Blind Successive Interference Cancellation for DS-CDMA Systems

Dragan Samardzija, Narayan Mandayam, *Senior Member, IEEE*, and Ivan Seskar, *Member, IEEE*

***Abstract*—In this paper, we propose a blind successive interference cancellation receiver for asynchronous direct-sequence code-division multiple-access (DS-CDMA) systems using a maximum mean energy (MME) optimization criterion. The covariance matrix of the received vector is used in conjunction with the MME criterion to realize a blind successive interference canceler that is referred to as the BIC-MME receiver. The receiver executes interference cancellation in a successive manner, starting with the most dominant interference component and successively cancelling the weaker ones. The receiver is compared against various centralized and decentralized receivers, and it is shown to perform well in the presence of estimation errors of the covariance matrix, making it suitable for application in time-varying channels. We also analyze properties of the covariance matrix estimates which are relevant to the performance of the BIC-MME receiver. Further, the BIC-MME receiver is particularly efficient in the presence of a few strong interferers as may be the case in the downlink of DS-CDMA systems where intracell user transmissions are orthogonal. An iterative implementation that results in reduced complexity is also studied.**

***Index Terms*—Blind interference cancellation, CDMA downlink, successive interference cancellation.**

I. INTRODUCTION

IN direct-sequence code-division multiple-access (DS-CDMA) systems, in general, cross correlations between signature (spreading) sequences are nonzero. This results in multiple-access interference (MAI) which can disrupt reception of highly attenuated desired user signals. This is known as the near–far effect. To combat this problem, several multiuser receivers have been proposed (for example, see [1]–[5]). These receivers are denoted as centralized because they require knowledge of parameters (signature sequences, amplitudes, and timing) for all users in the system. Therefore, they are more suitable for processing at the base station.

For the downlink, it is desirable to devise decentralized receivers. Decentralized receivers exploit knowledge of the desired user parameters only. The use of short signature sequences simplifies the task of multiuser detection and interference cancellation, since a receiver can adaptively learn (estimate) the structure of the MAI [6]. Decentralized receivers may be further classified into data-aided and nondata-aided receivers. Data-aided adaptive multiuser detection is an approach which does not require a prior knowledge of the interference parameters. But, it requires a training data sequence for every active user. For example, adaptive receivers in [3], [7], [8] are based on the minimum mean square error (MMSE) criterion, and the one in [9] is based on minimizing probability of bit-error. More recently, decision feedback detectors using the MMSE criterion have been proposed [10], [11].

Blind (or non data-aided) multiuser detectors require no training data sequence, but only knowledge of the desired user signature sequence and its timing. The receivers treat MAI and background noise as a random process, whose statistics must be estimated. Majority of blind multiuser detectors are based on estimation of second-order statistics of the received signal. In [12], a blind adaptive MMSE multiuser detector is introduced (proven to be equivalent to the minimum output energy (MOE) detector). A subspace approach for blind multiuser detection is presented in [13] where both the decorrelating and the MMSE detector are obtained blindly. Further, adaptive and blind solutions are analyzed in [14], with an overview in [6]. Recently, a blind solution based on higher order statistics and nonliner cancellation is presented in [15]. A comprehensive treatment of multiuser detection can be found in [16].

The receiver in this paper is based on determining the most (on average) dominant baseband interference components at the output of a DS-CDMA system. Preliminary results on this idea were first presented in [17]. In Section III, the maximum mean energy (MME) criterion is introduced. In Section IV, we present a novel blind receiver. It is based on the MME criterion and requires estimation of the second-order statistics. We use the term "blind" in this paper to describe our receiver even though it requires the power of the desired user in addition to the desired user signature sequence. While this may be slightly different from what is termed as "blind" in the literature [6], we still use this nomenclature because the receiver requires no knowledge of the interferers and also works well with estimates of the desired user power. The receiver executes interference cancellation (IC) in a successive manner, starting with the most dominant interference component and successively cancelling the weaker ones. Therefore, it may be viewed as a blind equivalent to the centralized successive interference cancellation (SIC) scheme [4], [18], and we refer to this receiver as the blind interference cancellation-maximum mean energy (BIC-MME) receiver. The difference between the two schemes is that the centralized SIC receiver cancels interferers one by one (using hard or soft decisions), usually following the sequence of ordered powers, while in the case of the BIC-MME receiver components

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D. Samardzija is with the Wireless Research Laboratory, Bell Labs, Lucent Technologies, Holmdel, NJ 07733 USA (e-mail: dragan@lucent.com).

N. Mandayam and I. Seskar are with the WINLAB, Rutgers University, Piscataway, NJ 08854 USA (e-mail: narayan, seskar@winlab.rutgers.edu).

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from the interference subspace (eigenvectors) are projected out and successively cancelled from the received vector. In order to reduce complexity of the receiver implementation, we also propose an iterative solution for the MME optimization. Simulation results are presented in Section V.

Time-varying systems are of special interest in future DS-CDMA systems. These variations could be due to either the radio channel or due to the variations in traffic such as anticipated in packet networks [19]–[22] that may result in high user activity (on/off) and short transmission periods (burstiness) in the channel. Feasibility of adaptive and blind interference cancellation in these systems is directly impacted by the reliability of required estimates, using a limited number of samples. Therefore, in this paper, special attention is paid to the analysis of the receiver performance in the case of a limited number of samples used for the estimation of the covariance matrix of the input signal. Our simulation results indicate that the BIC-MME receiver outperforms the blind MMSE receiver in all cases, and particularly when the number of samples used for estimation of the covariance matrix is limited. In Section VI, we present an interpretation for the above behavior using results from the estimation of eigenvectors based on sample covariance matrices. We conclude in Section VII.

II. Background

We now present the asynchronous DS-CDMA system model and briefly review the MMSE criterion. The received baseband signal, $r(t)$, in an antipodal K-user asynchronous DS-CDMA additive white Gaussian noise (AWGN) system is

$$r(t)=\sum_{i=-J}^{J}\sum_{k=1}^{K}A_k\,b_k\,(i)\,s_k(t-iT-\tau_k)\;+\;\sigma n(t) \tag{1}$$

where A_k is the received amplitude, $b_k(i)\in\{-1,+1\}$ is binary, independent, and equiprobable data, $s_k(t)$ is the signature sequence which is assumed to have unit energy, τ_k is relative time offset, all for the kth user, T is the symbol period, $n(t)$ is AWGN with unit power spectral density, σ^2 is the additive noise variance, and $2J+1$ is the number of data symbols per user per frame.

It is well known that an asynchronous system with independent users can be analyzed as synchronous if equivalent synchronous users are introduced, which are effectively additional interferers [16]. Sufficient statistics are obtained by sampling at $2f_0$, where f_0 is the maximum bandwidth of the chip waveforms in the desired user signature sequence [12], [16]. In this paper we consider the received signal $r(t)$ over only one symbol period that is synchronous to the desired user $(k=1)$. The discrete representation for the received signal in (1) can be written in vector form as

$$\mathbf{r}=\sum_{k=1}^{L}A_kb_k\mathbf{s}_k+\sigma\mathbf{n} \tag{2}$$

where the number of the interferers $(L-1=2(K-1))$ is doubled due to equivalent synchronous user analysis. $\mathbf{r}$, $\mathbf{s}_k$, and $\mathbf{n}$ are vectors in $\Re^M$, where M is the number of chips per bit.

For the sake of completeness, the well-known MMSE optimization criterion is briefly repeated here (proven to be equivalent to the MOE criterion [12]). For a vector $\mathbf{d}\in\Re^M$, the mean square error is $\mathrm{MSE}=E\left[\left(\mathbf{r}^\top\mathbf{d}-b_1\right)^2\right]$. The linear MMSE detector $\mathbf{c}$ is obtained as

$$\mathbf{c}=\arg\min_{\mathbf{d}}\left(E\left[\left(\mathbf{r}^\top\mathbf{d}-b_1\right)^2\right]-\beta\left(\mathbf{s}_1^\top\mathbf{d}-1\right)\right). \tag{3}$$

The solution of (3) is given as (for user 1) $\mathbf{c}=\mathbf{R}_r^{-1}\mathbf{s}_1$, where $\mathbf{R}_r=E\left[\mathbf{r}\,\mathbf{r}^\top\right]$ is the covariance matrix of the input process $\mathbf{r}$ [13]. The matrix $\mathbf{R}_r$ has to be invertible. If an estimate of the covariance matrix $\mathbf{R}_r$ i.e., sample covariance matrix $\hat{\mathbf{R}}_r$, is available, approximation of the optimal MMSE detector is

$$\hat{\mathbf{c}}=\hat{\mathbf{R}}_r^{-1}\mathbf{s_1} \tag{4}$$

which is denoted as a blind linear MMSE (BMMSE) receiver. In this paper, the above receiver is used as one of the references for performance evaluations. Different implementations of the blind linear MMSE detector are presented in the literature. One of the solutions that circumvent the inversion of the covariance matrix $\hat{\mathbf{R}}_r$ is presented in [23]. We will also refer to the solution in [23] in the numerical results section. The readers should note that in this paper we do not analyze and compare different receivers and their implementations that rely on using adaptive (i.e., stochastic gradient) algorithms. We focus only on closed-form solutions in order to avoid issues that arise from the adaptive stochastic gradient algorithm and, consequently, to make clear comparisons between basic forms of different receivers.

III. MME Optimization Criterion

Let us define, for an M-dimensional vector $\mathbf{u}$, the mean energy (ME) as

$$\mathrm{ME}(\mathbf{u})=E\left[\left(\mathbf{r}^\top\mathbf{u}\right)^2\right]. \tag{5}$$

Let us further constrain the vector $\mathbf{u}$ such that $\mathbf{u}^\top\mathbf{u}=1$. A necessary condition for a vector $\mathbf{v}\in\Re^M$ to maximize the $\mathrm{ME}(\mathbf{v})$ (5) is

$$\mathbf{R}_r\mathbf{v}=\gamma\mathbf{v}. \tag{6}$$

It is obvious from (6) that $\mathbf{v}$ and γ are an eigenvector and an eigenvalue of the matrix $\mathbf{R}_r$, respectively. In general, there is a set of eigenvectors and eigenvalues, which are related as $\mathbf{R}_r\mathbf{V}=\mathbf{VD}$, where $\mathbf{V}$ is a matrix whose columns are the eigenvectors $(\mathbf{v}_1,\ldots,\mathbf{v}_M)$, and $\mathbf{D}$ is diagonal matrix of the corresponding eigenvalues $(\lambda_1,\ldots,\lambda_M)$.

