Blind Multiuser Receiver Design in ISI Channels

Shu Wang
LG Electronics Mobile Research
San Diego, CA 92131-1807
Email: swang@lge.com

James Caffery, Jr.
University of Cincinnati
Cincinnati, OH 45221-0030
Email: jcaffery@ececs.uc.edu

***Abstract*— In this paper, we present an alternative multiuser signal model and discuss its applications for blind multiuser receiver design. We compare the model with the conventional and signal subspace-based signal models as well as their applications in receiver design. The geometric interpretation, bit-error rate, signal processing bounds, etc., of these signal models and blind receivers are compared and discussed. From the analyses, the trade-offs between the complexity and performance of blind multiuser receiver design are presented. Computer simulations are finally provided to demonstrate the performance and theoretic analysis.**

I. Introduction

The multiuser signal model not only enables understanding of signal structures but also plays a key role in multiuser receiver design. Multiuser detection (MUD) is a proven strategy for mitigating multiple access interference (MAI) effects and limiting the near-far problem by exploiting interference signal structure. MUD has received considerable attention over the past several years since MAI is the dominant impairment for CDMA systems and even exists in the systems with perfect power control [1]. It is believed to be one of the critical techniques for enabling the high reliability and throughput of next-generation mobile communication systems [2]. Most recent research on MUD has been devoted to blind detection and subspace-based signature waveform or channel estimation to reduce computational complexity and prior knowledge requirements [3]–[9]. Blind multiuser receivers can achieve good performance given knowledge of only the desired user's timing and signature waveform. Such limited knowledge is much closer to practical applications than conventional methods since information about the interference (i.e., timing, signal structure, channel gains, etc.) is typically unknown beforehand. However, most existing blind receivers are known to be too complicated for high-data-rate applications.

In the development of advanced multiuser receivers, it is known that a proper received signal model aids the understanding of received signals as well as receiver design. There are two popular multiuser signal models which have been extensively discussed for multiuser receiver design. They are the conventional multiuser signal model and the subspace-based multiuser signal model. In the conventional signal model, each received signal is directly taken as a linear combination of actual signal signatures [1], [3], [6]. Most related blind multiuser receivers are developed either by explicitly estimating the signal signature [4] or by removing interfering signal components using adaptive filtering techniques, e.g., blind receiver design with Wiener [3] and Kalman filter [6] techniques. Though the conventional signal model provides a natural view of received signals, the involved signature waveforms and/or amplitude information are unknown and require considerable processing to obtain before detection. To compensate for the weakness of the conventional signal model, the subspace signal model was developed with subspace-based signal processing techniques [5]. In the subspace signal model, each received signal is taken as a linear combination of signal subspace bases, which can be obtained by subspace signal processing techniques on the autocorrelation matrix of the received signals. The subspace signal model can be considered a result of parametric signal modeling and provides an in-depth description of the received signals. Though the subspace-based approach does not require explicit estimation of each user's signature waveform and the adaptive speed is improved with good performance, the signal subspace formation procedure is not trivial.

While the conventional signal model provides a foundation for both optimal and conventional multiuser receiver design and the subspace signal model aids understanding of the underlying signal structure, neither is simple enough for developing blind multiuser receivers for high-speed CDMA systems [2]. In order to address the near-far problem with minimum prior knowledge and computational complexity, we propose a new blind multiuser model by directly using current and past received signal vectors with no explicit signal structure estimation. With this blind signal model and widely employed signal estimation criteria including least squares (LS), minimum mean-squared error (MMSE), etc., several novel blind multiuser receivers are developed. No statistical signal estimation or subspace separation procedure is required. Only a minimum number of previously received signals and the desired user's signature waveform and timing are required. Hence, the computational complexity and detection delay can be reduced. We then compare the proposed blind signal model and receivers with the conventional and subspace signal models and the blind receivers based on them. The trade-off between the performance and complexity in blind receiver development is discussed as well. Computer simulations are provided to illustrate performance.

