used by the channel estimator $a_j(k)$ do not have to be equally spaced in time. The designer has the freedom to choose which samples will be used by the estimation filter; an example will be studied in the numerical results presentation. $\underline{a}^{(k)}$ is related to the fading parameters vector $\underline{f}^{(k)}$ through the following relation

$$\underline{a}^{(k)} = B_i^{(k)} \underline{f}^{(k)} + \underline{n}_d \tag{27}$$

where $B_i^{(k)}$ is a diagonal matrix of the kth user transmitted symbols; $\underline{n}_d$ is the white noise vector at the decorrelator output (note that the noise vector is white across time and colored across users). In the remainder of this section, the superscript (k) will be omitted for convenience. The optimum filter coefficients are obtained by minimizing the mean square error given by

$$\begin{aligned} e_f &= E\left[\left|\hat{f}_i - f_i\right|^2\right] \\ &= E\left[\left|\underline{c}_{ei}^T \underline{a} - f_i\right|^2\right] \\ &= E\left[\left|\underline{c}_{ei}^T \{B_i \underline{f} + \underline{n}_d\} - f_i\right|^2\right]. \end{aligned} \tag{28}$$

Through standard minimization techniques, the following solution for the optimum filter coefficients is obtained

$$\underline{c}_{ei} = \left(\sigma_d^2 I + E\left[B_i E\left[\underline{f}^* \underline{f}^T\right] B_i\right]\right)^{-1} E[B_i] E[f_i^* \underline{f}] \tag{29}$$

where σ_d^2 is the noise variance at the decorrelator output; $E[\underline{f}^* \underline{f}^T]$, $E[f_i^* \underline{f}]$ are obtained from the *a priori* fading correlation matrix; and $E[B_i E[\underline{f}^* \underline{f}^T] B_i]$ $E[B_i]$ are obtained using the following component-wise relations:

$$E[b_i] = \frac{e^{L(i)} - 1}{e^{L(i)} + 1} \tag{30}$$

$$E\left[b_i^2\right] = 1 \tag{31}$$

$$E[b_i b_j] = E[b_i] E[b_j]. \tag{32}$$

The independence assumption in (32) is achieved through the interleaving performed at the transmitter. The interleaver now plays the double role of breaking the memory of the fading process as well as the interference.

2) Complexity Considerations for the Channel Estimator: The soft input channel estimator presented in (29) has a polynomial complexity only in the filter length. The overall channel estimation process, for the K users, has a linear complexity in the number of users. This results from the use of K independent channel estimators. Note that the matrix inversion operation required by the decorrelator will be performed only once, assuming that the spreading codes are short and do not change with time. Hence, the complexity of the decorrelator can be considered linear in the number of users under the assumption of short spreading codes.

The computational requirements of the soft-input MMSE channel estimation algorithm may still be considered prohibitive for some applications. The reason is the matrix inversion operation in (29) which has to be repeated after each iteration and for each different symbol. To reduce this complexity, we propose the following suboptimal approach. Define $\underline{c}^{in}$ as

$$\underline{c}^{in} = \left(\sigma_d^2 I + E\left[\underline{f}^* \underline{f}^T\right]\right)^{-1} E\left[f_i^* \underline{f}\right]. \tag{33}$$

$\underline{c}^{in}$ is the filter coefficients assuming that all the transmitted symbols are ones. Then, the filter coefficients are obtained as follows:

$$\underline{c}_{ei} = \alpha_i E[B_i] \underline{c}^{in} \tag{34}$$

where α_i is a normalization constant to unbias the estimator, given by

$$\alpha_i = \frac{\underline{w}^T \underline{c}^{in}}{\underline{w}^T (E[B_i])^2 \underline{c}^{in}}. \tag{35}$$

$\underline{w}$ is a vector of the *a priori* cross correlations between the fading samples used by the filter and the ith bit fading parameter. The intuition behind this algorithm is to design the estimation filter under the assumption of prior knowledge of the transmitted data symbols (i.e., all ones). After each iteration, the decoders soft outputs are used to generate the appropriate weights used by the estimator (i.e., the less reliable symbols are multiplied by small weights to reduce the probability of error propagations). In this estimator, the matrix inversion is performed in the first iteration only, and does not have to be repeated for each symbol. This results in substantial reduction in complexity.