In order to set a basis for further discussion, we repeat the following well-known results from linear algebra.

Proposition 1: The eigenvector of $\mathbf{R}_r$ that corresponds to the maximum eigenvalue $(\lambda_{\max})$ is the vector that maximizes the ME (mean energy) in (5).

Let us denote the eigenvector from Proposition 1 as $\mathbf{v}_{\max}$ (the maximizer of ME).

Proposition 2: Furthermore, if the contribution of $\mathbf{v}_{\max}$ is removed from the matrix $\mathbf{R_r}$, as follows: $\mathbf{R}_r'=\mathbf{R}_r-\lambda_{\max}\mathbf{v}_{\max}\mathbf{v}_{\max}^\top$, then the eigenvector $\mathbf{v}_{\max}'$

that corresponds to the maximum eigenvalue of $\mathbf{R}_r'$ is the same as the eigenvector that corresponds to the second largest eigenvalue of $\mathbf{R}_r$. In addition, the matrix $\mathbf{R}_r'$ is covariance matrix of the vector $\mathbf{r}' = \mathbf{r} - \left(\mathbf{r}^\top \mathbf{v}_{\max}\right) \mathbf{v}_{\max}$.

Proposition 2 is a consequence of the spectral theorem [24]. The results in Propositions 1 and 2 form the basis for the blind interference cancellation scheme presented in this paper. We now sketch an outline of how the above two results can be exploited to derive a blind successive interference cancellation scheme. Note that the contribution of the desired user can be removed from the covariance matrix $\mathbf{R}_r$ as follows:

$$\mathbf{R}_i = \mathbf{R}_r - A_1^2 \mathbf{s}_1 \mathbf{s}_1^\top \tag{7}$$

where $\mathbf{R}_i = E\left[\mathbf{i}\mathbf{i}^\top\right]$ is the interference covariance matrix, with $\mathbf{i} = \sum_{k=2}^{L} A_k b_k \mathbf{s}_k + \sigma \mathbf{n}$. Observe that in the above procedure no knowledge is required of the desired user's bit decision (information). Only the knowledge of the desired signal power A_1^2 is needed. Further, if the MME criterion is now applied to $\mathbf{R}_i$ (i.e., we determine the eigenvector corresponding to the maximum eigenvalue of $\mathbf{R}_i$), then we can capture the most dominant interference (energy) component. The above process can be successively repeated and would result (due to Proposition 2) in the successive cancellation of components in the interference subspace, starting from the strongest to the weakest.

IV. An Application of the MME Criterion in the Blind IC Receiver

We now present a blind successive interference cancellation scheme where we incorporate the MME criterion and realize the blind interference cancellation-maximum mean energy (BIC-MME) receiver. As depicted in Figs. 1 and 2, the receiver executes the following steps (blocks in Fig. 1).

1) Estimation of the matrix $\mathbf{R}_r$ according to

$$\hat{\mathbf{R}}_r(i) = \frac{1}{n} \sum_{k=i-n+1}^{i} \mathbf{r}(k)\mathbf{r}^\top(k) \tag{8}$$

where $\hat{\mathbf{R}}_r$ is the sample covariance matrix, n is the size of the averaging window (number of samples), and i is time index (will be omitted in the following text).[1]

2) Remove the desired user contribution from $\hat{\mathbf{R}}_r$. If the desired user amplitude (A_1) is known or estimated, we can apply (7). The result of this step is that $\hat{\mathbf{R}}_i$ contains only the interference components and there is no desired user contribution $\left(A_1^2 \mathbf{s}_1 \mathbf{s}_1^\top\right)$.

Note that the amplitude A_1 may not be known at the receiver. Therefore, in our simulation results (in Section V), we considered the amplitude estimate $\hat{A}_1$ using the outputs of the MF for user 1. Our results indicate that the performance is not sensitive to the errors in amplitude estimation.

3) Find the maximizer $(\hat{\mathbf{v}}_{\max})$ of the ME, i.e., the vector that takes, on average, most of the interference energy. According to Proposition 1, the maximizer is the eigenvector

[1]Notation: $\hat{z}$ denotes an estimate of z.

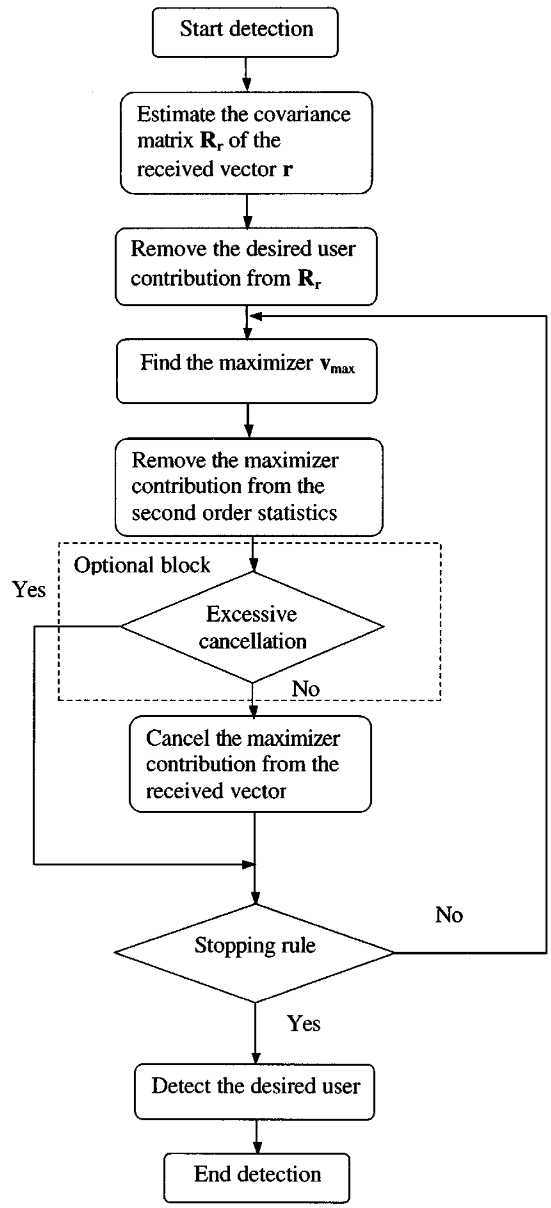


Fig. 1. Flow chart illustrating the BIC-MME scheme.

that corresponds to the maximum eigenvalue $\left(\hat{\lambda}_{\max}\right)$ of the matrix $\hat{\mathbf{R}}_i$.

To find the maximizer, it is not necessary to perform the eigendecomposition in full. An iterative solution can be applied. As an example, we use the power method (PM) [24] to derive an iterative solution for the MME criterion. Starting with an initial guess $\hat{\mathbf{v}}_{\max}^0$ which contains some component of $\hat{\mathbf{v}}_{\max}$

$$\hat{\mathbf{v}}_{\max}^{i+1} = \frac{\hat{\mathbf{R}}_i \hat{\mathbf{v}}_{\max}^i}{\left|\hat{\mathbf{R}}_i \hat{\mathbf{v}}_{\max}^i\right|} \tag{9}$$

where i is iteration step. While other advanced iterative and subspace tracking algorithms are well known [25], [26], this topic is not further analyzed in this paper. In the case of the simulations in Section V, the power method is

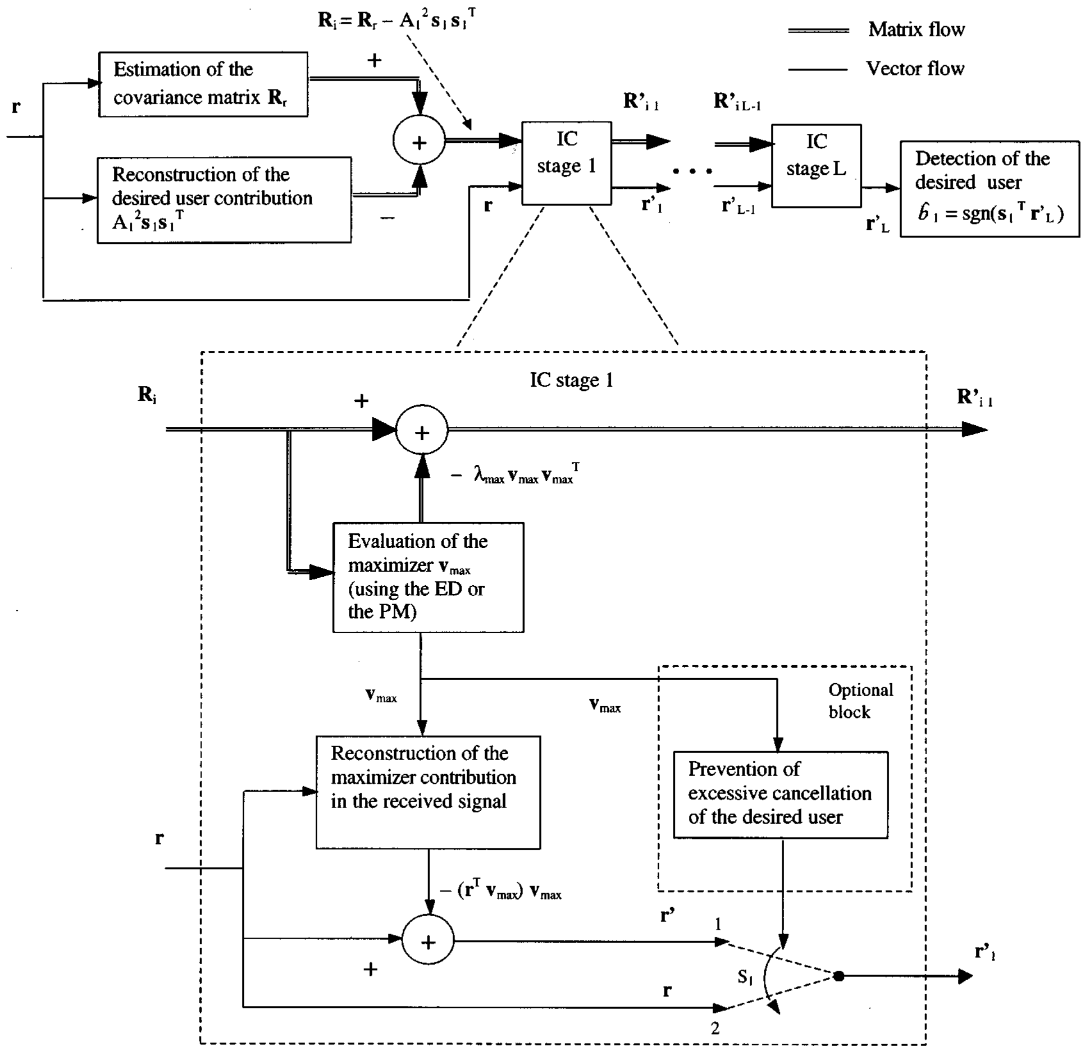


Fig. 2. Block scheme of the BIC-MME receiver.

observed to perform well. In Section V, as a stopping rule we have used

$$\left(\hat{\mathbf{v}}_{\max}^{i+1}\right)^{\top} \hat{\mathbf{v}}_{\max}^{i} \geq T_{\mathrm{PM}} \tag{10}$$

where T_{PM} is some threshold value.