II. Multiuser Signal Models

Forward-link transmission in a single-cell DS/CDMA system with K active users is considered. The channel is a multipath channel with P resolvable paths and corrupted by additive white Gaussian noise (AWGN). The baseband representation of the received signal due to user k is given by

$$r_k(t) = \sum_{p=1}^{P} \alpha_{pk} A_k[n] b_k[n] c_k(t - nT - \tau_p) + n_k(t) \tag{1}$$

where α_{pk} is the gain of the pth path of user k's signal and $b_k[n]$ is the nth bit sent by user k. We assume that the $\{b_k[n]\}$ are independent and identically distributed random variables with $E\{b_k[i]\} = 0$ and $E\left\{|b_k[i]|^2\right\} = 1$. The parameters $c_k(t)$ denote the normalized spreading signal waveform of user k during the interval $[0,\ T]$ and $A_k[n]$ is the signal amplitude for user k at time $t = nT$. Without loss of generality, the P transmission delays from the base station to user k are ordered such that $0 \le \tau_1 \le \tau_2 \le \ldots \le \tau_P$. The total baseband signal received for user k is

$$\tilde{r}(t) \quad = \quad \sum_{k=1}^{K} r_k(t) \ . \tag{2}$$

The received signal $\tilde{r}(t)$ is passed through the corresponding chip matched filter (CMF), $\phi(t)$, and RAKE combiner. The combined output $r(t)$ is[1]

$$\begin{aligned} r(t) \quad = \quad & A_k b_k c_k(t - nT - \tau_1) \otimes \phi(t - \tau_1) \\ & + m_{\mathrm{ISI}}(t) + m_{\mathrm{MAI}}(t) + n(t) \end{aligned} \tag{3}$$

where

$$m_{\mathrm{ISI}}(t) \quad = \quad \sum_{q \ne p}^{p,q=P} \beta_{qk} \alpha_{pk} A_k b_k c_k(t - nT + \tau_{q1} - \tau_1) \otimes \phi(t - \tau_1) \tag{4}$$

is the intersymbol interference (ISI) to user k,

$$\begin{aligned} m_{\mathrm{MAI}}(t) = & \sum_{i \ne k}^{K} A_i b_i c_i(t - nT - \tau_1) \otimes \phi(t - \tau_1) + \\ & \sum_{i \ne k}^{K} \sum_{q \ne p}^{p,q=P} \beta_{qk} \alpha_{pi} A_i b_i c_i(t - nT + \tau_{q1} - \tau_p) \otimes \phi(t - \tau_1) \end{aligned} \tag{5}$$

is the MAI to user k, β_{qk} is the weight of the qth RAKE finger with

$$\sum_{q=1}^{P} \beta_{qk} \alpha_{qk} \quad = \quad 1 \tag{6}$$

and $\tau_{q1} = \tau_q - \tau_1$ is the propagation delay difference between the first path and pth path and $n(t)$ is AWGN with variance σ^2. The symbol $\otimes$ denotes the convolutional product. Because of $m_{\mathrm{MAI}}(t)$ in the received signal, the performance of the conventional matched filter receiver suffers from the near-far problem [1].

A. Conventional Signal Model

After RAKE combining, user 1's output can be sampled at rate $f_s = 1/T_s$ and expressed in vector notation by[2]

$$\begin{aligned} \mathbf{r} \quad & = \quad [r(nT + T_s + \tau_1), \ldots, r(nT + LT_s + \tau_1)]^{\mathrm{T}} \\ & = \quad \sum_{k=1}^{K} A_k b_k \mathbf{s}_k + \mathbf{n} \\ & = \quad \mathbf{SAb} + \mathbf{n} \end{aligned} \tag{7}$$

where $\mathbf{S} = [\mathbf{s}_1\ \mathbf{s}_2\ \ldots\ \mathbf{s}_K]$ is the received spreading signature matrix containing inter-chip interference (ICI), ISI and MAI information, and $L = T/T_s$ is the number of samples per symbol, which should not be less than the spreading gain L_c. Most MUD schemes including optimum and conventional MUD are developed from (7), which is the conventional multiuser signal model. They are well documented in [1]. One of the major problems using (7) is that $\{\mathbf{s}_k,\ A_k : k \ne 1\}$ and possibly timing is unknown at the first user's receiver. This limits the multiuser receiver design possibilities unless estimation procedures are used to discover the interference information.

