Partially Blind Multiuser Receivers for CDMA Systems

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Abstract

Multiple access interference (MAI) significantly limits the performance of code-division multiple access (CDMA) systems. Existing multiuser receivers combat MAI using the knowledge of either all (conventional) or none (blind) of the interfering users. However, in practice, partial knowledge of the interference is often available at the receiver. For example, the base station of a cellular communication system typically has information about the interfering users within its cell only (about 60% of the total interference). Therefore, conventional multiuser receivers cannot be used. We show the degradation in performance resulting from treating the unknown (out-of-cell) interference as noise or using the blind receiver. We then develop a new "partially blind receiver" for joint synchronization and detection that combines a nonlinear interference cancellation technique for the in-cell interferers with the linear blind minimum mean squares error (MMSE) technique for the out-of-cell users. The new receiver significantly outperforms the blind receiver and the receiver that ignores the out-of-cell interference. Additionally, due to the nonlinear interference cancellation technique, the proposed receiver can even outperform conventional linear multiuser receivers with the knowledge of all the users.

1 Introduction

Direct sequence code-division multiple access (DS-CDMA) has emerged as the leading multiple access scheme for wireless communication. In DS-CDMA systems, users are multiplexed using distinct spreading codes as opposed to traditional methods of using distinct frequency or time intervals. Such DS-CDMA systems have been shown to provide better channel utilization and can lead to larger user capacity. The most significant limiting factor of user capacity for the conventional DS-CDMA system is multiple access interference (MAI). This

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This work was supported in part by Nokia Inc., by the Texas Advanced Technology Program under grant 1997-003604-044, and by NSF under grants NCR 9506681 and ANI-9979465.

interference results from the unavoidable non-zero cross-correlations that exist between active DS-CDMA users in an inherently asynchronous system.

Conventional single-user receivers treat this interference as background white Gaussian noise and therefore suffer from performance degradation. Multiuser receivers [1, 2] mitigate this interference and thereby improve the efficiency of wireless communication systems. These multiuser receivers estimate the transmitted data of a number of users simultaneously and have been designed particularly for the base-stations which can support the additional computational complexity. However, these multiuser receivers [3, 4, 5, 6, 7] assume the knowledge of the spreading sequence of all the users that contribute to the received signal.

Modern wireless communication systems have been designed to be inherently cellular, where each cell has an associated base-station and each user is assigned to the nearest base-station. Unfortunately, the actual transmitted signal of a particular user is not directional and can reach the neighboring base-stations, even though each user's signal is meant only for its associated base-station. In fact, cells could overlay on top of each other in areas of heavy traffic. Thus, the base-station receives signals not only from the users for which it is responsible but also from other users in the neighboring and overlay cells. In other words, the interference to a particular user's signal consists of in-cell interference and out-of-cell interference. Actual field measurements [8] show that almost 40% of the interference comes from out-of-cell users and cannot be ignored.

In a cellular system, where the users continuously enter and leave the cells, it is fair to assume that a particular base-station will only be aware of the codes of those users for which it is responsible. The conventional multiuser receiver (called the *ideal* multiuser receiver in this paper) that requires the knowledge of the spreading codes of all the users cannot be used in such a scenario, unless we assume there is a centralized control among the base-stations and they continuously exchange information about all the users in all the cells. However the amount of information that needs to be transferred will occupy precious bandwidth and also some of the channel parameters estimated at one base-station may not be valid for other base-stations. In such a circumstance, one can of course design multiuser receivers considering only the in-cell users, whose spreading codes are assumed to be known, completely ignoring the presence of the out-of-cell interferers. We will call such multiuser receivers *crippled* multiuser receivers. A second alternative is to use the *blind* multiuser receivers [9, 10], that work with the knowledge of the spreading codes and channel parameters of the user of concern only. These receivers estimate the background interference caused by other users and try to recover from it. Although this restriction may very well suit a hand-set, it is pessimistic for base-station design since we are not utilizing the entire information at hand.

We will show that in a practical system, where the base-station is aware of the interference information of only a subset of users, both the crippled receiver and the blind receiver suffer severe performance degradation compared to that of the ideal receiver which knows the information of all the users. In this paper, we will then present a *partially blind receiver* that successfully exploits the partial knowledge of the interfering users without ignoring the presence of out-of-cell users. Our receiver will combine the parallel interference cancellation technique for users whose spreading codes are known with the blind MMSE technique to mitigate the interference of unknown users.[1] The proposed partially blind receiver is designed based on the joint channel estimation and detection techniques in [13, 14]. The proposed receiver also shows significant performance gain over both the blind and crippled receiver technique.

This paper is organized as follows. We describe the system model and received signal representation in Section 2. In Section 3, we motivate the necessity of partially blind receivers by illustrating the problems with the blind and crippled multiuser receivers. Then, we design the partially blind receiver in Section 4. We show the effectiveness of the partially blind receiver in Section 5 by simulating its performance. Finally, we present some concluding remarks in Section 6.

[1]Detectors with partial knowledge of the interfering users have also been independently studied in [11, 12].

2 System model

We will use an asynchronous DS-CDMA system model which uses short codes of spreading gain N_c. The rectangular spreading sequence of the k^{th} user is given by $c_k(t)$ and it extends over the symbol period [0,T). The complex baseband representation of the k^{th} user's transmitted signal is given by

$$s_k(t) = \sqrt{P_k} \sum_{i=1}^{W} b_k(i) c_k(t - iT) \ , \tag{1}$$

where P_k is the transmitted power, $b_k(i) \in \{+1, \ -1\}$ is the i^{th} bit of binary antipodal information sequence of length W.

Let us assume that the channel for each user consists of P distinct and resolvable propagation paths [15]. The impulse response of the channel seen by user k is given by $h_k(t) = \sum_{p=1}^{P} w_{k,p} \delta(t - \tau_{k,p})$ where, $w_{k,p}$ is the complex amplitude with which the p^{th} path of the k^{th} user is received (includes contributions from the channel attenuation) and $\tau_{k,p}$ is the relative delay with respect to a reference at the receiver. The channel parameters are assumed to be unknown but constant during the estimation process. It may be noted that the assumption of P distinct paths is not essential for the development of our algorithm. It is introduced here only to illustrate the nature of the channel. In fact, in our specific representation, the number of paths do not affect the size of the problem or the structure of the algorithm.

Let N represent the total number of users in the system. The received signal at the base-station is a superposition of multiple copies of attenuated and delayed signals transmitted by all the users and is given by

$$r(t) = \sum_{k=1}^{N} \sum_{p=1}^{P} w_{k,p} s_k(t - \tau_{k,p}) + \nu(t), \tag{2}$$

where $\nu(t)$ is the additive white Gaussian noise.

2.1 Chip matched filter model

Before presenting the chip-matched filter model of our system it should be mentioned that the problem of estimating a parameter in a multi-user environment, where only partial information about the contributing users is available, does not arise because of any particular channel model or receiver design technique. This fundamental problem exists in all cellular systems and can be illustrated even in the channel model described above. In the rest of this section we will augment this basic channel model for the particular solution that we will present in latter sections. However, our framework is sufficiently flexible to accommodate most of the channel parameter estimation and detection algorithms. Our framework can be used to implement other traditional detection algorithms that are described in [1, 16]. We chose this model because it enables us to design an integrated solution to the channel estimation and detection problem. This model, which is described in more detail in [13, 14], can be used to design a joint channel estimation and detection algorithm that provides both computational and performance gain over the more traditional approach of separate synchronization and detection algorithms.