4) Remove the maximizer contribution from the matrix $\hat{\mathbf{R}}_i$ to yield

$$\hat{\mathbf{R}}_i' = \hat{\mathbf{R}}_i - \hat{\lambda}_{\max}\hat{\mathbf{v}}_{\max}\hat{\mathbf{v}}_{\max}^{\top}. \tag{11}$$

According to Proposition 2, this step prepares the estimate of the second-order statistics $(\hat{\mathbf{R}}_i')$ for evaluation of the maximizer in the next IC stage.

5) To prevent excessive cancellation of the desired user from the input vector $\mathbf{r}$, we introduce an optional block. This block is useful in the case when the cross correlation between the desired user signature sequence and the interferer signature sequences is very high. For example, a simple threshold criterion could be applied to determine if cancellation is viable. If

$$\left|\left(\mathbf{s}_1^{\top}\hat{\mathbf{v}}_{\max}\right)\right| > T_C \tag{12}$$

where T_C is some threshold value, then step 6) below is skipped, i.e., the IC is not performed (in Fig. 2, the switch S_1 is in the position 2). If this block is not applied, the switch S_1 is always in the position 1.

6) Cancel the maximizer contribution as

$$\mathbf{r}' = \mathbf{r} - \left(\mathbf{r}^{\top}\hat{\mathbf{v}}_{\max}\right)\hat{\mathbf{v}}_{\max}. \tag{13}$$

7) A variety of stopping rules can be defined for the whole procedure. If all significant components of the interference (defined by a specific rule) are cancelled, the detection $\hat{b}_1 = \mathrm{sgn}\left(\mathbf{s}_1^{\top}\mathbf{r}'\right)$ is performed, otherwise steps 3)–7) are repeated, where, for the new IC stage, $\mathbf{r}$ and $\mathbf{R}_i$ take the values of $\mathbf{r}'$ and $\mathbf{R}_i'$, respectively. For example, the last IC stage can be the one where the measured (estimated) signal-to-interference ratio (SIR) is maximum or above a target value. This particular method is used in the case of the numerical results that are presented in Section V. Furthermore, this step can be used to control the tradeoff between performance and complexity of the receiver.

While the linear blind MMSE receiver implementation in [23] is very attractive in that it requires no matrix inversion, it still implicitly requires not only the estimates of the eigenvectors but also the eigenvalues, which is a general property of all blind MMSE receivers. We will show in Section V that the BIC-MME receiver is more robust to estimation errors of the covariance matrix because it does not require eigenvalues but only their relative ordering for the purpose of determining the cancellation order. In Section VI, we will also show that the estimation errors of eigenvectors have a specific structure which makes the BIC-MME receiver particularly robust.

V. Simulation Results

We consider a synchronous AWGN DS-CDMA system, using randomly generated signature sequences with processing gain $M = 64$. The users are independent and three cases are analyzed:

1) System with $L = 16$ users, and equal-energy interferers: $A_i^2/A_1^2 = 25,\ i = 2, \ldots, 16$.
2) Lightly loaded system with $L = 4$ users, and very strong equal-energy interferers: $A_i^2/A_1^2 = 400,\ i = 2, \ldots, 4$. This scenario may correspond to the situation on the downlink where intracell interference is negligible (due to orthogonality of transmission) and few dominant intercell interferers may be present. This could also reflect a situation where the desired user is in a deep fade.
3) System with $L = 16$ users; three strong equal-energy interferers: $A_i^2/A_1^2 = 25,\ i = 2, \ldots, 4$, and twelve interferers with the same energy as the desired user: $A_i^2/A_1^2 = 1,\ i = 5, \ldots, 16$. This scenario may correspond to a system with different transmission powers that accommodate different quality of service (QoS).

Performance of the conventional matched filter (MF), centralized nonlinear SIC receiver [4], [5], centralized linear MMSE receiver [16], blind linear MMSE receiver (BMMSE) (detector in (4) [13]), and the single-user lower bound (SULB) are used as benchmarks for evaluation of the BIC-MME receiver. The centralized linear MMSE and SIC receiver assume the perfect knowledge of all amplitudes, signature sequences, and the variance of the AWGN. The SIC applies power ordering, and two different flavors of the receiver are presented: the first applies matched filtering (denoted as SIC-MF, see [4], [18]) and the second applies the MMSE detector (denoted as SIC-MMSE, see [5]) in detection of the interferers, which are nonlinearly reconstructed and cancelled. The BMMSE and the BIC-MME receiver use the same sample covariance matrix $\hat{\mathbf{R}}_r$. The matrix is estimated according to (8) and we show results for different sample size n used for the covariance matrix estimate. Note that the centralized linear MMSE receiver is equivalent to the BMMSE receiver that uses an infinite number of samples for estimating the covariance matrix $(n = \inf)$. We have used implementations from both [13] and [23] to realize the BMMSE receiver. Their performance is identical but [23] is attractive in that it circumvents matrix inversion. The BIC-MME receiver performs the eigendecomposition, while the iterative solution (using the power method) is denoted as the BIC-MME-PM receiver (where PM stands for power method). Unless stated otherwise, we assume that the amplitude of the desired user is known exactly.

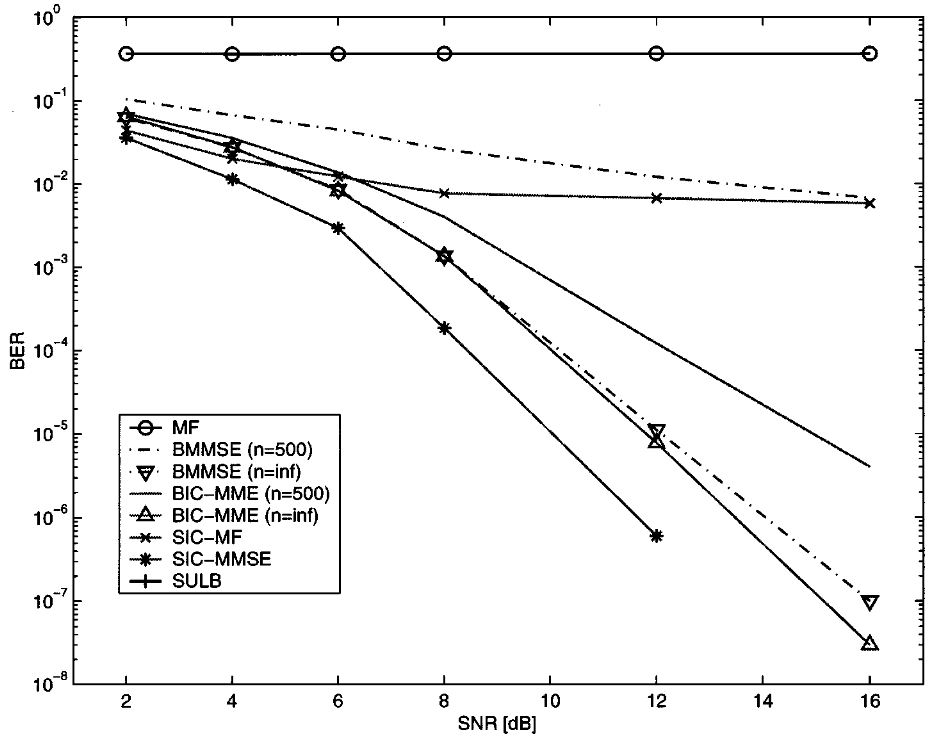
For case 1, Fig. 3(a) depicts the bit error rate (BER) as a function of the SNR (with respect to the desired user). The results are obtained after a total of 15 IC stages, which is where the estimated SINR reaches maximum. For the same case, the BER versus the number of IC stages is presented in Fig. 3(b) for an SNR$= 12$ dB. In this particular example, after stage 15, the performance deteriorates. This is due to an excessive cancellation of the desired user in stages 16 and 17. This occurs because the interference energy is already cancelled in the first 15 stages in this example. Note that, for this example, 15 is the number of independent dimensions in the interference subspace. Our stopping rule (maximum estimated SINR) recognized stage 15 as the last stage, while the results for stages 16 and 17 are used just to illustrate the effects of excessive cancellation. Note that the SIC-MF receiver fails to follow the performance of other receivers in the higher SNR region. This is due to error propagation in detection of the interferers that are sequentially cancelled. The reader should note that case 1 represents a scenario that is not favorable to the centralized SIC receiver [4] and hence its poor performance. This problem is not present in the case of the SIC-MMSE (overlaps with SULB) and the BIC-MME receiver.

Equivalent results, for case 2, with a total of 3 IC stages and SNR$= 8$ dB are shown in Fig. 4(a) and (b), respectively. Note that the performance of the BIC-MME is near optimum in case 2. In this lightly loaded system, even in the presence of very strong interferers, a small number of IC stages (three stages) is sufficient to fully cancel the interference with a negligible negative effect on the desired user (just a small fraction of the desired user energy is removed by the IC). In addition, in this particular example, the linear blind MMSE (BMMSE $(n = 500)$) receiver does not perform well because it is dominated by the estimation errors of the covariance matrix.