B. Subspace Signal Model

It is difficult to accurately estimate the parameters $\{\mathbf{s}_k : k \ne 1\}$ in (7) in order to directly apply the well-developed optimum or conventional multiuser detection schemes. Another approach is to use a subspace-based signal model and signal processing techniques to reconstruct the conventional detectors [5]. In the subspace

[1]Without loss of the generality, we drop the time index n in the following discussion.

[2]Without loss of the generality, we consider the first user as the desired user.

signal model, $\mathbf{r}$ is modeled by a combination of the signal subspace bases $\{\mathbf{u}_{sk} : 1 \leq k \leq K\}$ according to

$$\mathbf{r} = \mathbf{U}_s \boldsymbol{\phi} + \mathbf{n} \tag{8}$$

where $\mathbf{U}_s = [\mathbf{u}_{s1}\ \mathbf{u}_{s2}\ \ldots\ \mathbf{u}_{sK}]$, $\boldsymbol{\phi}$ is a vector defined by

$$\boldsymbol{\phi} \quad = \quad \mathbf{\Phi}\mathbf{A}\mathbf{b} \tag{9}$$

with $\mathbf{\Phi}$ being a $K \times K$ matrix. The original signal signature matrix $\mathbf{S}$ can now be expressed as

$$\mathbf{S} = \mathbf{U}_s \mathbf{\Phi} \ . \tag{10}$$

One of the major advantages of the subspace signal model (8) is that the signal subspace bases $\{\mathbf{u}_{sk} : 1 \leq k \leq K\}$ are much easier to estimate than the actual signal signature waveforms so that the blind receiver design can be simplified. These signal bases can be estimated by applying subspace decomposition on the autocorrelation matrix $\mathbf{R}$:

$$\begin{aligned} \mathbf{R} &= \mathrm{E}\{\mathbf{r}\mathbf{r}^{\mathrm{T}}\} \\ &= \begin{bmatrix} \mathbf{U}_s & \mathbf{U}_n \end{bmatrix} \begin{bmatrix} \mathbf{\Lambda}_s & \\ & \mathbf{\Lambda}_n \end{bmatrix} \begin{bmatrix} \mathbf{U}_s^{\mathrm{T}} \\ \mathbf{U}_n^{\mathrm{T}} \end{bmatrix} \end{aligned} \tag{11}$$

where $\mathbf{U}_n$ denotes the noise subspace bases.

C. The Proposed Blind Signal Model

As indicated above, one of the difficulties in using the conventional signal model or subspace signal model for blind receiver design is that the signal signatures $\{\mathbf{s}_k : k \neq 1\}$ in (7) or the signal subspace matrix $\mathbf{U}_s$ in (8) are unknown beforehand and must be estimated. Instead we propose a known blind signature matrix $\boldsymbol{\mathcal{S}}$

$$\begin{aligned} \boldsymbol{\mathcal{S}} &= \begin{bmatrix} \mathbf{s}_1 & \mathbf{r}_1 & \mathbf{r}_2 & \ldots & \mathbf{r}_{M-1} \end{bmatrix} \\ &= \mathbf{S}\mathbf{D} + \mathbf{N} \end{aligned} \tag{12}$$

where $\{\mathbf{r}_m : 1 \leq m \leq M-1\}$ are previously received and detected signal vectors and

$$\mathbf{D} = \begin{bmatrix} 1 & \bar{\mathbf{d}}^{\mathrm{T}} \\ \mathbf{0} & \tilde{\mathbf{D}} \end{bmatrix} = \begin{bmatrix} \mathbf{e} & \begin{matrix} \bar{\mathbf{d}}^{\mathrm{T}} \\ \tilde{\mathbf{D}} \end{matrix} \end{bmatrix} = \begin{bmatrix} & \mathbf{g}^{\mathrm{T}} & \\ \mathbf{0} & & \tilde{\mathbf{D}} \end{bmatrix} \tag{13}$$

is the $K \times M$ data matrix associated with $\boldsymbol{\mathcal{S}}$. Now the received signal can be expressed by

$$\mathbf{r} \quad = \quad \boldsymbol{\mathcal{S}}\mathbf{f} + \tilde{\mathbf{n}} \tag{14}$$

with the $M \times 1$ vector $\mathbf{f}$ defined by

$$\mathbf{f} = \mathbf{D}^{+}\mathbf{A}\mathbf{b} \tag{15}$$

and $\tilde{\mathbf{n}}$ is the new $L \times 1$ AWGN vector defined by

$$\tilde{\mathbf{n}} \quad = \quad \mathbf{n} - \mathbf{N}\mathbf{D}^{+}\mathbf{A}\mathbf{b} \ . \tag{16}$$

The vector $\mathbf{e} = [1 \quad \mathbf{0}]^{\mathrm{T}}$ is a vector of length K and $\mathbf{g} = [1 \quad \bar{\mathbf{d}}]^{\mathrm{T}}$ is a vector of length M.