B. Multiuser Detection Module

The updated fading parameter estimates, obtained from the soft-input channel estimators, are used by the multiuser detector after each iteration to calculate better estimates of the users data. Based on the MMSE approach, the kth user MMSE filter coefficients are obtained by minimizing the mean square error, conditioned on the fading parameters estimates, given by

$$\begin{aligned} e &= E\left[\left|\underline{c}_{fi}^{(k)^T} \underline{r}_i + c_{bi}^{(k)} - b_i^{(k)}\right|^2 | F_i = \hat{F}_i + E_{fi}\right] \\ &= E\left[\left|\underline{c}_{fi}^{(k)^T} \left\{\underline{S}^{(k)} \left(\hat{f}_i^{(k)} + e_{fi}^{(k)}\right) b_i^{(k)} \right.\right.\right. \\ &\qquad \left. + \left(\hat{F}_i^{(K/k)} + E_{fi}^{(K/k)}\right) S^{(K/k)} \underline{b}_i^{(K/k)} + \underline{n}_i\right\} \\ &\qquad \left.\left. + \; c_{bi}^{(k)} - b_i^{(k)}\right|^2\right] \end{aligned} \tag{36}$$

where $\hat{F}_i$, $\hat{F}_i^{(K/k)}$, $\hat{f}_i^k$ are the $[K \times K]$, $[K-1 \times K-1]$, $[1 \times 1]$ diagonal matrices of the fading parameter estimates in the ith bit interval, respectively. E_{fi}, $E_{fi}^{(K/k)}$, $e_{fi}^{(k)}$ are the $[K \times K]$, $[K-1 \times K-1]$, $[1 \times 1]$ diagonal matrices of the errors in the fading parameter estimates. These errors are zero mean Gaussian random variables which are assumed to be uncorrelated. The optimum solution, which minimizes the mean square error, must satisfy the following relations

$$E\left[\underline{c}_{fi}^{(k)^T}\left\{\underline{S}^{(k)}\hat{f}_i^{(k)}b_i^{(k)} + \hat{F}_i^{(K/k)}S^{(K/k)}\underline{b}_i^{(K/k)} + \underline{n}_i\right\} + c_{bi}^{(k)}\right] = 0 \tag{37}$$

$$E\left[\left(\underline{c}_{fi}^{(k)^T}\left\{\underline{S}^{(k)}\left(\hat{f}_i^{(k)} + e_{fi}^{(k)}\right)b_i^{(k)} + \left(\hat{F}_i^{(K/k)} + E_{fi}^{(K/k)}\right)S^{(K/k)}\underline{b}_i^{(K/k)} + \underline{n}_i\right\} + c_{bi}^{(k)} - b_i^{(k)}\right)\underline{r}_i^H\right] = 0 \tag{38}$$

where (37) ensures that the output of the MMSE filter is unbiased, while, (38) is a direct application of the orthogonality principle (i.e., the minimum mean square error should be orthogonal to the set of observations). Solving (37) and (38), we obtain the following results for the feedforward and feedback filter coefficients

$$\underline{c}_{fi}^{(k)} = \left(A_f + B_f + R_n + \sigma_f^2 SS^T - F_f^* F_f^T\right)^{-1}\underline{S}^{(k)}\hat{f}_i^{(k)^*} \tag{39}$$

$$c_{bi}^{(k)} = -F_f^T\underline{c}_{fi}^{(k)} \tag{40}$$

where

$$A_f = \underline{S}^{(k)}\underline{S}^{(k)^T}\hat{f}_i^{(k)}\hat{f}_i^{(k)^*} \tag{41}$$

$$B_f = S^{(K/k)}\hat{F}_i^{(K/k)}\left[I_{(K-1)\times(K-1)} - \mathrm{Diag}\left(\underline{E}_b^{(K/k)}\underline{E}_b^{(K/k)^T}\right) + \underline{E}_b^{(K/k)}\underline{E}_b^{(K/k)^T}\right] \cdot \hat{F}_i^{(K/k)^H}S^{(K/k)^T} \tag{42}$$

$$F_f = \hat{F}_i^{(K/k)}S^{(K/k)}\underline{E}_b^{(K/k)} \tag{43}$$

σ_f^2 is the variance of the fading parameters estimation errors, and R_n is as defined in (17). The input to the kth decoder is now given by

$$y_i^{(k)} = \mathrm{Re}\left(\underline{c}_{fi}^{(k)^T}\underline{r}_i + c_{bi}^{(k)}\right). \tag{44}$$

Note that when the receiver is only capable of decoding a subset of users, it is clear that the argument given in Section III-B still holds.