In this model, the continuous time signal (2) is discretized by sampling the output of a chip-matched filter at the chip rate. The observation vectors are formed by collecting together N_c successive outputs of the chip matched filter $r[n]$. Each observation vector corresponds to a time interval equal to one bit period. The receiver has an arbitrary timing reference since the system is asynchronous and will not be aligned to actual transmitted bit boundaries. We will assume that this uncertainty in the timing reference is within one bit duration. The results can be easily extended to incorporate models that allow multipath delay spread to extend beyond one bit period [17]. Each observation vector can be viewed as a linear combination of $2N$ *signal vectors* - two components from each user due to the two adjacent bits as shown in Figure 1. In Figure 1, the received vector $\mathbf{r}(i)$ overlaps the past and current transmitted bits $b(i-1)$ and $b(i)$. Therefore, the contribution of the spreading code of the user to vector $\mathbf{r}(i)$ appears in two parts - the right part (shown as R) of bit $b(i-1)$ and the left part (shown as L) of bit $b(i)$. Expressing $\mathbf{r}(i)$ in terms of its various components:

$$\mathbf{r}(i) = A\mathbf{b}(i) + \nu(i), \qquad \nu(i) \sim \mathcal{N}(\mathbf{0}, \mathcal{K}). \tag{3}$$

We denote the i^{th} bit of the k^{th} user by $b_k(i)$ and the vector $\mathbf{b}(i) = [b_1(i-1), b_1(i), \ldots, b_k(i-$

$1), b_k(i), \ldots, b_N(i-1), b_N(i)]^\top$. If we distinguish the three type of users in the system as: the user of concern c, the set of in-cell interfering users K and the set of out-of-cell interfering users U, then the discretized chip matched filtered version of the received signal for the i^{th} bit interval can also be expressed as

$$\mathbf{r}(i) = A_c \mathbf{b}_c(i) + A_K \mathbf{b}_K(i) + A_U \mathbf{b}_U(i) + \nu(i). \tag{4}$$

In our following discussion, the subscript in a matrix or vector notation will denote the contribution from that corresponding class of users and the absence of a subscript would represent the data corresponding to all the users in the system. The matrix I will denote the identity matrix and its rank would be given by its subscript. It should be noted that the matrix A is a function of the spreading codes of the corresponding users as well as all the channel parameters.

In conventional channel parameter estimation algorithms, the individual channel parameters, such as the the delays and the attenuation corresponding to each path of each user, are estimated separately and are subsequently used in the multiuser detector design. For our receiver algorithm, we will use a different representation of the channel parameters. Most of these ideas are developed along the lines of the system model described in more detail in [13, 14].

Let us consider the columns of the matrix A. As explained in Figure 1, the contribution of the spreading code of the user to vector $\mathbf{r}(i)$ appears in two parts - R and L. Hence, matrix A has columns corresponding to these two parts: denoted by the superscripts R and L and is given by $A = [\mathbf{a}_1^R \quad \mathbf{a}_1^L \quad \cdots \quad \mathbf{a}_N^R \quad \mathbf{a}_N^L]$. Each of the columns $\mathbf{a}_k^R$ and $\mathbf{a}_k^L$ for each user k are functions of the corresponding delays ($\tau_{k,1}$ to $\tau_{k,P}$) and attenuation factors ($w_{k,1}$ to $w_{k,P}$).

If T_c is the chip period, and $\tau_{k,p}/T_c = q + \gamma$, where $q \in \{0, 1, \cdots, N_c - 1\}$, and $\gamma \in [0, 1)$, we have [15]:

$$\mathbf{a}_k^R = \sum_{p=1}^{P} [w_{k,p}\{(1-\gamma)\mathbf{c}_k^R[q] + \gamma \mathbf{c}_k^R[q+1]\}]$$

$$\mathbf{a}_k^L = \sum_{p=1}^{P} [w_{k,p}\{(1-\gamma)\mathbf{c}_k^L[q] + \gamma \mathbf{c}_k^L[q+1]\}]$$

where $\mathbf{c}_N^R[q]$ and $\mathbf{c}_N^L[q]$ are the spreading codes shifted by integer (multiples of chips) delays.

$$\begin{aligned}
\mathbf{c}_k^R[q] &= [c_{k,N_c-q} \cdots c_{k,N_c-1}\, 0 \cdots 0]^\top \\
\mathbf{c}_k^L[q] &= [0 \cdots 0\, c_{k,0} \cdots c_{k,N_c-q-1}]^\top
\end{aligned}$$

It may be noted that the size of $\mathbf{a}_k^R$ or $\mathbf{a}_k^L$ (and hence A) does not depend on the number of paths. As the number of paths increases, the vectors (and hence the matrices) become more dense but do not increase in size.

We can now represent the matrix A as the product of two matrices - the matrix $\mathcal{U}$, which is a function of the known spreading codes and $\mathbf{Z}$ that consists of all the unknown channel parameters of all the paths of all the users. So the received signal can be rewritten as:

$$\mathbf{r}(i) = \mathcal{U}\mathbf{Z}\mathbf{b}(i) + \nu(i). \tag{5}$$

The structure $(\mathcal{U}\mathbf{Z})$ shows the reason why the matrix A is referred to as the *effective spreading code* matrix - it is the output of the channel when the input is the spreading codes of all the users. In other words, it encapsulates the effect of the channel on the spreading codes. The matrix $(\mathcal{U}\mathbf{Z})$ is constructed from two components (R and L) for each user:

$$\mathbf{r}(i) = [\mathcal{U}_1^R\mathbf{z}_1 \quad \mathcal{U}_1^L\mathbf{z}_1 \cdots \mathcal{U}_N^R\mathbf{z}_N \quad \mathcal{U}_N^L\mathbf{z}_N]\mathbf{b}(i) + \nu(i) \tag{6}$$

where $\mathcal{U}_k^R$ and $\mathcal{U}_k^L$ are matrices of the spreading codes of the k^{th} user and the vector $\mathbf{z}_k$ is composed of all the channel parameters of the same user.

The aim of our channel estimation algorithm is to estimate the composite channel response vector $\mathbf{z}_k$ rather than individual delay and attenuation parameters. This estimate of $\mathbf{z}_k$, in conjunction with the known structure of $\mathcal{U}_k$, can be used to construct the code-matched filter that serves as a front-end for most of the multiuser detectors. It is worth repeating that the fundamental problem that we are investigating in this paper is to estimate the channel parameters and ultimately the transmitted bits corresponding to the user of concern c using the knowledge of the spreading codes of in-cell interferers only. We will solve this problem only in terms of our system model representation, but the technique is equally applicable to many other system models and receiver algorithms.

2.2 Multishot model

As we have mentioned earlier, most of the multiuser detection algorithms use the output of the code matched filters as the front-end. Most of the earlier efforts that use individual channel parameters, such as the delay and the attenuation, require realignment of the processing window of the code-matched filter to bit boundaries of each user. Therefore, the chip matched filters had to be essentially recomputed for each user after the delays were estimated and fed back, in order to align the processing window of the code-matched filters to bit boundaries of each user. This meant that the chip matched filters used for channel estimation that were not aligned to bit boundaries could not be used to generate the code-matched filter outputs.

The use of the framework described in the previous section does not require such realignment and re-computation of the chip matched filter. This is because the delay information is embedded within the effective spreading code and the detection process described in the latter section will not require that the processing window of the code-matched filter be aligned to bit boundaries.

Moreover, previous efforts that have used a similar approach [18, 19] are essentially single shot detectors. Since the contribution of bit $\mathbf{b}(i)$ extends over two received signal periods, $\mathbf{r}(i)$ and $\mathbf{r}(i+1)$, two estimates of $\mathbf{b}(i)$ are obtained from them. A maximal ratio combining technique is used to arrive at the final estimate. Single-shot detection means that the detector deals with one symbol period at a time and does not account for the fact that two consecutive symbols of each interferer overlap with each symbol of the desired user. Performance gains may be expected if this asynchronous nature [2] of the system can be accounted for by detecting a block of bits for all the users simultaneously. In addition, the multishot detector is near-far resistant as it accounts for the interference from the overlapping symbols of the interfering users.