Compared to the models in (7) and (8), the key component $\boldsymbol{\mathcal{S}}$ in (14) is known beforehand. This makes the new model ready for designing new blind multiuser receivers from the beginning without additional estimation procedures. After we estimate $\mathbf{f}$ with conventional signal estimation techniques, the detection of user 1's information can easily be accomplished by knowing $d_1 = A_1 b_1$, which can be estimated by

$$\hat{d}_1 \quad = \quad \mathbf{g}^{\mathrm{T}}\mathbf{f} \quad . \tag{17}$$

III. Blind Multiuser Receiver

In conventional blind multiuser receiver design, adaptive filtering techniques are employed for removing noise and interference. Statistical signal spectrum analysis techniques are used in subspace-based blind multiuser receiver design. With the proposed blind multiuser signal model (14), we use conventional multiuser detection techniques for blind receiver design.

A. Conventional Blind Multiuser Detection

With the conventional signal model in (7), there are two popular directions for designing blind multiuser receivers. One is to estimate the unknown $K-1$ signal signatures $\{\mathbf{s}_k : k \neq 1\}$ and then apply known optimal/conventional detectors on $\mathbf{r}$. This approach is known to be computationally intensive since the signal waveform estimation itself is not simple [4]. The other approach is to use adaptive filtering techniques with some signal processing criteria. With this approach, there are well-known minimum output energy (MOE) detectors, blind MMSE detectors and blind Kalman detectors [1], [3], [6]. However, these blind detectors are known to be slow in their adaptation.

B. Subspace-Based Blind Multiuser Detection

With the subspace signal mode in (8), the first step is usually to separate the signal and noise subspaces and estimate $\mathbf{U}_s$ using (11). Then, the least-squares-based decorrelating detector is given by [5]

$$\mathbf{d}_{\mathrm{DD}1} = \frac{\mathbf{s}_1^{\mathrm{T}}\mathbf{U}_s\left(\mathbf{\Lambda}_s - \sigma\mathbf{I}\right)^{-1}\mathbf{U}_s^{\mathrm{T}}\mathbf{r}}{\mathbf{s}_1^{\mathrm{T}}\mathbf{U}_s\left(\mathbf{\Lambda}_s - \sigma\mathbf{I}\right)^{-1}\mathbf{U}_s^{\mathrm{T}}\mathbf{s}_1} \tag{18}$$

and the MMSE detector can be expressed by

$$\mathbf{d}_{\mathrm{MMSE}1} = \frac{\mathbf{s}_1^{\mathrm{T}}\mathbf{U}_s\mathbf{\Lambda}_s^{-1}\mathbf{U}_s^{\mathrm{T}}\mathbf{r}}{\mathbf{s}_1^{\mathrm{T}}\mathbf{U}_s\mathbf{\Lambda}_s^{-1}\mathbf{U}_s^{\mathrm{T}}\mathbf{s}_1} \quad . \tag{19}$$

C. New Blind Multiuser Detection Approaches

The key component in the proposed blind receiver design framework is estimation of $\mathbf{f}$. Given $\mathbf{f}$, $\mathbf{d}_1$ can be estimated with (17).

Different signal estimation criteria will lead to different solutions. If the LS criterion is applied,the traditional LS estimate of $\mathbf{f}$ can be expressed by

$$\begin{aligned} \mathbf{f}_{\mathrm{LS}} &= \arg\min_{\mathbf{x}} \|\mathbf{r} - \boldsymbol{\mathcal{S}}\mathbf{x}\|_2 \\ &= \boldsymbol{\mathcal{S}}^{+}\mathbf{r} \end{aligned} \tag{20}$$

with the assumption that $\boldsymbol{\mathcal{S}}$ is error-free. Obviously this assumption may not be accurate, since only the first column of $\boldsymbol{\mathcal{S}}$ is known to be error-free. With different assumptions of $\boldsymbol{\mathcal{S}}$, there are other possible LS solutions, e.g., total least-squares estimation and mixed least-squares estimation [7], [9].