V. Multiuser Detector Performance Results

In this section, we assume that the number of users is $K = 7$, and the spreading gain is $N = 7$ which corresponds to a fully loaded system. These low values of K and N were used for the sake of computational speed (short running times) in the multiuser detector simulation. The short spreading codes assigned to different users were chosen randomly.

The random phase offsets effect was not accounted for in the simulations (i.e., all users were assumed to have zero phase offset). The FEC codes used are rate 1/2, 4 states convolutional codes with generator polynomial (5_8, 7_8). The results were obtained by averaging the bit-error rates (BER's) of all decoded users. The channel decoder is based on the soft output viterbi algorithm (SOVA).

A. Performance Results for AWGN Channels

Fig. 2 compares the performance of different receiver architectures in AWGN channels when joint decoding of all users is possible. All users were assumed to have equal powers. In the figure, Iterative SIC refers to the iterative soft interference cancellation scheme proposed in [2]. The iterative MMSE receiver is referred to as Iterative MMSE in the figure. We have also included the performance of the MMSE receiver proposed in [7], the conventional matched filter receiver, and the single user system. Note that we have not included the iterative MAP receiver proposed in [3], [5], and [6] because of its prohibitive exponential complexity. It is clear that the proposed iterative MMSE receiver achieves superior performance to the other receivers in this scenario. It is also shown that the performance gap between the proposed algorithm and the soft interference cancellation increases with the SNR. We believe that the difference in the performance of the iterative soft interference cancellation receiver reported in the figure and that reported in [2] can be attributed to the different conditions in each scenario. In [2], the users were assigned long and random spreading codes in an asynchronous multipath channel. Rake receivers that assumed perfect channel knowledge were used. We believe that the additional randomness introduced by the long spreading codes, the asynchronous operation, and the multipath propagation allowed the soft interference canceler to converge to the single user performance. This may not be the case in practical situations where channel and timing estimation errors exist. Also, in some practical applications, short spreading codes are used because of their desirable synchronization properties. This nonconvergence phenomenon will generally become more apparent as the number of simultaneous users sharing the channel increases. While Fig. 2 does not represent a very practical setting, it indicates that in cases where the soft interference canceler is unable to converge to the single user performance, the iterative MMSE receiver would provide better performance at the expense of added complexity.

Figs. 3 and 4 elaborate further on the comparison between the proposed scheme and the soft interference canceler in terms of the near–far resistance. Four iterations were performed at the receiver in each case. In Fig. 3, the performance is compared assuming the decoding of three and five users out of a total of seven. It is clear that the performance of the soft interference cancellation scheme is limited by an error floor at moderate to high SNR's. The BER at which the floor begins depends on how many users are decoded at the receiver (i.e., the floor begins at higher BER when decoding smaller number of users). On the other hand, it is shown that the performance of the proposed