The model for the received signal is given by $\mathbf{r}(i) = \mathcal{U}\mathbf{Z}\mathbf{b}(i) + \nu(i)$, where $\mathbf{b}(i) = [b_1(i-1), b_1(i), \ldots, b_N(i-1), b_N(i)]^\top$. Rearranging the columns and the vector we can write

$$\mathbf{r}(i) = \left[\underbrace{(\mathcal{U}_1^R \mathbf{z}_1) \cdots (\mathcal{U}_N^R \mathbf{z}_N)}_{\mathbb{U}^R} \quad \underbrace{(\mathcal{U}_1^L \mathbf{z}_1) \cdots (\mathcal{U}_N^L \mathbf{z}_N)}_{\mathbb{U}^L} \right] \begin{bmatrix} b_1(i-1) \\ \vdots \\ b_N(i-1) \\ b_1(i) \\ \vdots \\ b_N(i) \end{bmatrix} + \nu(i).$$

In order to do multishot detection, the above model should be extended to include multiple bits. Let us assume that we will consider D bits at a time ($i = 1, 2, \cdots, D$). So, we form the multishot received vector $\mathbf{r}$ of length $N_c(D-1)$ by concatenating $D-1$ received $\mathbf{r}(i)$'s ($i = 1, 2, \cdots, D-1$). The vector $\mathbf{r}$ can be written as:

$$\mathbf{r} = \begin{bmatrix} \mathbb{U}^R & \mathbb{U}^L & 0 & 0 & 0 \\ 0 & \mathbb{U}^R & \mathbb{U}^L & 0 & 0 \\ \vdots & \ddots & \cdots & \ddots & \vdots \\ 0 & 0 & 0 & \mathbb{U}^R & \mathbb{U}^L \end{bmatrix} \begin{bmatrix} b_1(1) \\ \vdots \\ b_N(1) \\ \vdots \\ b_1(D) \\ \vdots \\ b_N(D) \end{bmatrix} + \nu$$

The model can be written in more compact matrix form as $\mathbf{r} = \mathcal{A}\mathbf{b} + \nu$. We will use this multishot model to design our partially blind receiver in the subsequent sections.

Once the channel response vector is estimated, an estimate of the effective spreading code $\mathcal{A}$ can be obtained and used in the multishot detection procedure. We can apply most of the known ideal multiuser detection techniques to estimate the data bits $\mathbf{b}$. In the next section, we will elaborate on the fundamental problem for any multiuser receiver in estimating the data bits of a user of concern when equipped with only partial knowledge of interference.

3 Multiuser receivers

We are often faced with the problem of estimating a signal which is corrupted by a number of other interfering signals with a receiver that has only partial knowledge of the interference signals at its disposal. One example of such a problem is the wireless communication problem in a cellular setup. Here, we have to estimate certain parameters for an user of concern at the base-station when the signal is corrupted by both in-cell and out-of-cell interferers. We have limited knowledge of only the in-cell interferers.

Usually, multiuser data estimation is a two-step process. In an asynchronous system, the first step is to estimate the channel parameters. Channel parameters can be estimated either in terms of individual delays, τ, and attenuation, w, corresponding to each path of each user [15, 20] or as a combined impulse response $\mathbf{Z}$ [10, 14]. In the second step, these estimated channel parameters are used to detect the data bits in the detection process.

There are two types of multiuser receivers that have been proposed in the literature. Most of the ideal multiuser channel estimation techniques or the ideal multiuser detection techniques estimate the channel parameters or the data bits of all the users in the system simultaneously and require knowledge of the spreading codes of all the users in the system. A second class of multiuser receivers use blind algorithms for channel estimation [21] or for detection of data bits [9, 10]. These blind estimation algorithms use the knowledge of the user of concern only.

These techniques are either too optimistic or pessimistic in their required knowledge of interference pattern. In fact, we cannot design an ideal multiuser receiver but only a crippled receiver that only uses the information of the in-cell users and totally ignores the out-of-cell interferers. We claim that as neither of the assumptions fit the practical situation exactly, neither of the approaches produce satisfactory performance.

Even though our subsequent discussions are equally applicable to both the synchronization and detection problem we will illustrate the incompetency of the above two approaches (crippled and blind) using the example of a detector. For simplicity of discussion, we will consider linear MMSE detection as an example.

A linear detector for user c is characterized by the linear transformation f, such that the decision on $\mathbf{b}_c$ is obtained as $\hat{\mathbf{b}}_c = \mathrm{sgn}(\langle f, \mathbf{r} \rangle)$ where $\langle \cdot, \cdot \rangle$ denotes the vector dot product operation. The linear MMSE detector is characterized by the filter

$$f_c = \arg\min_{f} E[(||\mathcal{A}_c \mathbf{b}_c|| - \langle f, \mathbf{r} \rangle)^2]$$

where $||\cdot||$ denotes the $\mathcal{L}_2$ norm of a vector. Following similar derivations as in [6, 22] it can be shown that this filter is described by the c^{th} row of the matrix

$$F_{MMSE} = [R + \sigma^2 I_N]^{-1} \mathcal{A}^\top, \tag{7}$$

where $R = \mathcal{A}^\top \mathcal{A}$ is the effective spreading code correlation matrix and σ^2 is the variance of the additive white Gaussian noise.

It is evident from the above expression that in order to design a linear MMSE receiver we need to know all the columns of the $\mathcal{A}$ matrix. In a regular setup, this means that we need to know the signature waveforms of *all* the users that contribute to the received signal $\mathbf{r}$. However, in a cellular system it is fair to assume that the base-station receiver would be aware of the signature waveforms of the in-cell users (c and the set of users K) only. Since the ideal multiuser receiver techniques require the information of all the users they cannot be used directly for this system. The effective spreading code matrix $\mathcal{A}$ is composed of the effective spreading code matrices $\mathcal{A}_{cK}$ of the in-cell users and $\mathcal{A}_U$ of the out-of-cell users. The crippled MMSE detector estimates the information bits of the in-cell users as

$$\mathbf{b}_{cripp} = [R_{cK} + \sigma^2 I_{cK}]^{-1} \mathcal{A}_{cK}^\top r, \tag{8}$$

where $R_{cK} = \mathcal{A}_{cK}^\top \mathcal{A}_{cK}$.

The blind receivers, on the other hand, are designed for those systems where the signature waveforms of the interfering users may not be known. In these receivers, it is assumed that the signature waveform of the user of concern c is available. The blind MMSE receiver estimates the colored structure of the interfering users and exploits this knowledge.

Even though the performance of the blind MMSE receiver asymptotically approximates that of an ideal MMSE receiver there is a significant gap in their performance in any practical system. We perform simulations to study the performance of both the blind MMSE receiver and the crippled receiver and compare them with that of the ideal linear MMSE receiver. We consider a system with 12 in-cell interferers and 12 out-of-cell interferers using a spreading length of 31. The power of the out-of-cell interferers are suitably reduced. Our simulation study, shown in Figure 3, demonstrates that the ideal MMSE receiver that has the knowledge of all the users spreading waveforms far outperforms both the blind MMSE and crippled MMSE receiver. It should be mentioned here that we have used the MMSE receiver as a typical example. Similar qualitative differences in performance can be observed in any form of receiver.

It should also be noted that this particular result is not indicative of the relative performance of the two suboptimal options under all situations. In fact, as shown in the appendix, in certain other situations the relative performance of the two receivers are reversed and hence there is no clear winner among these two options. The analysis in the appendix also quantifies the error that creeps into the system when we use either of these detector options. Our simulation results in Figure 4 show that for low out-of-cell interference the crippled MMSE performs better than the blind MMSE, while the situation is reversed for high out-of-cell interference.

This result (in Figure 4) not only shows the tradeoff between the crippled MMSE and the blind MMSE receivers but also suggests that the performance of the blind MMSE receiver varies with the level of out-of-cell interference or, in general, the background interference. We have also performed simulations to study the sensitivity of the blind MMSE receiver by varying the number of interfering users all of whose signature waveforms are unknown.

Our results, in Figure 5, show that for a given signal to noise ratio (SNR) there is a significant gap in the bit error rate between a system with 8 interfering users and a system with 24 interfering users. In other words, if we can reduce the level of background interference, we can hope to significantly improve the performance of the blind MMSE algorithm.

The above analysis of the two different linear MMSE detectors leads us to two important insights that will help us design the receivers with partial knowledge of interference. First, even if we have more knowledge of the users, ignoring any portion of the interference can lead to the significant loss in performance as is evident from the behavior of the crippled MMSE receiver. Secondly, we observe that even though blind MMSE technique can be asymptotically effective in combating the unknown interference, its performance is quite sensitive to the level of interference. In fact lesser the unknown interference, the better it can be mitigated.

4 Partially blind multiuser receiver

In this section, we present a new multiuser receiver algorithm motivated by the above two observations. We will use the system model described in Section 2 and develop a multiuser receiver for an asynchronous system with the multipath channel. We have observed from our earlier analysis and simulation that in order to estimate data bits in a system where we do not have information for all the users, we need to use blind receiver algorithms and the performance of these blind algorithms degrades with the increase in the interference level.