If the minimum variance unbiased (MVU) criterion is applied, $\mathbf{f}$ can be estimated by

$$\mathbf{f}_{\mathrm{MVU}} = \left(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{R}_{\tilde{\mathbf{n}}}^{-1}\boldsymbol{\mathcal{S}}\right)^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{R}_{\tilde{\mathbf{n}}}^{-1}\mathbf{r} \qquad (21)$$

where $\mathbf{R}_{\tilde{\mathbf{n}}} = \mathrm{E}\left\{\tilde{\mathbf{n}}\tilde{\mathbf{n}}^{\mathrm{T}}\right\}$ denotes the autocorrelation matrix of $\tilde{\mathbf{n}}$.

If the MMSE criteria is applied, $\mathbf{f}$ can be estimated by

$$\begin{aligned}\mathbf{f}_{\mathrm{MMSE}} &= \arg\min_{\hat{\mathbf{f}}} \mathrm{E}\|\hat{\mathbf{f}}-\mathbf{f}\|_2^2 \\ &= \left(\mathbf{R}_{\mathbf{f}}^{-1}+\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{R}_{\tilde{\mathbf{n}}}^{-1}\boldsymbol{\mathcal{S}}\right)^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{R}_{\tilde{\mathbf{n}}}^{-1}\mathbf{r} \qquad (22)\end{aligned}$$

Note that the proposed blind MMSE detector additionally requires the estimation of channel noise power through $\mathbf{R}_{\tilde{\mathbf{n}}}$.

IV. Implementation Issues

A. Detection with Training Symbols

It is known that the the performance of conventional MMSE detectors can be enhanced using known training symbols. Periodic training symbols allows the receiver to estimate and track the time-varying channel and offer possible link recovery, although it reduces capacity. Typically without training, the receiver may converge slowly and become unstable when the channel changes rapidly. For subspace-based approaches, training symbols are usually unnecessary since they use second-order statistical information of the received symbols. However, the receiver may take advantage of known data carried by each training symbol for faster and more accurately channel tracking [10]. For the proposed blind multiuser detection approaches, training symbols can be helpful for constructing the blind spreading matrix $\boldsymbol{\mathcal{S}}$ and $\mathbf{g}$. With more accurate $\mathbf{g}$, the estimation of $\mathbf{d}_1$ with (17) can be improved.

B. Decision Feedback

In a decision-feedback-based multiuser receiver, previously detected information is fed back to help detect current symbols. If the feedback information is correct, detection of current symbols can be improved. Otherwise, error propagation issues arise [1], [2]. This problem can be serious for the proposed blind multiuser detectors without training. In addition to using training symbols, another possible approach for mitigating this problem is to combine channel coding and decoding with multiuser detection so that the feedback information will first pass through the channel decoder before being used for detecting the current symbols [2]. However, this approach can introduce additional delays.

V. Performance Analysis and Comparison

A. Comparison with Existing Blind Detectors

A comparison between the proposed framework and other major schemes is presented in Table 1. The proposed framework only requires M, where $L \geq M \geq (K-G)$, previous received signals for signal detection and its complexity is closed to conventional detectors, while other blind approaches typically require more than L signals [5], [6], [11].

B. Geometric Interpretation

It is known that the conventional decorrelating detector can be interpreted as an oblique projection of $\mathbf{s}_1$ onto the orthogonal complement of the signal subspace $\bar{\mathbb{S}}_1 = \mathrm{span}\{\mathbf{s}_k : k = 2,\ 3,\ \ldots,\ K\}$ along the orthogonal complement of $\mathbb{S}_1 = \mathrm{span}\{\mathbf{s}_1\}$ [12], while MMSE detection can be taken as a balance between the single-user matched filter and decorrelating detector. Given enough previously received symbols, the subspace-based decorrelating detectors have the same geometrical interpretation as the conventional decorrelating detectors.