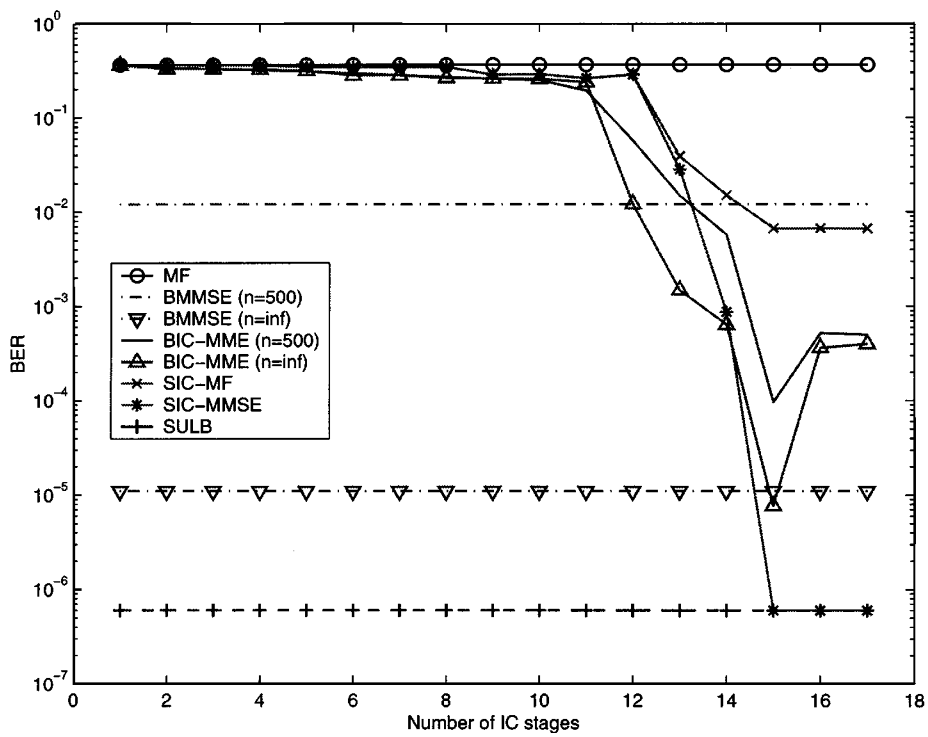
In Fig. 5, we present the performance of the various receivers as a function of the disparity between the desired user and interferers. For a system with 16 users, the BER is shown as a function of the ratio of the interferer power to the desired user power. The SNR for the desired user is set to 12 dB. The results suggest that the BIC-MME receiver is near–far resistant.

We now study the effect of accuracy of the covariance matrix estimation on the performance of the BIC-MME receiver. Fig. 6(a) and (b) correspond to case 1 (for SNR$= 12$ dB) and the case 2 (for SNR$= 8$ dB), respectively. The above figures depict BER with respect to different window size n. According to the results above, the BIC-MME receiver outperforms the BMMSE receiver. The gain introduced by the BIC-MME receiver, with respect to the BMMSE receiver, increases as the averaging window gets smaller.

Considering the iterative solution (BIC-MME-PM, where PM stands for te power method), Fig. 6 shows that the power method successfully replaces the eigendecomposition (the difference in performance between the two schemes is negligible). For the above example, the threshold in (10) is $T_{\rm PM} = 0.999$. Regarding the convergence of the power method, we have observed that the number of iterations, before the criterion in (10) is met, has never exceeded 25, and most of the vectors (maximizers) required less than 10 iterations. Furthermore, in our results, no effort has been made to improve the initial guess $\hat{\mathbf{v}}_{\max}^0$. It is selected randomly. Therefore, the convergence could be further accelerated if $\hat{\mathbf{v}}_{\max}^0$ is improved (see [24]).



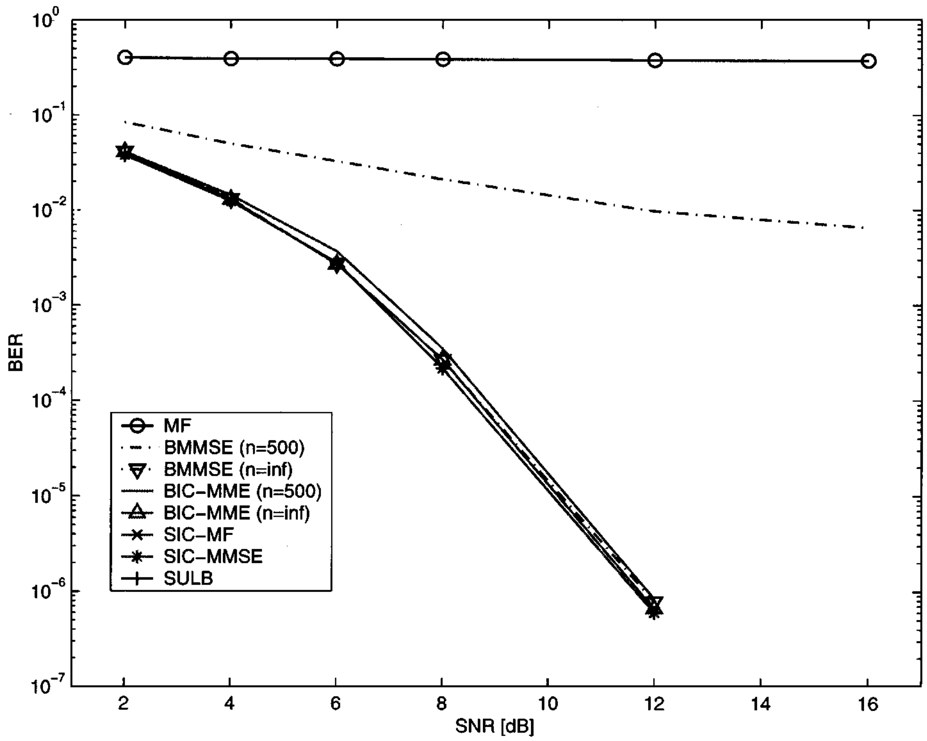
(a)



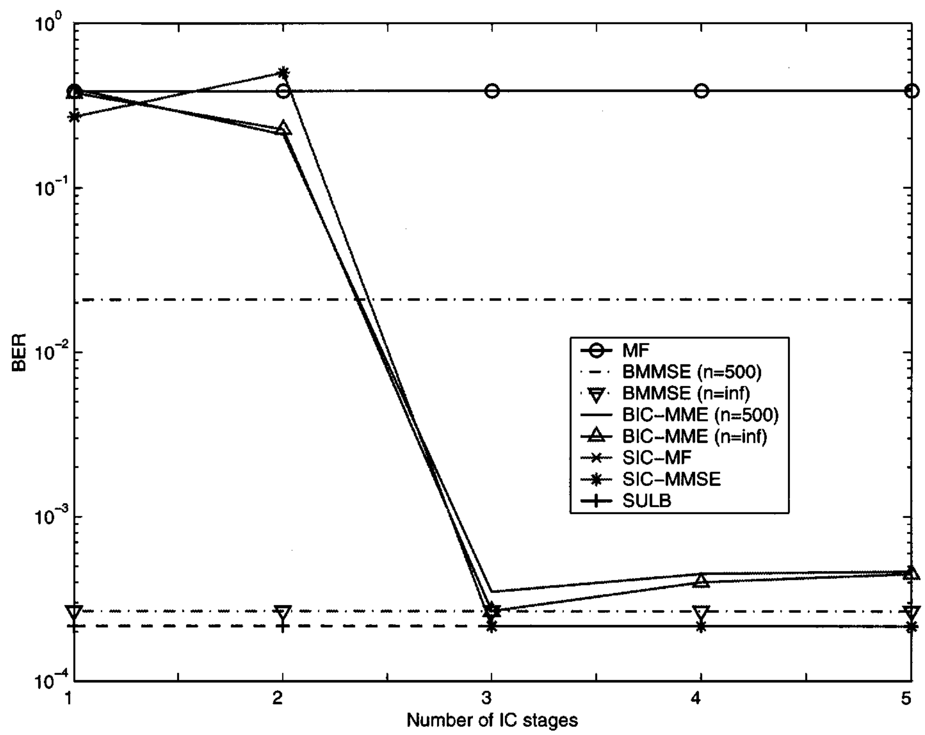
(b)

Fig. 3. (a) BER versus SNR, case 1, $M = 64$ spreading, $L = 16$ users, $A_i^2/A_1^2 = 25,\ i = 2, \ldots, 16$. (b) BER versus number of IC stages, case 1, $M = 64$ spreading, $L = 16$ users, $A_i^2/A_1^2 = 25,\ i = 2, \ldots, 16, \mathrm{SNR} = 12$ dB.

We consider the performance of our receiver in case 3. Fig. 7 depicts the BER with respect to the number of IC stages, SNR$=$ 8 dB and $n = 500$. The same figure presents the performance of the match filter (MF-12) for the system without the strong interferers (only the desired user and the twelve equal-energy interferers, with perfect power control with respect to the desired user). The performance of the MF-12 corresponds to the case of perfect cancellation of the strong interferers. Note, that after three IC stages, the BIC-MME receiver completely cancels the strong users (it reaches the MF-12 performance). For this particular case, the maximum estimated SINR is reached after 15 IC stages; but, for the sake of lower complexity of the receiver



(a)



(b)

Fig. 4. (a) BER versus SNR, case 2, $M = 64$ spreading, $L = 4$ users, $A_i^2/A_1^2 = 400,\ i = 2, \ldots, 4$. (b) BER versus number of IC stages, case 2, $M = 64$ spreading, $L = 4$ users, $A_i^2/A_1^2 = 400,\ i = 2, \ldots, 4$, SNR= 8 dB.

(i.e., smaller number of IC sages), interference cancellation can be stopped in some earlier IC stage at the expense of lower performance (higher BER). Furthermore, the performance of the iterative solution (BIC-MME-PM) seems to follow that of the BIC-MME receiver. This suggests that the low-complexity iterative solution cancels the strongest interferers completely and brings the system into the well-studied perfectly power controlled state. This scheme may be applied for the interference cancellation of strong users in a system with different transmission powers that accommodate different QoS, or in a system with very few strong interferers, as may be the case for the downlink where intracell user transmissions are orthogonal.