We will describe a maximum likelihood method of estimating the channel parameters given by $\mathbf{Z}$ in (5) and use it in our detection scheme. Both channel estimation and detection will be two step techniques in our case. Our strategy will be to form a preliminary estimate of the required parameter for all the in-cell users. Then, using the previously known information about the in-cell interferers, we will reproduce the signal contributed by these interferers and remove them from the received signal. If our estimation is accurate this would provide us with a reduced interference signal. We will then use a blind algorithm to finally estimate the parameter for the user of concern.

4.1 Partially blind channel estimation algorithm

We use the maximum likelihood (ML) channel estimation algorithm which is similar to the one developed in [13, 20]. We use training sequences that are transmitted by all the in-cell-users and are known to the base-station. Given W observations $\mathbf{r}(1), \mathbf{r}(2), \ldots, \mathbf{r}(W)$ of the received signal, the log-likelihood function (Λ) of these observations can be expressed as

$$-\ln|\mathcal{K}| - \operatorname{tr}\left\{\frac{1}{W}\sum_{i=1}^{W}(\mathbf{r}(i) - A\mathbf{b}(i))^{\top}\mathcal{K}^{-1}(\mathbf{r}(i) - A\mathbf{b}(i))\right\}$$

where $|\cdot|$ represents the determinant operator and $\operatorname{tr}(\cdot)$, the trace operator. In this expression $\mathcal{K}$ represent the covariance structure of the background noise and unaccounted interference. If we knew the training sequence of all the users, then this covariance matrix would represent only the background noise and from our assumption would be white. However, since we do not have the interference information due to the unknown users, we cannot assume a white covariance structure for the background noise and interference. It should be noted that in the absence of any other knowledge, for the maximization we make a simplifying assumption that the interference due to the out-of-cell users is Gaussian and the data of all users are independent.

In order to estimate the covariance structure $\mathcal{K}$ of the background noise we first make a preliminary estimate of the channel parameters of the in-cell users. In fact we estimate the effective spreading code of all the in-cell users by using a training sequence. Since the noise is independent of the data and has zero mean the unbiased maximum likelihood estimate of the effective spreading code $\hat{A}_{cK}$ can be obtained from the known transmitted preamble $\mathbf{b}_{cK}$ as

$$\hat{A}_{cK} = E[\mathbf{r}\mathbf{b}_{cK}^{\top}][E[\mathbf{b}_{cK}\mathbf{b}_{cK}^{\top}]]^{-1}$$

We use this unconstrained estimate of the effective spreading code and the corresponding known training sequence to recreate the signal contributions of the in-cell users. This information is then subtracted from the received signal to estimate the background noise covariance structure as

$$\hat{\mathcal{K}} = E[\left(\mathbf{r} - \hat{A}_{cK}b_{cK}\right)\left(\mathbf{r} - \hat{A}_{cK}b_{cK}\right)^{\top}]$$

These expressions for $\hat{A}$ and $\hat{\mathcal{K}}$ are then replaced in the log-likelihood objective function. The modified cost function is then optimized with respect to $\mathbf{Z}$. The constrained estimate of A of the form $\mathcal{U}\mathbf{Z}$ is obtained as in [23]. Each $\mathbf{z}_k$ is estimated as

$$\hat{\mathbf{z}}_k = (\hat{\mathbf{a}}_{2k-1}^{H}\hat{\mathcal{K}}^{-1}\mathcal{U}_k^{R} + \hat{\mathbf{a}}_{2k}^{H}\hat{\mathcal{K}}^{-1}\mathcal{U}_k^{L})(\mathcal{U}_k^{R'}\hat{\mathcal{K}}^{-1}\mathcal{U}_k^{R} + \mathcal{U}_k^{L'}\hat{\mathcal{K}}^{-1}\mathcal{U}_k^{L})^{-1} \tag{9}$$

where $\hat{\mathbf{a}}_{2k-1}$ and $\hat{\mathbf{a}}_{2k}$ are the $(2k-1)^{th}$ and $(2k)^{th}$ columns of $\hat{A}$.

4.2 Partially blind multiuser detector

Following our theme of our partially blind algorithms, we will first make an initial estimate of all the in-cell users in our detection process also. We will then eliminate the interference due to the in-cell users by using the knowledge of their spreading waveforms and the channel parameters estimated earlier (given by $\mathcal{A}_k$). This clean signal will now contain the signal from the user of interest c and the out-of-cell interferers. We will then use a blind algorithm to estimate data bits of the user of concern c.

Even though the first blind algorithm described by [9] was based on maximizing output energy using an iterative algorithm, we will use a different blind MMSE algorithm which is more suitable for a multishot implementation in our framework. The blind MMSE receiver for the user c (with ideal channel estimates) is given by

$$F_{blind} = \mathcal{A}_c^\top [\mathcal{A}\mathcal{A}^\top + \sigma^2 I_{N_c}]^{-1}. \tag{10}$$

We will first show that this receiver gives the same estimate of the data bits corresponding to the user of concern c as does the ideal MMSE receiver given by (7).

We will first define $\mathbf{b}_{MMSE}$ and $\mathbf{b}_{blind}$ as $\mathbf{b}_{MMSE} = F_{MMSE}\mathbf{r}$ and $\mathbf{b}_{blind} = F_{blind}\mathbf{r}$. We will now show that $\mathbf{b}_{MMSE}$ is the same as $\mathbf{b}_{blind}$, which means that F_{MMSE} and F_{blind} are equivalent. From the definition of $\mathbf{b}_{MMSE}$, we have

$$\begin{aligned}
[\mathcal{A}^\top \mathcal{A} + \sigma^2 I_N]^{-1}\mathcal{A}^\top \mathbf{r} &= \mathbf{b}_{MMSE} \\
\mathcal{A}^\top \mathbf{r} &= [\mathcal{A}^\top \mathcal{A} + \sigma^2 I_N]\mathbf{b}_{MMSE}.
\end{aligned}$$

From the definition of the blind MMSE detector (from equation (10)) for all the N users, we have

$$\mathcal{A}^\top \underbrace{[\mathcal{A}\mathcal{A}^\top + \sigma^2 I_{N_c}]^{-1}\mathbf{r}}_{\mathbf{x}} = \mathbf{b}_{blind}.$$

From this equation we get that $\mathbf{b}_{blind} = \mathcal{A}^\top \mathbf{x}$, where $[\mathcal{A}\mathcal{A}^\top + \sigma^2 I_{N_c}]\mathbf{x} = \mathbf{r}$. Now,

$$\begin{aligned}
[\mathcal{A}^\top \mathcal{A} + \sigma^2 I_N]\mathbf{b}_{blind} &= [\mathcal{A}^\top \mathcal{A} + \sigma^2 I_N]\mathcal{A}^\top \mathbf{x} \\
&= \mathcal{A}^\top \mathcal{A}\mathcal{A}^\top \mathbf{x} + \mathcal{A}^\top \sigma^2 \mathbf{x} \\
&= \mathcal{A}^\top [\mathcal{A}\mathcal{A}^\top + \sigma^2 I_{N_c}]\mathbf{x} \\
&= \mathcal{A}^\top \mathbf{r} \\
&= [\mathcal{A}^\top \mathcal{A} + \sigma^2 I_N]\mathbf{b}_{MMSE}.
\end{aligned}$$

Therefore, $\mathbf{b}_{MMSE}$ and $\mathbf{b}_{blind}$ are equivalent.

We see that in order to estimate the data bits of the user of concern c we need to know $\mathcal{A}_c$ and $[\mathcal{A}\mathcal{A}^\top + \sigma^2 I_{N_c}]^{-1}$. However, the latter expression can be estimated from the received signal without the knowledge of the interfering users as $\mathrm{E}[\mathbf{r}\mathbf{r}^\top]$. Thus, this blind algorithm requires the knowledge of only the user of concern c.

But in this estimation process we have not used the knowledge of other in-cell interferers. Our earlier results show that the performance of a blind receiver degrades significantly with the increase in the number of interferers. The most important technique that we will use to reduce the known interference is based on multistage detection or parallel interference cancellation (PIC) [5, 24]. This improves the performance of the blind algorithm in combating the unknown interference significantly.