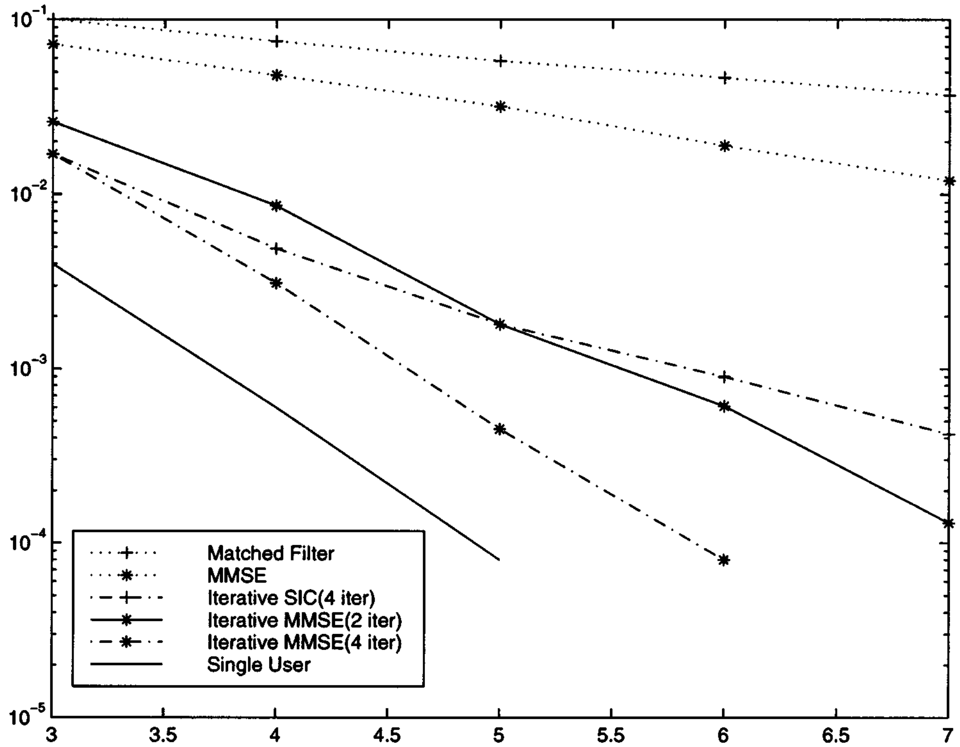

Fig. 2. Performance of the different CDMA receivers in AWGN channels.

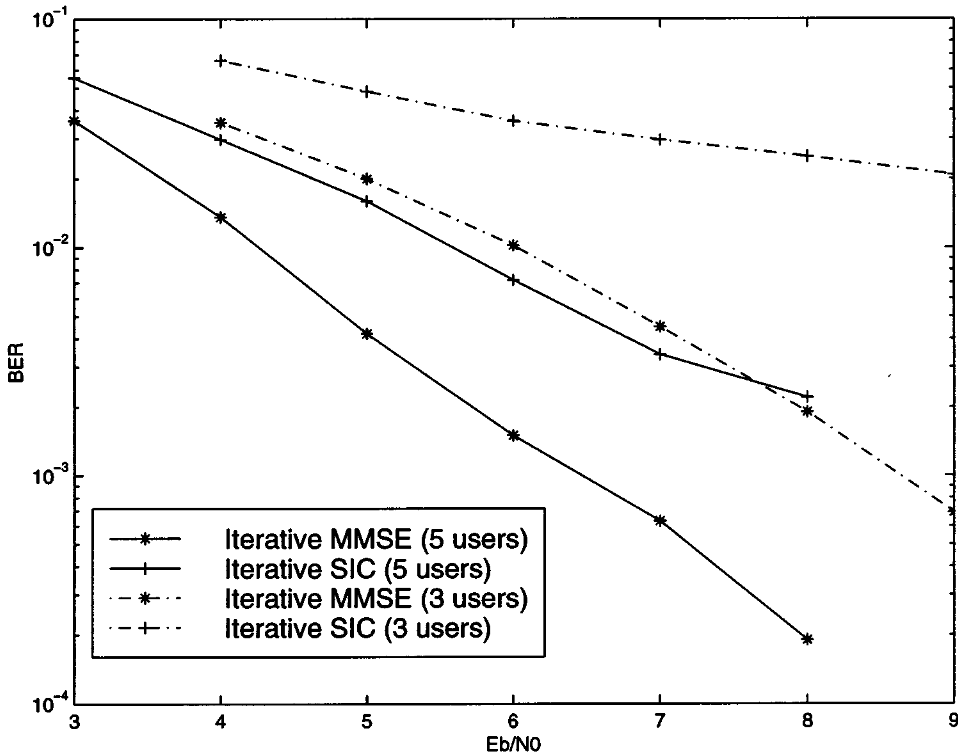

Fig. 3. Joint decoding of a subset of users in AWGN channels.

scheme does not suffer from the error floor phenomenon, as predicted by the discussion in Section III-C.

Fig. 4 compares the performance of the two schemes in the case of unequal power levels. Four users were assumed to transmit at 3 dB's higher than the nominal E_b/N_0. The receiver is assumed to have prior knowledge of the transmitted power levels. Quite interestingly, it is noted that the performance of both schemes is better than the equal power levels case for small SNR's. This phenomenon is similar to what was observed in the successive interference cancellation detector. At small SNR's, the unbalance in power levels increases the correct decoding probability for the high power users. Canceling those