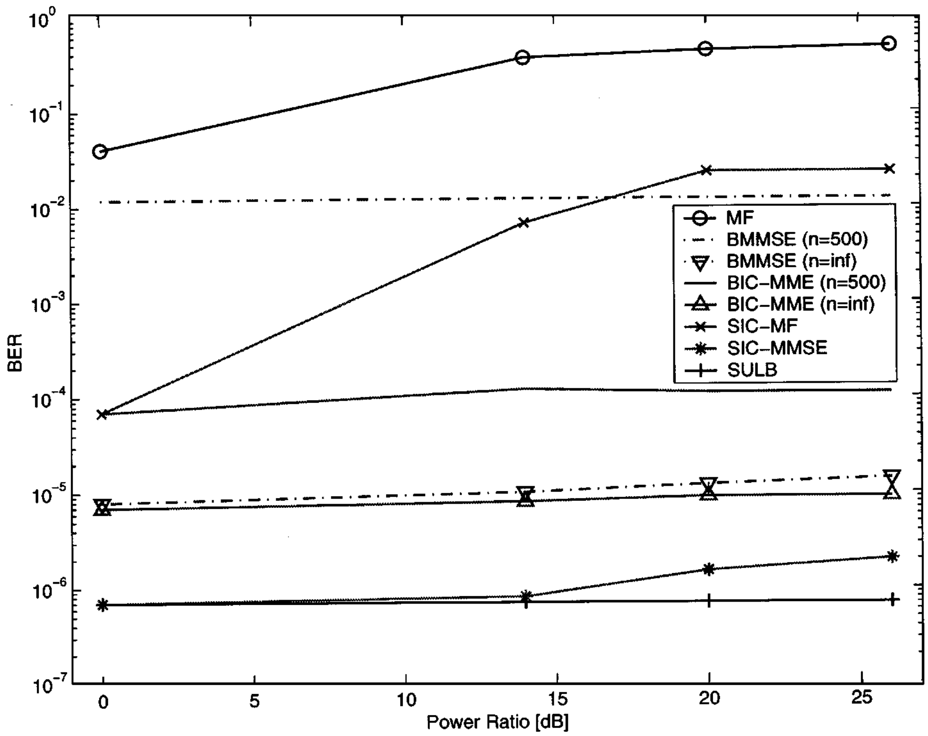


Fig. 5. BER versus power ratio: $10\log(A_i^2/A_1^2)$, $i=2,\ldots,16$, $M=64$ spreading, $L=16$ users, SNR$=12$ dB.

We also study the performance of the receiver if an estimate of the desired user amplitude is used instead of the perfectly known amplitude. We have tested the performance of the scheme that applies a simple estimation of the amplitude as $\hat{A}_1 = 1/n\sum_{i=1}^{n}\left|\mathbf{r}^T(i)\mathbf{s}_1\right|$. The results, for case 3, are presented in Fig. 7, as the BIC-MME-AE receiver (where AE stands for amplitude estimation). In this and many other examples explored, we have not observed much difference in the performance with respect to the solution for the case when the amplitude is known exactly.

In summary, based on the above results, we may conclude that the BIC-MME receiver successfully follows and in some cases exceeds the performance of various centralized receivers (unlike the BIC-MME receiver, we have assumed that the centralized receivers possess the knowledge of all system parameters). In all cases, it is shown that the BIC-MME receiver exceeds the performance of the well-known linear blind MMSE detector.

VI. Interpretation of the BIC-MME Performance

We now present an interpretation of why the BIC-MME receiver performs well in the case of iterative implementation using the power method and in the presence of estimation errors of the covariance matrix. Let us first emphasize the following properties of the BIC-MME scheme.

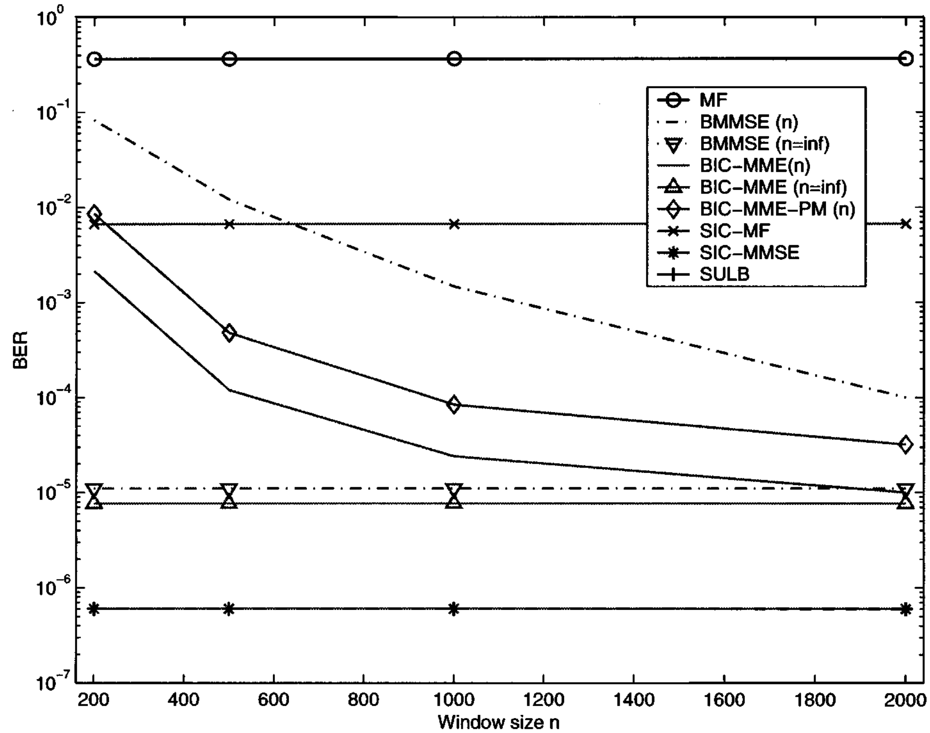
Property 1: For the matrix $\mathbf{R_i}$, assume that there is a set $\mathbf{S}$ of eigenvectors $\mathbf{v}_i \in \mathbf{S}$ that correspond to dominant eigenvalues with small absolute difference between them, i.e., the interference has almost the same energy in all directions of the subspace spanned by the true eigenvectors from $\mathbf{S}$. The BIC-MME scheme tends to cancel the whole subspace, rather than to cancel just a specific eigenvector in $\mathbf{S}$. Therefore, there is no need for the vectors to be estimated with a high degree of accuracy. It is sufficient that the estimated vectors $(\hat{\mathbf{v}}_i)$ are orthogonal and fall well into the subspace spanned by the true eigenvectors $(\mathbf{v}_i \in \mathbf{S})$ (i.e., $\hat{\mathbf{v}}_i$ has most of its energy confined to the subspace formed by the true eigenvectors from $\mathbf{S}$.)

The following property is the consequence of Proposition 2.

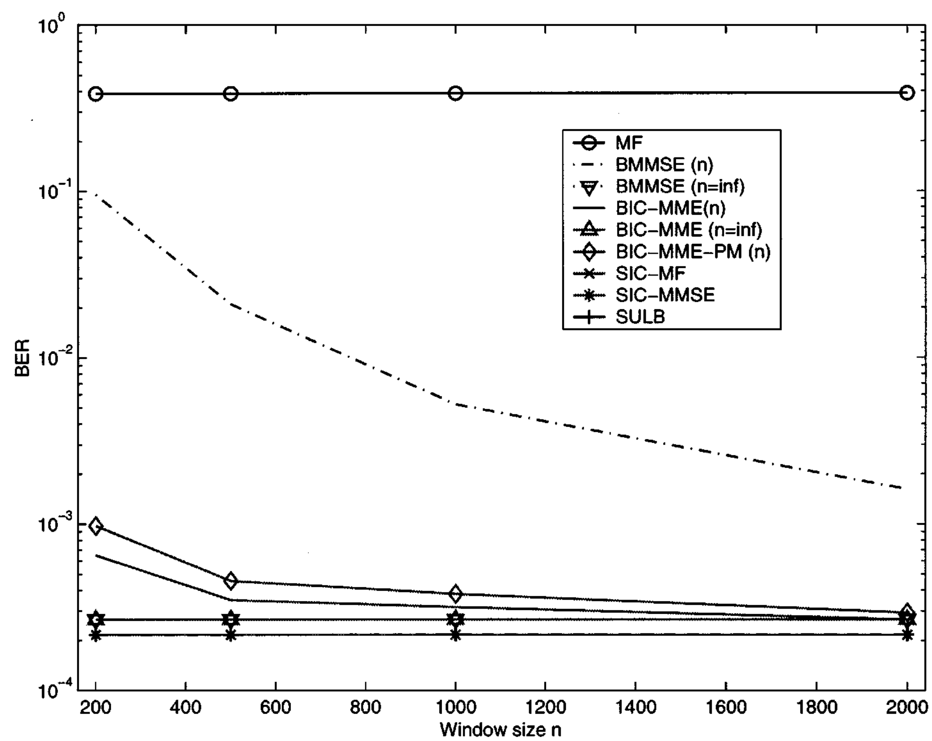
Property 2: Assuming that the BIC-MME scheme executes a total of Q IC stages, the total contribution of Q eigenvectors of the matrix $\mathbf{R_i}$ is cancelled from the input vector $\mathbf{r}$. The order in which the vectors are processed (i.e., their contribution is cancelled) does not affect the performance of the scheme (assuming perfect estimation of the vectors).

A. Iterative Implementation Using the Power Method

We now discuss the performance of the BIC-MME scheme that uses the power method iterative implementation. An attractive feature of such an implementation is that it avoids the need for a full-scale eigendecomposition of the covariance matrix at every IC stage (see step 3 in Section IV). The power method exhibits very good convergence properties if the absolute difference between dominant eigenvalues are significant [24]. If $\mathbf{v}_{\max}$ is one of the vectors that are described in Property 1 $(\mathbf{v}_{\max} \in \mathbf{S})$, $\hat{\mathbf{v}}_{\max}^i$ [see (9)] converges very quickly with respect to the vectors that are out of the set, i.e., the estimate lies in the subspace spanned by the set $\mathbf{S}$ after a very small number of iterations. However, once inside the subspace, the convergence is significantly slowed down. According to Property 1, this drawback should not affect the performance of the BIC-MME scheme significantly. This is the reason why the BIC-MME receiver with the iterative power method works well even after a small number of iterations, which is also confirmed by the simulation results in Section V. Furthermore, Property 2 shows that the BIC-MME scheme with the iterative power method solution works well



(a)



(b)

Fig. 6. (a) BER versus window size n, case 1, $M = 64$ spreading, $L = 16$ users, $A_i^2/A_1^2 = 25,\ i = 2, \ldots, 16$, SNR= 12 dB. (b) BER versus window size n, case 2, $M = 64$ spreading, $L = 4$ users, $A_i^2/A_1^2 = 400,\ i = 2, \ldots, 4$, SNR= 8 dB.

even when the descending order for evaluated eigenvalues is not guaranteed. In other words, if there are a few strong interference vectors in the interference subspace, then the order in which the interference vectors (maximizers) are cancelled does not affect the performance. These are favorable characteristics for low-complexity iterative solutions.