The basic idea behind these interference cancellation algorithms is to estimate the known interference and then remove it from the received signal to obtain a cleaner signal for the user of concern. This process is repeated iteratively until the required performance is achieved. In our system, if we estimate the information bits of the in-cell interferers, we can use the knowledge of their estimated effective spreading code to obtain a cleaner signal for the user of concern c and then use a blind MMSE algorithm to estimate $\mathbf{b}_c$ from the reduced interference statistic. Thus, we estimate $\mathbf{b}_c$ as

$$\hat{\mathbf{b}}_c = F_c^\top(\mathbf{r} - \mathcal{U}_K \hat{\mathbf{Z}}_K \hat{\mathbf{b}}_K)$$

where $\hat{\mathbf{b}}_K$ is the estimate of the information bits of the known interfering users and F_c is the blind MMSE filter for the user of concern corresponding to the reduced interference signal. The estimate $\hat{\mathbf{b}}_K$ is obtained using a blind MMSE filter for each of the known users. Even if we completely eliminate the contribution of the known interferers K, we still have to deal with the unknown interference since it will limit the performance of the receiver. Therefore, we use a blind MMSE filter F_c to combat the remaining interference. This estimate is better than the initial blind MMSE estimate because of the reduction in interference due to parallel interference cancellation and can be improved iteratively. This is based on the earlier study in Section 3 and gives us the partially blind (P-BLIND) receiver (shown in Figure 2).

We should, however, note that in order to reduce the interference level we must feed back *correct* estimates of $\mathbf{b}_K$. If the estimates are incorrect, instead of reducing the interference, we might actually increase the interference. This will adversely affect the performance of the blind MMSE receiver. In order to minimize the power of the residual interference after cancellation, we need to feed back the soft estimate of the interference equal to $E[\mathcal{U}_K \hat{\mathbf{Z}}_K \mathbf{b}_K | \mathbf{x}]$ where $\mathbf{x}$ is the signal at the output of the detector used to make hard decisions. Since it is analytically difficult to model the distribution of $\hat{\mathbf{Z}}_K$, we could use a suboptimal soft feed back equal to $\mathcal{U}_K \hat{\mathbf{Z}}_K E[\mathbf{b}_K | \mathbf{x}]$. Thus, the soft estimate of a bit b in the vector $\mathbf{b}_K$ is approximated by its conditional expected value given the corresponding element x of $\mathbf{x}$.

$$E[b|x] = (1)pr(b = 1|x) + (-1)pr(b = -1)|x)$$

If we assume that x is Gaussian with variance σ, then $pr(x|b = 1) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(\frac{(x-1)^2}{2\sigma^2}\right)$. Using Bayes' rule, $pr(b = 1|x) = \frac{pr(x|b=1)pr(b=1)}{pr(x)}$ where $p(x) = pr(x|b = 1)pr(b = 1) + pr(x|b = -1)pr(b = -1)$. Using a similar expression for $pr(b = -1|x)$ and assuming that the transmitted bits are equally likely, we get

$$\begin{aligned}
\mathrm{E}[b|x] &= \frac{\exp\left(\frac{(x-1)^2}{2\sigma^2}\right) - \exp\left(\frac{(x+1)^2}{2\sigma^2}\right)}{\exp\left(\frac{(x-1)^2}{2\sigma^2}\right) + \exp\left(\frac{(x+1)^2}{2\sigma^2}\right)} \\
&= \frac{\exp(\frac{-x}{\sigma^2}) - \exp(\frac{x}{\sigma^2})}{\exp(\frac{-x}{\sigma^2}) + \exp(\frac{x}{\sigma^2})} \\
&= \tanh\left(\frac{x}{\sigma^2}\right)
\end{aligned}$$

At this point it is also worthwhile to revisit an assumption made for our channel estimation algorithm. We assumed that all the in-cell users will be coordinating to transmit the training sequences at the same time. This assumption might be a little unrealistic as, usually at one time, we will have only a few users (if not one) user in a base-station whose channel impulse responses need to be estimated. But, since we have already estimated the impulse response of the rest of the in-cell interferers, we could use their detected bit decisions in place of the training sequences directly in the maximum likelihood channel estimation algorithm. We could also use a parallel interference cancellation scheme to remove their contribution from the signal which is used to estimate the channel parameters. Thus our channel parameter estimation algorithm could be preceded by a PIC step where the contribution of the in-cell, whose channel parameters are already known, are eliminated.

4.3 Performance of the partially blind detector

In this section, we determine a lower bound on the bit error rate performance of the partially blind detector. A casual observation might suggest that the P-BLIND detector can never outperform the ideal MMSE detector. But this is not necessarily true. Since the P-BLIND detector uses a non-linear interference cancellation technique it is possible to conceive that it can perform better than the ideal linear MMSE receiver.

A simple analysis of the P-BLIND detector can be done to obtain a lower bound on its performance. The detector has two stages, parallel interference cancellation and blind MMSE detection. Given the ideal performance of both these stages, namely perfect interference cancellation (of all the in-cell users) and ideal MMSE detection, the probability of error of the partially blind detector is lower bounded by the probability of error of an MMSE detector for a system with the unknown (out-of-cell) interferers alone. We will refer to this detector corresponding to the best case scenario as the MMSE-LB in Section 5, where the performance of the partially blind detector is compared with that of the lower bound.

It is also clear that the performance of the MMSE-LB receiver is better than the performance of the ideal linear MMSE receiver, as the former has fewer interfering users. In a P-BLIND detector usually the first stage estimation of in-cell users may not be always accurate and the performance of the blind MMSE algorithm hardly ever approaches the desired asymptotic performance. But if the errors are not significant, the P-BLIND detector can outperform the ideal linear MMSE detector, but will fall short in performance compared to the MMSE-LB detector. We will illustrate this in Section 5 using simulations.

5 Simulation Results

In this section, we will present the simulation results obtained for the partially blind receiver described in Section 4 and discuss their implications. The simulation results are obtained for an asynchronous DS-CDMA system with 12 known interferers and 12 unknown interferers. Simulation results have been obtained for various interference conditions within and outside the cell. However, in each of the simulations, the out-of-cell interference is about 36% of the overall interference. The channel is as described in Section 2 and random spreading codes of length 31 were assigned to the users. In all the simulation results we will show the bit error rate of the user of concern c.

Initially, we will show the results for a simple system where all the in-cell users have the same power and all the out-of-cell users have the same power (which is 36% of the power of an in-cell user). In Figure 6, the performance of the proposed partially blind multiuser receiver (P-BLIND) is compared with that of the matched filter detector, the blind MMSE detector and the conventional MMSE detector for a system with the out-of-cell interferers only (this is the lower bound from Section 4.3 and is denoted as MMSE-LB). It is evident that significant gains in performance over the blind MMSE detector can be achieved by the partially blind receiver. This is achieved by obtaining the reduced interference signal for the blind algorithm using the knowledge of the in-cell interference.

Similar performance gains compared to the blind MMSE detector can be achieved in near-far situations also. In Figure 7, we show the performance of the partially blind multiuser receiver (P-BLIND) in a near-far situation, where the 12 users in the cell have powers 0-6 dB higher than the user of concern. The 12 out-of-cell interferers also have powers 0-6 dB higher than the weakest out-of-cell interferer (which has 36% power of the user of concern).

In Section 4.3, we discussed the fact that the performance of the proposed partially blind receiver can be better than the ideal linear MMSE receiver (with complete knowledge) because of the use of non-linear interference cancellation techniques. Here, we show by simulations, that this is actually observed in practice. This performance is achieved even with the non ideal performance of the PIC and the blind MMSE stages. Figure 8 illustrates this result by comparing the performance of the partially blind receiver with the ideal linear MMSE receiver for all the in-cell and out-of-cell users.

It should be mentioned again that although the simulations here have been carried out with the specific system model in Section 2 similar results (qualitatively) can be obtained using other system models, channel estimation methods and channel knowledge assumptions. In fact, the performance gains from a partially blind detector in the presence of complete channel information (i.e., perfect channel estimation assumption) have already been presented in [25]. Here, we extend those results to solve both the channel estimation and detection problems simultaneously.

6 Conclusions

In this paper, we propose and analyze a new class of multiuser receivers that use partial knowledge of interference. Partial knowledge of the interference is often available in practice. One such common situation with partial knowledge of interference is at the base-station of a CDMA cellular communication system, which receives interfering signals from neighboring (and overlay) cells in addition to its own signals. While the base-station may be expected to know the modulation signals of the users within the cell, it may not have any information on the out-of-cell interferers.