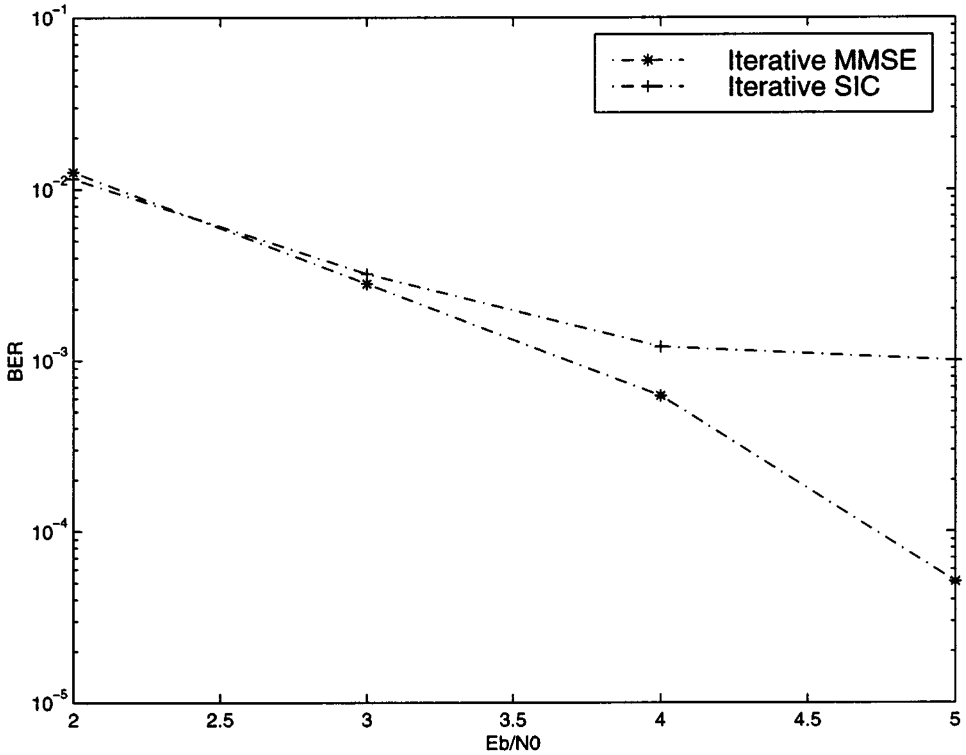

Fig. 4. Performance in the case of unequal power levels in AWGN channels.

correctly decoded signals in the subsequent iterations, increases the correct decoding probability for the low power users. For the soft interference canceler, the performance is again limited by the error floor phenomenon. As expected, the performance gap between the two algorithms increases with the SNR.

B. Performance Results for Fading Channels

For the Rayleigh fading component, we used the model in [14] where the *a priori* cross correlation function is given by

$$R_c(\tau) = J_0(2\pi f_B \tau) \tag{45}$$

where J_0 is the zero order modified Bessel function of the first type, f_B is the fading bandwidth, and τ is the timing difference.

The estimation of the fading parameters at the receiver is enhanced through the insertion of known symbols in the data stream periodically [10]. The insertion of these symbols is expected to improve the power efficiency of the system at the expense of a reduction in throughput. This tradeoff in performance will be investigated in the following. Note that these known symbols are necessary to avoid the phase ambiguity at the receiver. Without loss of generality, we also assume that the known symbols are all ones.

The relation between the energy per bit E_b and the energy per symbol E_s is now given by

$$E_s = \frac{E_b \times r \times (f_s - 1)}{f_s} \tag{46}$$

where r is the code rate, and f_s is the inverse of the relative rate, with respect to the encoded data, at which the known symbols are inserted (i.e., one known symbol is followed by $f_s - 1$ data symbols).

In Figs. 5 and 6, we first study the performance of the different channel estimation schemes for a single user system in a Rayleigh fading channel. The coherent curve corresponds to the situation where the receiver has perfect side information about the channel parameters. This curve is a lower bound on the performance achieved by any channel estimation scheme. The "SAD" curves refer to the performance achieved by the conventional symbol aided scheme, where only the known symbols are used for channel estimation [10]. The estimation filter used in the SAD scheme has four taps. Scheme A refers to the MMSE soft-input channel estimation scheme, and B refers to the linear suboptimal scheme. In both cases, the estimation filter used has eight taps, where four known and four data symbols are used by the filter. The symbols used by the filter, are not equally spaced (the data symbols used are the immediate neighbors of the symbol under consideration). The rates at which the known symbols are inserted correspond to $f_s = 7$ for $f_B T_s = 0.05$ and $f_s = 13$ for $f_B T_s = 0.02$. The interleaver depth used was 400 symbols for $f_B T_s = 0.05$ fading rate, and 1000 symbols for $f_B T_s = 0.02$ fading rate. Several conclusions can be drawn from these figures.