B. Estimation of Eigenvectors

We now analyze properties of the eigenvector estimates of the sample covariance matrix in (8). This analysis is used to explain why the BIC-MME scheme performs well in the presence of eigenvector estimation errors that result when the sample co-

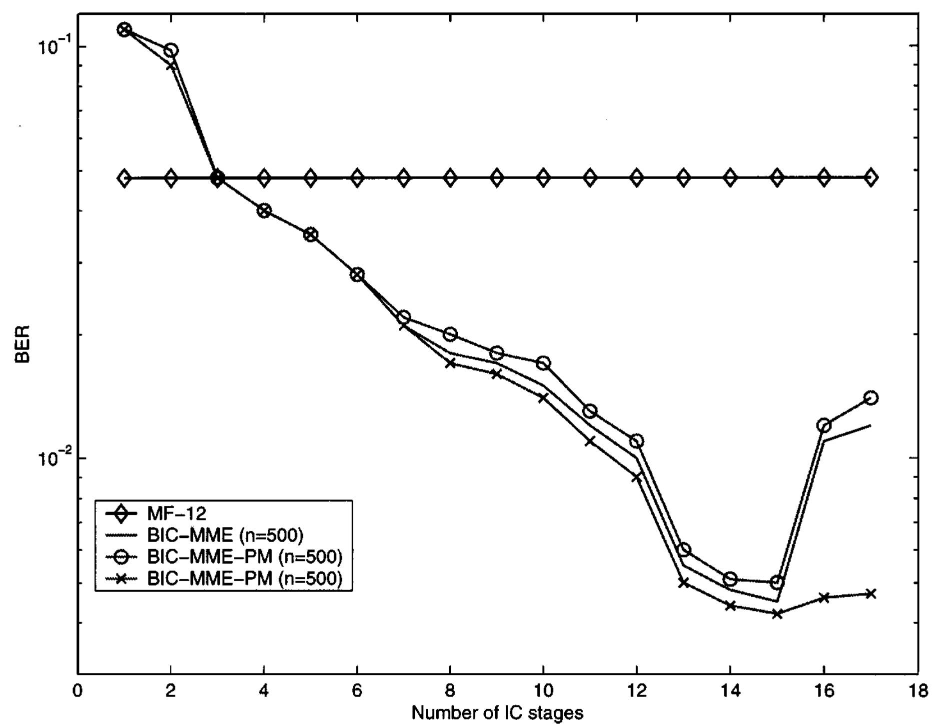


Fig. 7. BER versus number of IC stages, case 3, $M = 64$ spreading, $L = 16$ users, $A_i^2/A_1^2 = 25,\ i = 2, \ldots, 4$, $A_j^2/A_1^2 = 1,\ j = 5, \ldots, 16$, SNR= 8 dB.

variance matrix is estimated using small sample sizes. In the following, we will assume that the sample covariance matrix is that of observation vectors that are multivariate Gaussian. Even though this assumption is not true in the presence of MAI, we will justify the following analysis through a numerical validation. Let the subspace spanned by the eigenvectors that correspond to distinct and significant eigenvalues $(\lambda_1, \ldots, \lambda_P)$ be denoted as the signal subspace. The dimension of the signal subspace is P. The noise subspace is spanned by the eigenvectors that correspond to repeated eigenvalues $(\lambda = \lambda_{P+1}, \ldots, \lambda_M)$ with multiplicity $M - P$[13], [27]. To analyze estimation of the eigenvectors, let us observe the cross correlation (projection) $\hat{\mathbf{v}}_i^\top \mathbf{v}_j$ between the estimate of the ith eigenvector $(\hat{\mathbf{v}}_i,\ i = 1, \ldots, P)$ and the jth true eigenvector $(\mathbf{v}_j,\ j = 1, \ldots, M)$. These values, $\hat{\mathbf{v}}_i^\top \mathbf{v}_j$, can be used to characterize errors of the eigenvector estimates. When $i \neq j$, it can be shown that $\hat{\mathbf{v}}_i^\top \mathbf{v}_j$ is unbiased, i.e., $E\left[\hat{\mathbf{v}}_i^\top \mathbf{v}_j\right] = 0$. Further, the variance can be approximated as (see the Appendix)

$$E\left[\left(\hat{\mathbf{v}}_i^\top \mathbf{v}_j\right)^2\right] \approx \frac{1}{n} \frac{\lambda_i \lambda_j}{(\lambda_i - \lambda_j)^2}. \tag{14}$$

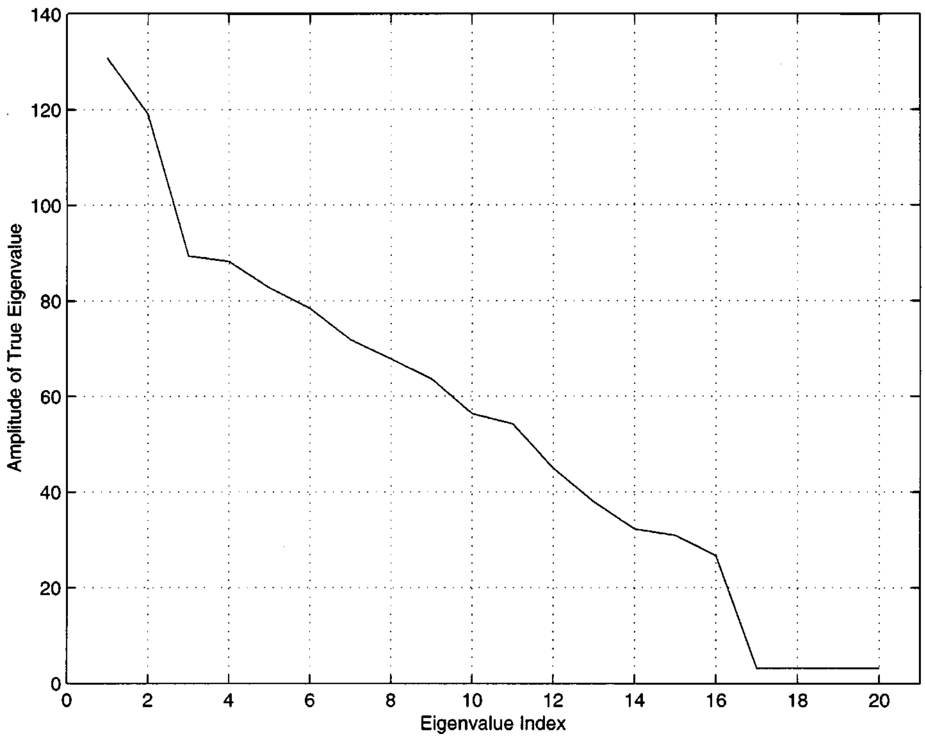
Note that the second-order moment $E\left[\left(\hat{\mathbf{v}}_i^\top \mathbf{v}_j\right)^2\right]$ is the mean energy of the eigenvector estimate $\hat{\mathbf{v}}_i$ in the direction of the true eigenvector $\mathbf{v}_j$. We have constrained the eigenvector estimates to be unit energy, i.e., $E\left[\left(\hat{\mathbf{v}}_i^\top \hat{\mathbf{v}}_i\right)^2\right] = 1$. From the above, an observation follows.

Observation 1: The estimate $\hat{\mathbf{v}}_i$ of the eigenvector $\mathbf{v}_i$ tends to be clustered (i.e., $\hat{\mathbf{v}}_i$ has most of its energy) within the subspace spanned by the true eigenvector $\mathbf{v}_i$ and eigenvectors that correspond to eigenvalues that are very close to λ_i. Inspection of (14) reveals that the above statement is true even when the number of samples is small.

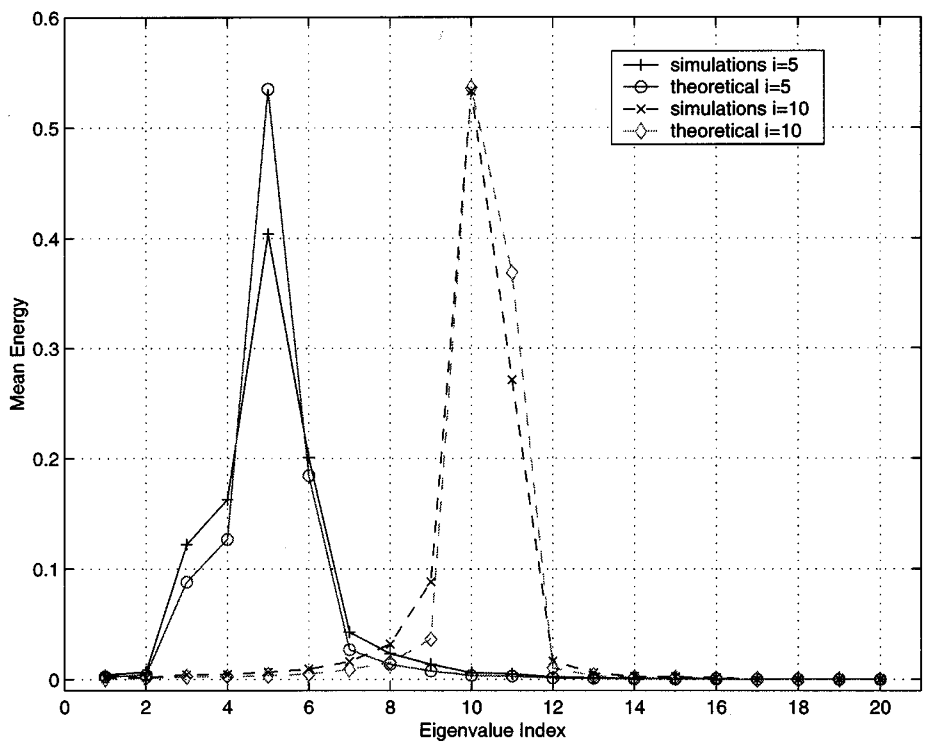
To justify Observation 1 (that is based on analysis using Gaussian statistics), and to validate its claims for a DS-CDMA system with MAI, the following simulation example is presented.