Although blind MMSE receivers are applicable in such situations of unknown interference, they do not use all the available information and suffer from severe performance degradation with increasing interference. The proposed partially blind receiver uses the knowledge of the in-cell interfering users to significantly improve upon the blind MMSE receiver. Nonlinear parallel interference cancellation (multistage cancellation) is used to combat the known interference and provide reduced interference signals for the blind MMSE receiver. The performance gains from the proposed receiver are demonstrated using simulations. Due to the nonlinear nature of the proposed receiver, its performance is better than the ideal linear MMSE receiver. We also analyze and simulate a lower bound on the performance of the partially blind receiver.

The proposed receiver solves both the channel estimation and the detection problems. The partially blind multiuser receiver is developed for an asynchronous DS-CDMA system over a multipath channel. The system model and the proposed receiver can be directly extended to multiple receiver antenna systems [13, 23].

Appendix

In this section we present the quantitative comparison of the blind and the crippled MMSE detector and analyze the errors of these receivers compared to the ideal MMSE detector. As presented in Section 3 the ideal MMSE detector for the user c is given by the c^{th} row of the matrix $F_{MMSE} = [R + \sigma^2 I_N]^{-1}\mathcal{A}^\top$ where $R = \mathcal{A}^\top\mathcal{A}$ is the effective spreading code correlation matrix. The blind MMSE receiver is given by $F_{blind} = \mathcal{A}_c^\top[\mathcal{A}\mathcal{A}^\top + \sigma^2 I_{N_c}]^{-1}$ and the crippled MMSE detector is given by $F_{cripp} = [R_{cK} + \sigma^2 I_{cK}]^{-1}\mathcal{A}_{cK}^\top$ where $R_{cK} = \mathcal{A}_{cK}^\top\mathcal{A}_{cK}$ is the code covariance matrix of the known in-cell users. The ideal MMSE estimate using the knowledge of all the users can be rewritten as

$$[\mathcal{A}^\top\mathcal{A} + \sigma^2 I_N]\mathbf{b}_{MMSE} = \mathcal{A}^\top\mathbf{r}.$$

Separating the contribution of in-cell users and out of cell users, we can rewrite the above equation as

$$\begin{bmatrix} R_{cK} & \rho \\ \rho^\top & R_U \end{bmatrix} + \begin{bmatrix} I_{cK} & 0 \\ 0 & I_U \end{bmatrix} \begin{bmatrix} \mathbf{b}_{cK} \\ \mathbf{b}_U \end{bmatrix} = \begin{bmatrix} \mathcal{A}_{cK}^\top \\ \mathcal{A}_U^\top \end{bmatrix}\mathbf{r}$$

where ρ is the cross correlation matrix $\mathcal{A}_{cK}^\top\mathcal{A}_U$. It can be seen that the correct equation

$$[R_{cK} + \sigma^2 I_{cK}]\mathbf{b}_{cK} = \mathcal{A}_{cK}^\top\mathbf{r} - \rho\mathbf{b}_U$$

to solve for the bits of the in-cell users, is incorrectly modeled by equation (8) by the crippled MMSE detector. Thus, the error $err_{cripp} = \mathbf{b}_{cripp} - \mathbf{b}_{cK}$ is given by

$$[R_{cK} + \sigma^2 I_{cK}]err_{cripp} = \rho\mathbf{b}_U.$$

Thus, it is evident that the more the number of out-of-cell users the more is the error in the estimate. We will see, later in this section, that this leads to significant performance losses.

In blind MMSE detection, we estimate the covariance matrix, C, of the received vector given by $C = [\mathcal{A}\mathcal{A}^\top + \sigma^2 I_{N_c}]$ as $\hat{C} = \mathrm{E}[\mathbf{r}\mathbf{r}^\top]$. The error, in this case, can be given by

$$err_{blind} = \mathcal{A}_{cK}^\top[\hat{C}^{-1} - C^{-1}]\mathbf{r}$$

Since a closed form analytic expression of this error in terms of number of out-of-cell users is not possible, we resort to simulation studies to show the effect of estimation errors.

We simulated systems with variable number of out-of-cell users. All the in-cell users are assigned the same power and the background SNR is 6dB. Our simulation results in figure 4 show that for low out-of-cell interference the crippled MMSE performs better than the blind MMSE. This is because the blind MMSE receiver couldn't perfectly approximate the behavior of the ideal MMSE receiver and error due to treating the out-of-cell users as noise is not significant enough. However as the number of out-of-cell interferers increase the performance of the crippled MMSE receiver start degrading and in fact becomes worse than that of blind MMSE receiver which is using lesser information but is trying to at least estimate the interference pattern of both the in-cell and out-of-cell interferers.

References

[1] S. Verdu, *Multiuser detection*, Cambridge University Press, 1st edition, 1998, New York, NY.

[2] S. Moshavi, "Multi-user detection for DS-CDMA communications," *IEEE Communications Magazine*, vol. 34, pp. 124–136, October 1996.

[3] S. Verdu, "Minimum probability of error for asynchronous Gaussian multiple-access channels ," *IEEE Transactions on Information Theory*, vol. IT-32, no. 1, pp. 85–96, Jan 1986.

[4] R. Lupas and S. Verdu, "Linear multiuser detectors for synchronous code-division multiple-access channels," *IEEE Transactions on Information Theory*, vol. 35, no. 1, pp. 123–136, Jan 1989.

[5] M. K. Varanasi and B. Aazhang, "Multistage detection in asynchronous code-division multiple-access communications," *IEEE Transactions on Communications*, vol. 38, no. 4, pp. 509–519, Apr 1990.

[6] Z. Xie, R. T. Short, and C. K. Rushforth, "A family of suboptimum detectors for coherent multi-user communications," *IEEE Journal on Selected Areas in Communications*, vol. 8, no. 4, pp. 683–690, May 1990.

[7] A. Duel-Hallen, J. Holtzman, and Z. Zovonar, "Multiuser Detection for CDMA Systems," *IEEE Personal Communication*, vol. 2, no. 2, pp. 46–58, 1995.

[8] A. J. Viterbi, *CDMA : Principles of Spread Spectrum Communication*, Addison-Wesley Publishing Company, 1995.

[9] M. Honig, U. Madhow, and S. Verdu, "Blind Adaptive Multiuser Detection," *IEEE Transactions on Information Theory*, vol. 41, no. 4, pp. 944–960, July 1995.

[10] X. Wang and H. V. Poor, "Blind Multiuser Detection: A Subspace Approach," *IEEE Transactions on Information Theory*, vol. 44, no. 2, pp. 677–689, March 1998.

[11] A. Host-Madsen, "Semi-blind decorrelating multi-user detectors for CDMA:Subspace methods," in *Proceedings PIMRC '98*, Sep 1998.

[12] A. Host-Madsen and K. S. Cho, "MMSE/PIC multi-user detection for DS/CDMA systems with inter- and intra-cell interference," in *Proceedings ISIT '98*, Aug 1998, p. 38.

[13] C. Sengupta, *Algorithms and Architectures for Channel Parameter Estimation in Wireless CDMA Communication Systems*, Ph.D. thesis, ECE Dept., Rice University, Houston, TX, 1998.

[14] C. Sengupta, S. Das, J. R. Cavallaro, and B. Aazhang, "Efficient Multiuser Receivers for CDMA Systems," in *IEEE Wireless Communication and Networking Conference*, Sept. 1999, pp. 1461–1465.

[15] S. E. Bensley and B. Aazhang, "Subspace-based channel estimation for code division multiple access communication systems," *IEEE Transactions on Communications*, vol. 44, no. 8, pp. 1009–1020, August 1996.

[16] S. Moshavi, "Multi-user detection for DS-CDMA communications," *IEEE Communications Magazine*, pp. 124–136, Oct 1996.

[17] E. Ertin, U. Mitra, and S. Siwamogsatham, "Iterative techniques for DS/CDMA multipath channel estimation," in *Allerton Conference, Monticello, IL*, September 1998, pp. 772–781.

[18] S. E. Bensley and B. Aazhang, "Maximum likelihood synchronization of a single user for CDMA c ommunication systems," *IEEE Transactions on Communications*, vol. 46, no. 3, pp. 392–399, March 1998.

[19] C. Sengupta, A. Hottinen, J. R. Cavallaro, and B. Aazhang, "Maximum likelihood multipath channel parameter estimation in CDMA systems," *Conference on Information Sciences and Systems, Princeton, NJ*, vol. 1, pp. 6–11, March 1998.