Regarding the SAD scheme, it is clear that increasing the known symbol's insertion rate, above a certain value, provides only marginal improvement in the performance. This is due to the reduction in E_s, for a fixed E_b, as the known symbols relative rate increases. The difference in performance between the coherent case and the SAD case is between 3–4 dB's depending on the BER required and the fading rate. From Fig. 5, we can conclude that there is not much difference in performance between the MMSE channel estimation scheme and the subop-

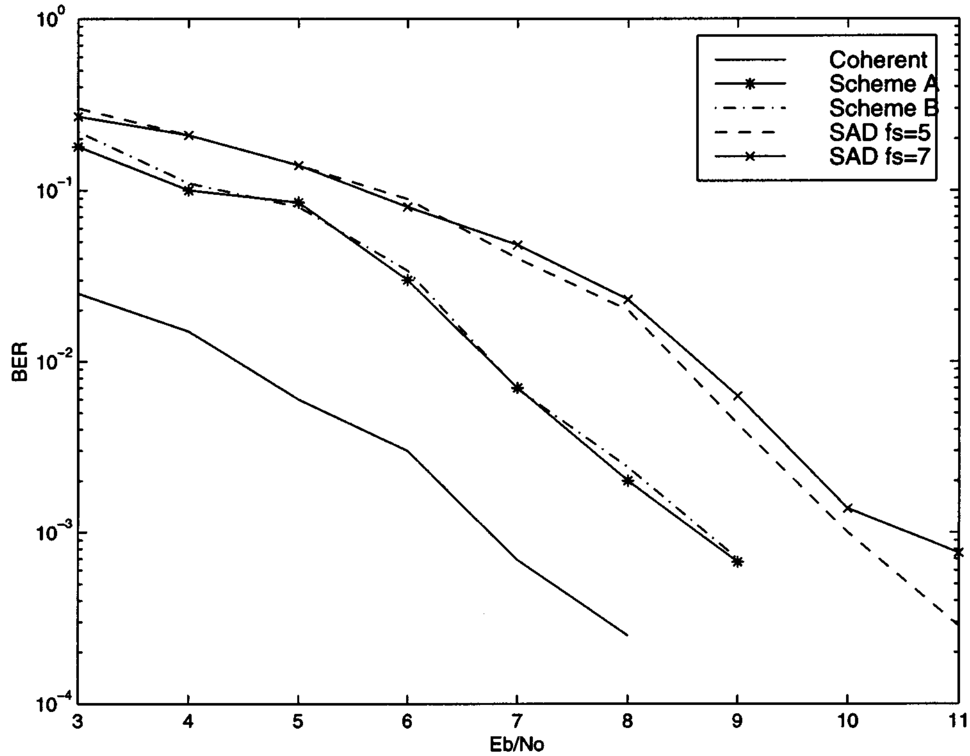

Fig. 5. Performance of the different channel estimation schemes for $B_f T_s = 0.05$.