Example 1: We consider a synchronous AWGN DS-CDMA system, using randomly generated signature sequences with $L = 16$ users and processing gain $M = 64$. The signature sequences have happened to be linearly independent in this example; therefore, the dimension of the signal subspace is $P = 16$. The users are independent and have the same SNR= 10 dB. The sample covariance matrix is evaluated according to (8). The eigendecomposition is performed for 1000 different sample covariance matrices, and the results are averaged. Because of the identical behavior of the values which correspond to the repeated eigenvalues $(\lambda_i,\ i = 17, \ldots, 64)$, the results for $\lambda_i,\ i = 21, \ldots, 64$ are omitted from the following figures.

In Fig. 8(a), a true eigenvalue profile $(\lambda_i,\ i = 1, \ldots, 20)$ is presented where the eigenvalues are sorted in descending order. In Fig. 8(b), we present analytical [see (14)] and simulation results for $E\left[\left(\hat{\mathbf{v}}_i^\top \mathbf{v}_j\right)^2\right]$ for $i, j = 1, \ldots, M$ (which is the normalized mean energy of the eigenvector estimate $\hat{\mathbf{v}}_i$ in the direction of the true eigenvector $\mathbf{v}_j$). Specifically, we have shown the results for $i = 5$ and $i = 10$, but the results appear to be similar for all $i = 1, \ldots, P$. The abscissa represents the index j arranged in descending order of the eigenvalues. The sample size is $n = 1000$. From the figure, the theoretical results closely resemble the simulations. This confirms the applicability of the above theoretical analysis (based on Gaussian statistics) for the case of DS-CDMA systems. In addition, in



(a)

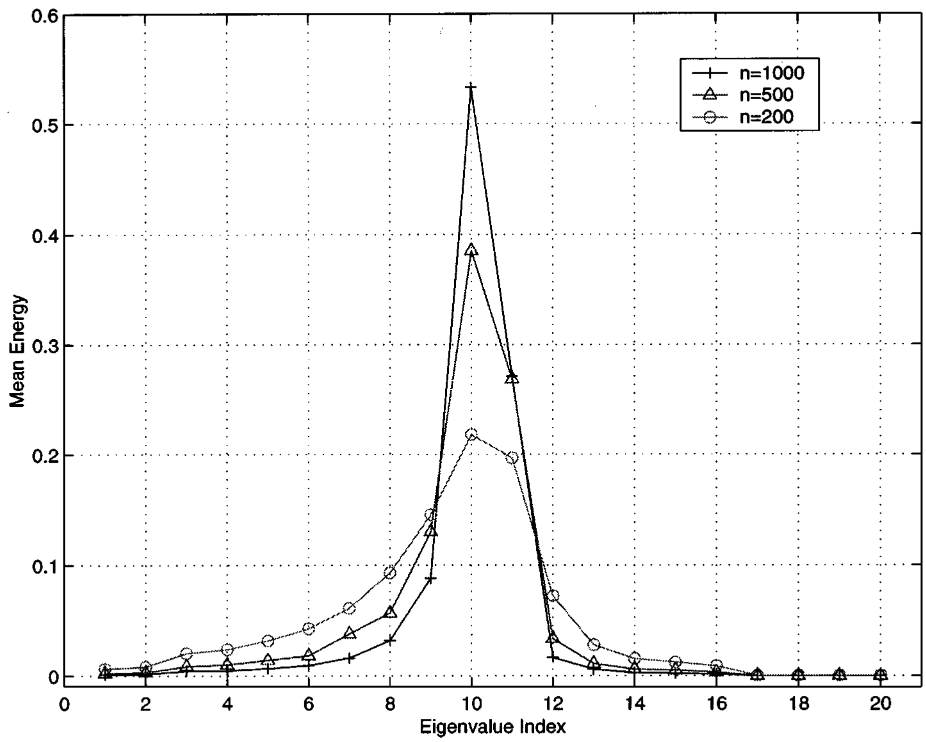


(b)

Fig. 8. (a) Eigenvalue profile, $M = 64$ spreading, $L = 16$ users, $\mathrm{SNR} = 10$ dB, $n = 1000$. (b) The mean energy $E\left[(\hat{\mathbf{v}}_i^\top \mathbf{v}_j)^2\right]$: simulations and theoretical results for $i = 5, 10, n = 1000$.

Fig. 8(c), we show the simulation results results for $i = 10$, with different sample size values $(n = 200, 500, 1000)$ used for estimating the sample covariance matrix. Both Fig. 8(b) and (c) reveal that most of the energy of the eigenvector estimate $\hat{\mathbf{v}}_i$ is confined within the space spanned by the true eigenvector $\mathbf{v}_i$ and eigenvectors that correspond to the closest (neighboring) eigenvalues to λ_i even for different sample size n. These results support Observation 1. □

Now, let us discuss how the estimation errors of the eigenvectors affect performance of the BIC-MME scheme. According to Property 1, there is no need for the eigenvectors from the set $\mathbf{S}$ to be estimated exactly. Rather, it is sufficient that the eigenvector



(c)

Fig. 8.*(Continued.)* (c) The mean energy $E\left[(\hat{\mathbf{v}}_i^\top \mathbf{v}_j)^2\right]$ depending on the sample size n (simulations), $i = 10$, $n = 200,\ 500,\ 1000$.

estimates $(\hat{\mathbf{v}}_i)$ are orthogonal and well confined within the subspace spanned by the true eigenvectors $(\mathbf{v}_i \in \mathbf{S})$. Under these conditions, the BIC-MME scheme will successfully cancel the whole subspace spanned by $\mathbf{S}$. Recall that the set $\mathbf{S}$ corresponds to the span of the eigenvectors that have eigenvalues that are very close in amplitude. By Observation 1, even in the case of small sample size n used for the estimation of the sample covariance matrix, the estimates $\{\hat{\mathbf{v}}_i | \mathbf{v}_i \in \mathbf{S}\}$ are clustered within the subspace $\mathbf{S}$. Consequently, the BIC-MME receiver will perform well when small sample sizes are used for the estimation of the covariance matrix. For example, in Fig. 8(c), it is seen that the estimate $\hat{\mathbf{v}}_i$ for $i = 10$, has most of its energy confined to the subspace formed by $\mathbf{v}_j$, $j = 8,\ 9,\ 10,\ 11,\ 12$. This is true for all values of n shown, i.e., $n = 200,\ 500,\ 1000$.

Unlike the BIC-MME receiver, the BMMSE receiver, in addition to the eigenvector estimates, also requires the eigenvalue estimates [13], [23]. This results in the performance of the BMMSE receiver being more sensitive to the sample size n. Using the analysis in the Appendix and the results in [28], it can be shown that the BMMSE receiver requires a greater number of samples for the estimation of the covariance matrix than the BIC-MME receiver to achieve the same performance [see simulation results in Fig. 6(a) and (b)]. Further investigation of this issue is beyond the scope of this paper.

VII. Discussion and Conclusion

We have introduced the MME optimization criterion which is then used to implement a blind IC receiver. The ability of the receiver to exceed the performance of the blind MMSE receiver is confirmed via simulation results. It is seen that this scheme is particularly effective for a system with fewer, very strong interferers and smaller number of samples used for the estimation of the covariance matrix. This may be a very viable solution for implementation on the downlink where transmissions are usually synchronized within a cell such that intracell users are orthogonal and intercell interference may be dominant. However, in the presence of multipath, these assumptions do not necessarily hold, but the receiver is still effective since it does not use knowledge of interference parameters. Regarding the use of sample covariance estimates, we have presented an explanation of why the BIC-MME receiver performs well in the presence of estimation errors. A low-complexity iterative solution using the power method for eigendecomposition is also studied. The properties of the receiver make it an attractive solution for implementation in time-varying channels as well as packet DS-CDMA systems with bursty traffic. This is an area of further investigation.

Appendix

In this appendix, we present analysis that leads to the approximation in (14). Consider the M-dimensional covariance matrix $\mathbf{R} = E\left[\mathbf{r}\mathbf{r}^\top\right]$ of the random vector $\mathbf{r}$. Let λ_i and $\mathbf{v}_i$, $i = 1, \ldots, M$, be the true eigenvalues and eigenvectors, respectively. Let $\mathbf{V}$ denote a matrix whose columns are the true eigenvectors, sorted in descending order of the corresponding true eigenvalues. The sample covariance matrix is defined as

$$\hat{\mathbf{R}}(i) = \frac{1}{n} \sum_{k=i-n+1}^{i} \mathbf{r}(k)\mathbf{r}^\top(k) \qquad (15)$$

where i and k are time indices (and will be omitted in the following) and $\hat{\lambda}_i$ and $\hat{\mathbf{v}}_i$, $i = 1, \ldots, M$, are the eigenvalue and eigenvector estimates, respectively. Let us perform a similarity transformation as

$$\mathbf{A} = \mathbf{V}^{-1}\hat{\mathbf{R}}\mathbf{V} = \mathbf{V}^{\top}\hat{\mathbf{R}}\mathbf{V}. \tag{16}$$