[20] E. G. Strom, S. Parkvall, S. L. Miller, and B. E. Ottersten, "DS-CDMA synchronization in time-varying fading channels," *IEEE JSAC*, pp. 1636–1642, Oct. 1996.

[21] D. Zheng, J. Li, S. L. Miller, and E. G. Strom, "An efficient code-timing estimator for DS-CDMA signals," *IEEE Transactions on Signal Processing*, vol. 45, no. 1, pp. 82–89, Jan. 1997.

[22] U. Madhow and M. L. Honig, "MMSE interference suppression for direct-sequence spread-spectrum CDMA," *IEEE Transactions on Communications*, vol. 42, no. 12, pp. 3178–3188, Dec 1994.

[23] R. Madyastha, *Antenna arrays for wireless CDMA communications systems*, Ph.D. thesis, ECE Dept., Rice University, Houston, TX, 1997.

[24] R. Kohno, H. Imai, M. Hatori, and S. Pasupathy, "Combination of an adaptive array antenna and a canceller of interference for direct-sequence spread-spectrum multiple-access system," *IEEE Journal on Selected Areas in Communications*, vol. 8, no. 4, pp. 675–682, May 1990.

[25] S. Das, S. Bhashyam, J. R. Cavallaro, and B. Aazhang, "Partially Blind Multiuser Detection," in *Conference on Information Sciences and Systems '99*, Mar. 1999, pp. 650–655.

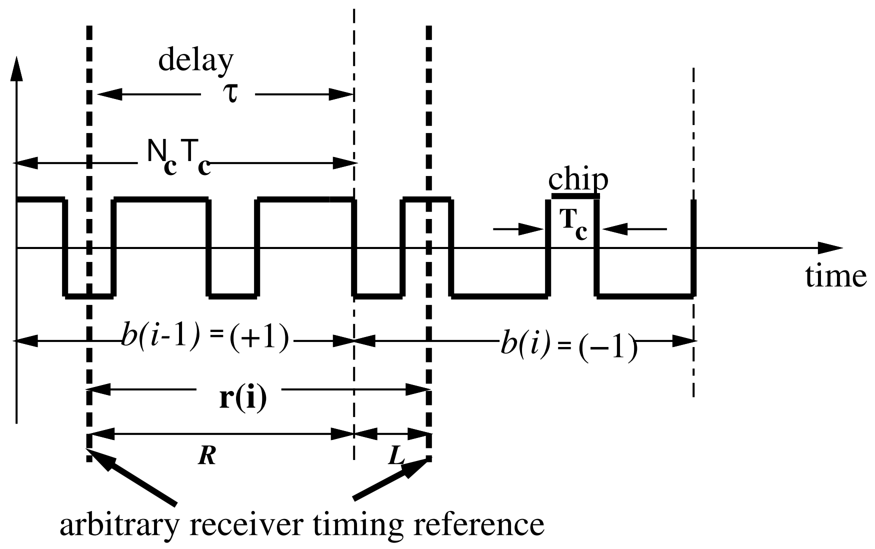

Figure 1: System model - received signal.

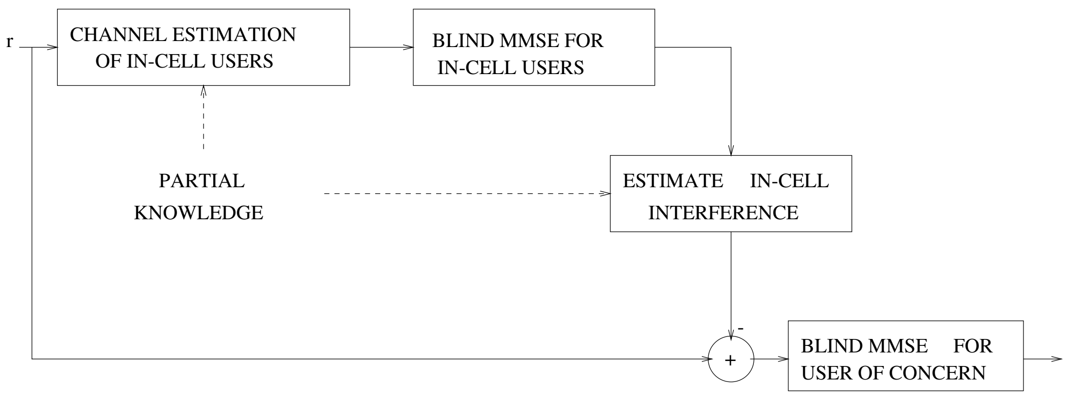

Figure 2: Partially blind multiuser receiver

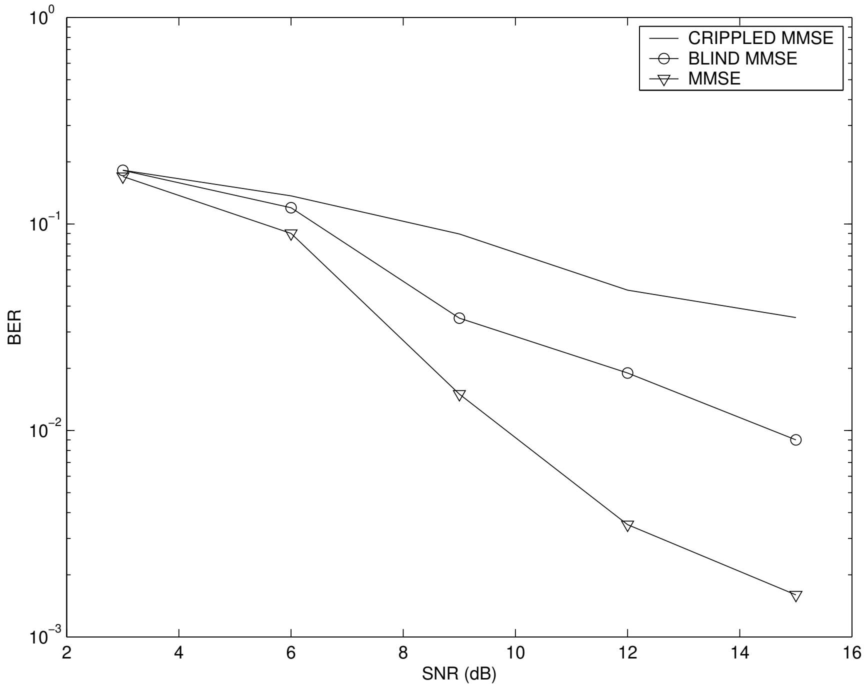

Figure 3: Performance comparison of blind and crippled MMSE receivers with the ideal MMSE receiver

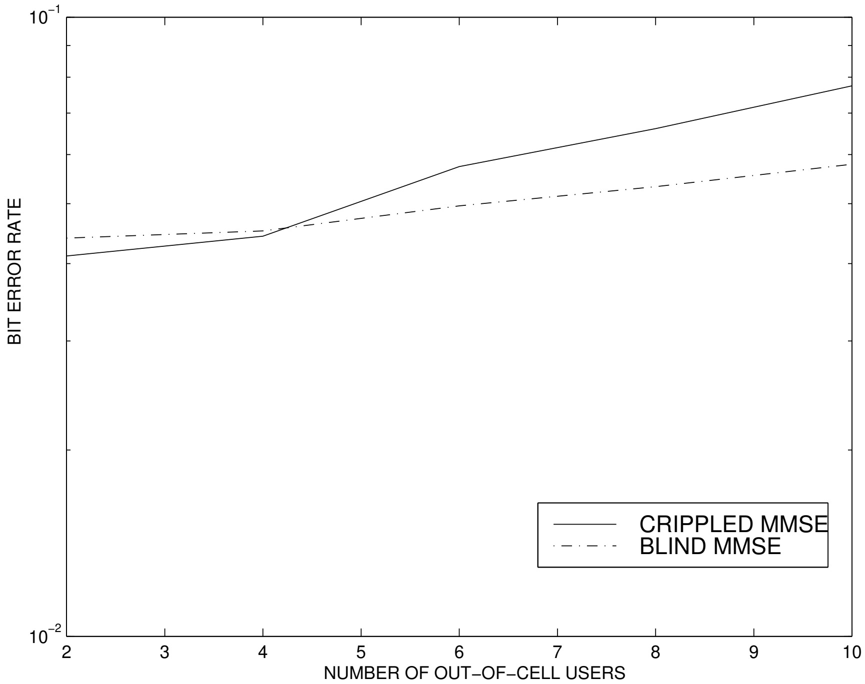

Figure 4: Performance of blind MMSE and crippled MMSE receivers – number of in-cell users = 10, all users have equal power