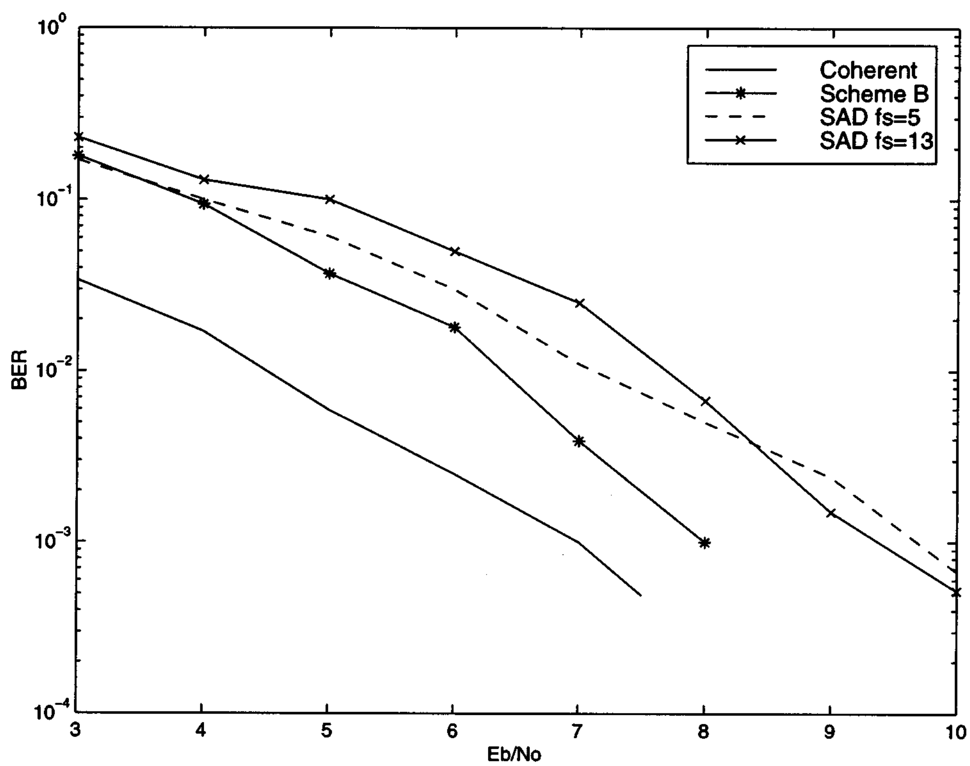

Fig. 6. Performance of the different channel estimation schemes for $B_f T_s = 0.02$.

timal approximation (i.e., Schemes A, B). Accordingly, we will focus our attention on the suboptimal approximation because of its lower complexity.

For both fading rates, the performance of the proposed soft-input linear estimation scheme is much better than the performance achieved by the SAD technique. The gain is between 1.5–2 dB's depending on the fading rate. It is also clear that the difference in performance between the coherent case and the iterative estimation scheme becomes smaller for slower fading rates.

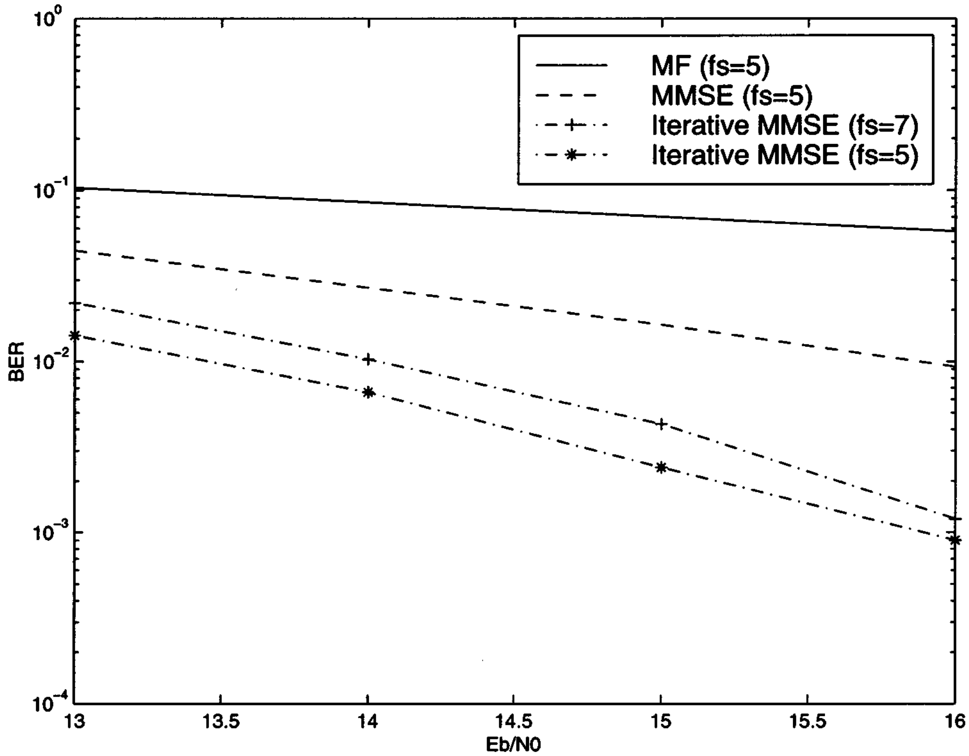

Fig. 7. Performance of the proposed multiuser receiver in Rayleigh fading channels.