In the case of perfect estimate $\left(\hat{\mathbf{R}} = \mathbf{R}\right)$, the matrix $\mathbf{A}$ is diagonal, with eigenvalues λ_i, $i = 1, \ldots, M$, on the diagonal. But, in general

$$\mathbf{A} = \begin{bmatrix} \lambda_1 + a_{11} & a_{12} & \cdots & a_{1M} \\ a_{21} & \lambda_2 + a_{22} & \cdots & a_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ a_{M1} & a_{M2} & \cdots & \lambda_M + a_{MM} \end{bmatrix} \tag{17}$$

where a_{ij}, $(i, j = 1, \ldots, M)$ is the deviation of the sample value. The matrix $\mathbf{A}$ is symmetric $(a_{ij} = a_{ji})$ and for the off-diagonal elements $(i \neq j)$

$$a_{ij} = \frac{1}{n} \sum_{k=i-n+1}^{i} x_i(k) x_j(k) \tag{18}$$

and for the diagonal elements

$$a_{ii} = \frac{1}{n} \sum_{k=i-n+1}^{i} x_i(k) x_i(k) - \lambda_i \tag{19}$$

where $x_i(k) = \mathbf{r}^{\top}(k)\mathbf{v}_i$ and $x_j(k) = \mathbf{r}^{\top}(k)\mathbf{v}_j$, where k is time index. We assume that $x_i(k)$ $(i = 1, \ldots, M)$ are observations from a zero-mean normal distribution, and $E[x_i(k)^2 x_i(l)^2] = E[x_i(k)^2] E[x_i(l)^2]$ for $k \neq l$. Under the above assumptions, it can be shown that

$$E\left[a_{ij}^2\right] = \frac{\lambda_i \lambda_j}{n}. \tag{20}$$

Further [28],

$$O(a_{ij}) = O\left(\sqrt{E[a_{ij}^2]}\right) = \frac{1}{\sqrt{n}} \equiv O(\delta) \tag{21}$$

where we have used $O(\delta)$ to represent $O(a_{ij})$. In order to evaluate the eigenvector estimates, let us introduce a similarity transformation which suppresses the off-diagonal elements of $\mathbf{A}$. Let us denote this new matrix (with off-diagonal elements suppressed) as $\mathbf{B}$. Originally, the idea was presented in [28] and applied in order to analyze the eigenvalue estimates, but here we extend the approach to study characteristics of eigenvector estimates. Specifically, the transformation is

$$\mathbf{B} = \mathbf{C}\mathbf{A}\mathbf{C}^{-1} \tag{22}$$

where the diagonal elements of $\mathbf{B}$ will further approach the eigenvalue estimates (i.e., the eigenvalues of $\hat{\mathbf{R}}$). In general, a similarity transformation leaves the eigenvalues unaltered [24]. In the following, we construct the matrix $\mathbf{C}$ that yields the necessary transformation in (22). Let us assume that

$$\mathbf{C} = \mathbf{I} + \mathbf{Y} \tag{23}$$

where the entries of $\mathbf{Y}$ are defined as follows:

$$\mathbf{Y} = \begin{bmatrix} 0 & y_{12} & \cdots & y_{1M} \\ y_{21} & 0 & \cdots & y_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ y_{M1} & y_{M2} & \cdots & 0 \end{bmatrix}. \tag{24}$$

To simplify the derivations, we may assume that

$$\mathbf{Y}^{\top} = -\mathbf{Y} \Rightarrow y_{ij} = -y_{ji}, \ (i, j = 1, \ldots, M). \tag{25}$$

Further, let us assume that

$$O(y_{ij}) \leq O(\delta) \ (i, j = 1, \ldots, M). \tag{26}$$

Any element b_{ij} of the matrix $\mathbf{B}$ is

$$\begin{aligned} b_{ij} = \sum_{l=1}^{M} \Bigg\{ &\left[\lambda_l c_{il} + \sum_{k=1}^{M} c_{ik} a_{kl}\right] \\ &\times \Bigg[c_{jl} - \sum_{k=1, k\neq l, k\neq j}^{M} c_{lk} c_{jk} \\ &+ \sum_{m=1, m\neq l}^{M} c_{lm} \sum_{k=1, k\neq l, k\neq j}^{M} c_{lk} c_{jk} + \cdots \Bigg]\Bigg\} \end{aligned} \tag{27}$$

where $c_{ii} = 1$ and $c_{ij} = y_{ij} \Rightarrow c_{ij} = -c_{ji}$. Under the assumptions in (23)–(26), all off-diagonal elements b_{ij} $(i \neq j)$ can be further simplified as

$$b_{ij} = \lambda_j c_{ij} + \lambda_i c_{ji} + a_{ji} + O(\delta^2). \tag{28}$$

Now, in the case of $\lambda_i \neq \lambda_j$, we can suppress the off-diagonal elements b_{ij} in (28) as follows. Choose

$$y_{ij} = \frac{a_{ij}}{\lambda_i - \lambda_j}. \tag{29}$$

This implies $O(b_{ij}) = O(\delta^2)$. Note that, to satisfy the assumption in (26), it follows from (29) that we require

$$O(a_{ij}) < O(|\lambda_i - \lambda_j|) \tag{30}$$

or, in other words, we require that the sampling errors a_{ij} (which are of order $1/\sqrt{n}$) be smaller than the distances $|\lambda_i - \lambda_j|$ between the corresponding eigenvalues. In the case of $\lambda_i = \lambda_j$ (as would happen in noise subspace), we set

$$y_{ij} = 0. \tag{31}$$

This results in $O(b_{ij}) = O(\delta)$, which implies that the off-diagonal elements in $\mathbf{A}$ that correspond to the noise subspace are left unaltered by the transformation in (22).

Having the off-diagonal elements suppressed, the diagonal elements of the matrix $\mathbf{B}$ approach the eigenvalue estimate, i.e., eigenvalues of $\hat{\mathbf{R}}$. We now study the eigenvector estimates. Note that

$$\mathbf{C}^{-1} = (\mathbf{I} + \mathbf{Y})^{-1} = (\mathbf{I} - \mathbf{Y} + \mathbf{Y}^2 - \mathbf{Y}^3 \ldots). \tag{32}$$

Let us approximate

$$\mathbf{C}^{-1} \approx (\mathbf{I} - \mathbf{Y}) \Rightarrow \mathbf{C}^{-1} = \mathbf{C}^{\top}. \tag{33}$$

This approximation is justified by (26) and (32). Then the transformations in (16) and (22) can be written as

$$\mathbf{B} = \mathbf{C}\mathbf{V}^{\top}\hat{\mathbf{R}}\mathbf{V}\mathbf{C}^{\top}. \tag{34}$$

Based on the above, the matrix $\mathbf{B}$ can be approximated as a diagonal matrix. From (33), the matrix $\mathbf{VC}^{\top}$ is orthogonal. Therefore, according to the spectral theorem [24], the columns of the matrix $\mathbf{VC}^{\top}$ in (34) are approximately the eigenvectors of the sample covariance matrix $\hat{\mathbf{R}}$. Thus

$$\tilde{\mathbf{V}} \approx \left(\mathbf{V}\mathbf{C}^{\top}\right) \Rightarrow \mathbf{C}^{\top} \approx \left(\mathbf{V}^{\top}\tilde{\mathbf{V}}\right) \tag{35}$$

where $\tilde{\mathbf{V}}$ is the matrix whose columns are the eigenvectors $(\hat{\mathbf{v}}_i,\ i = 1, \ldots, M)$ of $\hat{\mathbf{R}}$. To characterize the estimation errors of the eigenvector estimates we observe crosscorrelations (projections) $\hat{\mathbf{v}}_i^{\top}\mathbf{v}_j,\ i \neq j,\ (i, j = 1, \ldots, M)$. Now, we study the first and second moments of the above projections. From (35), it follows that

$$c_{ij} \approx \left(\hat{\mathbf{v}}_i^{\top}\mathbf{v}_j\right). \tag{36}$$

For $i \neq j$ and $\lambda_i \neq \lambda_j$

$$E\left[\left(\hat{\mathbf{v}}_i^{\top}\mathbf{v}_j\right)\right] \approx E[c_{ij}] = 0 \tag{37}$$

and

$$E\left[\left(\hat{\mathbf{v}}_i^{\top}\mathbf{v}_j\right)^2\right] \approx E[c_{ij}^2] = \frac{1}{n}\frac{\lambda_i\lambda_j}{(\lambda_i - \lambda_j)^2} \tag{38}$$

which is the required result in (14).

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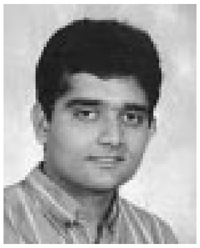
Dragan Samardzija received the B.S. degree in electrical engineering and computer science from the University of Novi Sad, Yugoslavia, in 1996 and the M.S. degree in electrical engineering from Rutgers University, New Brunswick, NJ. in 2000. He is currently working toward the Ph.D. degree at the Wireless Information Network Laboratory (WINLAB), Rutgers University, Piscataway, NJ.

He currently works at te Wireless Research Laboratory, Bell Labs, Lucent Technologies, where he is also involved in research in the field of MIMO wireless systems. His research interests include detection, estimation and information theory for MIMO wireless systems, interference cancellation, and multiuser detection for multiple-access systems. He also works on implementation aspects of various receiver architectures and implementation platforms.



Narayan Mandayam (S'90–M'95–SM'00) received the B.Tech (Hons.) degree from the Indian Institute of Technology, Kharagpur, India, in 1989 and the M.S. and Ph.D. degrees from Rice University, Houston, TX, in 1991 and 1994, respectively, all in electrical engineering.

Since 1994, he has been at the Wireless Information Network Laboratory (WINLAB), Rutgers University, Piscatway, NJ, where he is currently an Associate Professor in the Department of Electrical & Computer Engineering and also serves as Associate Director at WINLAB. He also served as the interim Director of WINLAB from January to July 2001. His research interests are in various aspects of wireless data transmission including software defined radios for interference cancellation, wireless system modeling and performance, multiaccess protocols and radio resource management with emphasis on pricing.

Dr. Mandayam is a recipient of the Institute Silver Medal from the Indian Institute of Technology, Kharagpur in 1989 and the National Science Foundation CAREER Award in 1998. He was selected by the National Academy of engineering in 1999 for the Annual Symposium on Frontiers of Engineering. He serves as an Associate Editor for IEEE COMMUNICATIONS LETTERS.

Ivan Seskar (S'86–M'86) received the B.S. degree in electrical engineering and computer science from the University of Novi Sad, Yugoslavia, and the M.S. degree in electrical engineering from Rutgers University, New Brunswick, NJ.

Since 1991 he has been at the Wireless Information Networks Laboratory (WINLAB) at Rutgers, Piscataway, NJ, where he is currently Associate Director of Information Technology. His research interests include software and reconfigurable radios, spread spectrum systems, multiuser detection, mobility management, and traffic simulations.