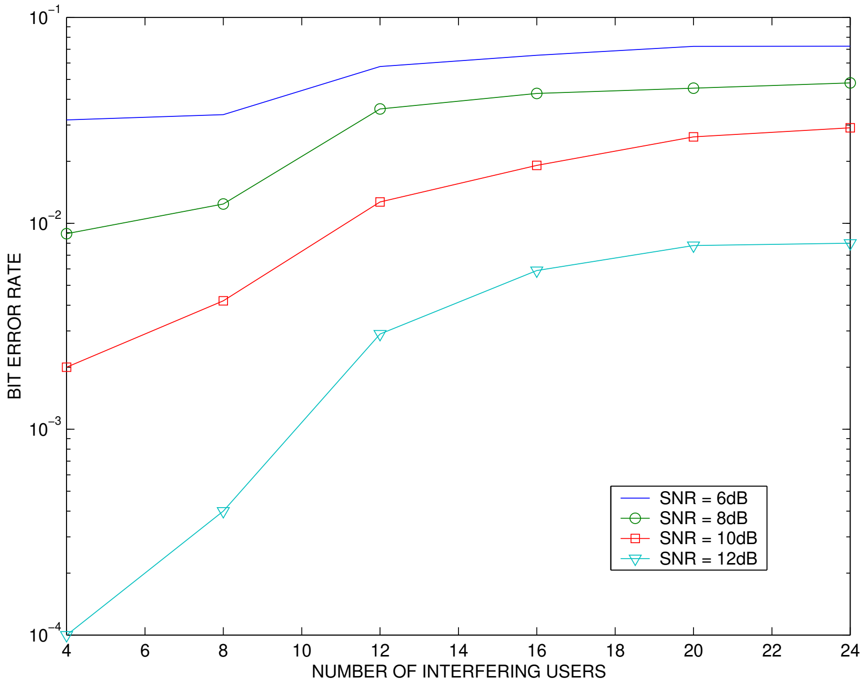

Figure 5: Sensitivity of blind MMSE algorithm to background interference, all users have equal power.

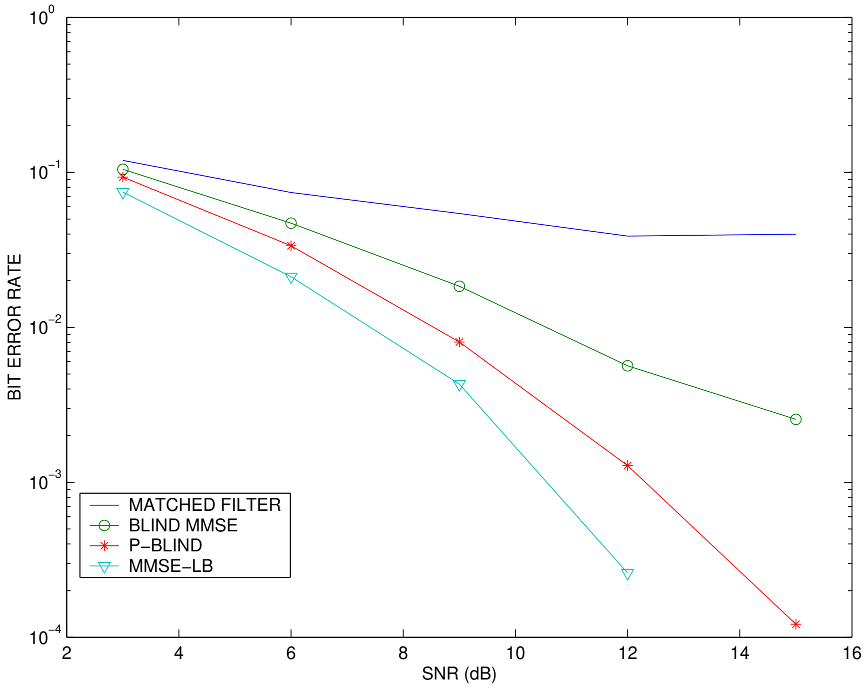

Figure 6: Equal power case : performance of partially blind multiuser receiver based on soft-decision feedback – number of in-cell users = 12, number of out-of-cell users = 12, users within cell have equal power, power of out-of-cell users = 36% of power of in-cell users.

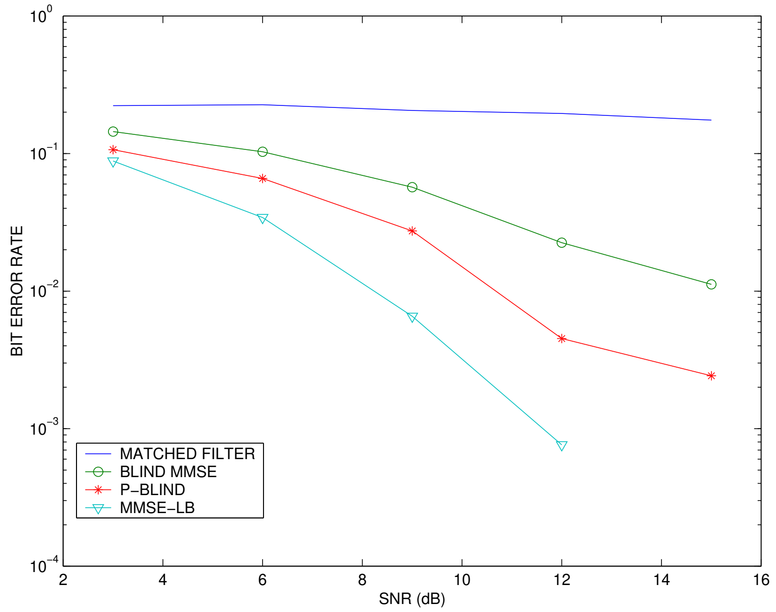

Figure 7: Near-far case : performance of partially blind multiuser receiver based on soft-decision feedback – number of in-cell users = 12, number of out-of-cell users = 12, users within cell have power between 0 and 6 dB higher than the user-of-concern, power of out-of-cell users = 36% of power of in-cell users.

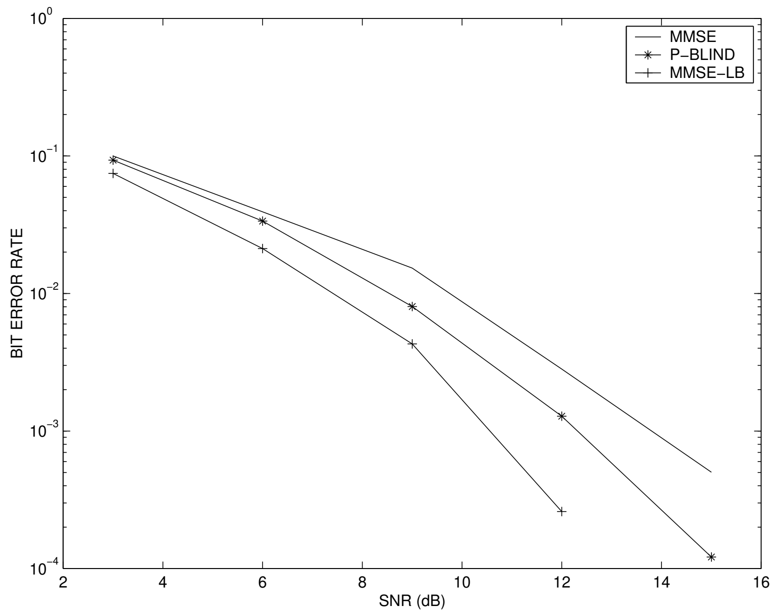

Figure 8: Performance comparison of the partially blind multiuser receiver with the ideal MMSE receiver for all users (MMSE) and the ideal MMSE receiver for a system with the out-of-cell interferers only (MMSE-LB) – number of in-cell users = 12, number of out-of-cell users = 12, users within cell have power between 0 and 6 dB higher than the user-of-concern, power of out-of-cell users = 36% of power of in-cell users.