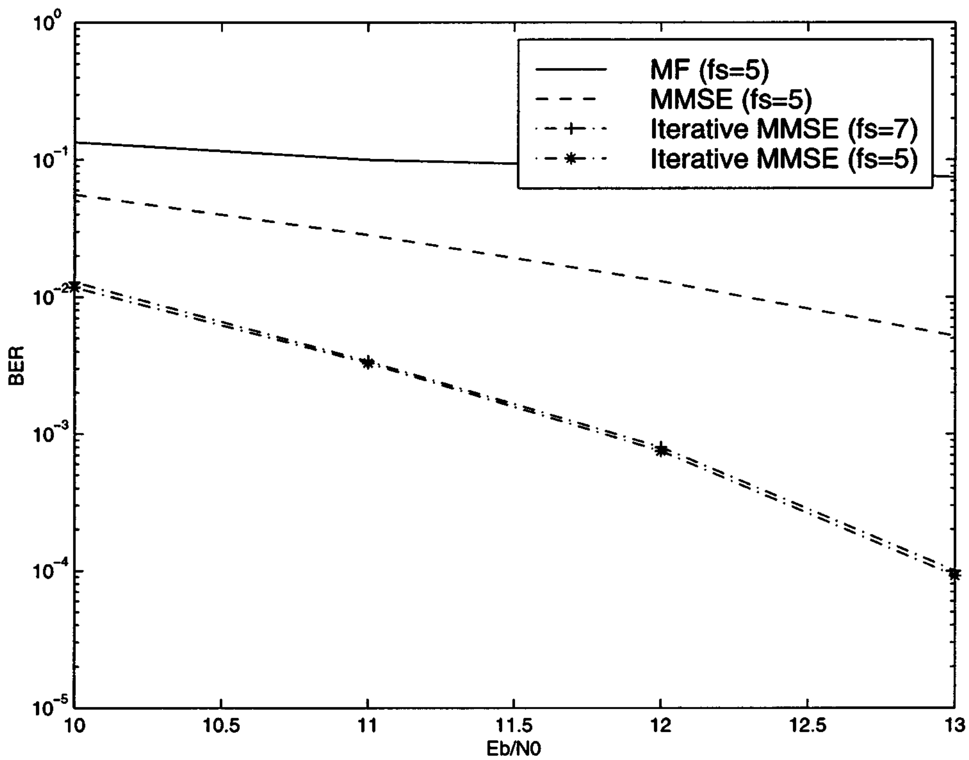

Fig. 8. Performance of the proposed multiuser receiver in Rician fading channels.

Fig. 7 compares the performance of the matched filter receiver, the MMSE receiver, and the proposed iterative MMSE receiver with only two iterations in a Rayleigh fading channel and multiuser environments. The same comparison is repeated in Fig. 8 for a Rician channel where the ratio of the direct path to the Rayleigh fading component $K_r = 10$. We assumed that $f_B T_s = 0.02$ and interleaver depth of 400 symbols. In both the matched filter and the MMSE receivers, only the known symbols are used for channel estimation. In all cases, it was assumed that a decorrelator is used to separate the different fading channels before the channel estimation filters. In the proposed receiver, the decoding, multiuser detection, and channel estimation are performed jointly in an iterative fashion with the exchange of soft information between the different modules as described in Section IV. The performance of the proposed algorithm is reported for two different insertion rates of the known symbols. The remarkable gain in performance achieved by the proposed algorithm is clear in the figure. It is also shown that the gain increases with the SNR. Increasing the insertion rate of the known symbols from 1/7 to 1/5 results only in a very marginal gain in performance, especially in the Rician fading channel.

VI. Conclusion

In this paper, a novel iterative algorithm for joint decoding and multiuser detection. The performance of the proposed algorithm was compared with the iterative soft interference canceler [2] in AWGN channels. It was shown that the proposed algorithm achieves superior performance under different conditions. The superiority of the proposed algorithm, with respect to the near–far resistance, was demonstrated in the case of joint decoding of a subset of users and the case of unequal power levels.

We also addressed the problem of channel parameters estimation in fading channels. An iterative algorithm for joint decoding, multiuser detection, and channel estimation was presented. In the proposed algorithm, soft information is exchanged between the different modules to increase the efficiency of the information passing mechanism. The remarkable gain in performance achieved by the proposed algorithm, compared to both the matched filter and the MMSE receivers, was established through simulations. The complexity and performance of the proposed multiuser and channel estimation algorithms make them suitable for several terrestrial and satellite applications involving CDMA.

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