Following the explanation of conventional decorrelating detection, the projection using $\boldsymbol{\mathcal{S}}$ can be interpreted as an oblique projection of $\mathbf{s}_1$ onto the orthogonal complement of the signal subspace $\tilde{\mathbb{S}}_1 = \mathrm{span}\{\mathbf{r}_m : k = 1,\ 2,\ \ldots,\ M-1\}$ along the orthogonal complement of $\mathbb{S}_1$, in the proposed blind LS receiver. Since $\tilde{\mathbb{S}}_1 \neq \bar{\mathbb{S}}_1$, there is some deviation between this projection and the previous one using $\bar{\mathbb{S}}_1$ and there is a difference between d_1 and the first element of $\mathbf{f}$. Fortunately, this difference can be compensated with (17).

C. Noise Enhancement

It is known that there is a noise enhancement issue in LS-based conventional decorrelating detection. With conventional decorrelating detection, the output signal-to-noise ratio (SNR) for user k is decreased by $[\mathbf{R}_{\mathbf{s}}^{+}]_{kk}^{-1}$, where $[\cdot]_{kk}$ denotes the kth diagonal element of the matrix. With the proposed blind LS multiuser receiver, there is another noise enhancement issue. Following Girko's law, provided that $\alpha = (K-1)/M$ is fixed, the diagonal element of $\frac{1}{M}\left(\mathbf{D}^{+}\mathbf{b}\right)\left(\mathbf{D}^{+}\mathbf{b}\right)^{\mathrm{T}}$ can be approximated to be $1-\alpha$ with $K,\ M \to \infty$ [13]. The autocorrelation matrix of $\tilde{\mathbf{n}}$ can then be expressed by

$$\mathbf{R}_{\tilde{\mathbf{n}}} = \frac{2M+K-1}{M}\sigma^2\mathbf{I} \qquad (23)$$

Table 1. The comparison of the proposed framework and other detection approaches

Parameters	Conv. MUD	Conv. IC	Blind MMSE	Subspace Approaches	Blind MUD
Signature of desired user(s)	✓	✓	✓	✓	✓
Signature of other users	✓	✓			
Timing of desired user(s)	✓	✓	✓	✓	✓
Timing of other users	✓	✓			
Received amplitudes	✓	✓			
ECC decoding-integratable	✓	✓			✓
Initialization *			$\geq L$	$\geq L$	M
Latency	1	$K-1$	1	1	1
Complexity order	1	K	1	1	1

* For blind MMSE or subspace approaches, they typically require much more than L signals before their first detection.

which shows that the noise variance is increased by $(2M+K-1)/M$. This noise enhancement is different than that found with conventional decorrelating detection.

D. Cramér-Rao Lower Bound

The Cramér-Rao lowerbound (CRLB) is given by the inverse of the Fisher information matrix (FIM). For the conventional signal model, CRLB of $\mathbf{d} = \mathbf{A}\mathbf{b}$ is given by

$$\mathrm{CRLB}(\mathbf{d}|\mathbf{S}) \quad = \quad \sigma^2 \left(\mathbf{S}^{\mathrm{T}}\mathbf{S}\right)^{-1} \ . \qquad (24)$$

For the blind signal model, if the blind spreading matrix $\boldsymbol{\mathcal{S}}$ is known beforehand, we first define the parameter vector $\boldsymbol{\psi} = \left[\tilde{\sigma}^2 \ \mathbf{f}^{\mathrm{T}}\right]^{\mathrm{T}}$, where $\tilde{\sigma}^2 = \left(1 + \frac{M-1}{M-K}\right)\sigma^2$, for computing the FIM

$$\mathbf{I}(\boldsymbol{\psi}) = \mathrm{E}\left\{\left(\frac{\partial \ln \mathcal{L}}{\partial \boldsymbol{\psi}}\right)\left(\frac{\partial \ln \mathcal{L}}{\partial \psi}\right)^{\mathrm{T}}\right\} \qquad (25)$$

where $\ln \mathcal{L}$ is the log-likelihood function given by

$$\ln \mathcal{L} = C - L \ln \tilde{\sigma}^2 - \frac{1}{2\tilde{\sigma}^2}\|\mathbf{e}\|_2^2 \ . \qquad (26)$$

where C is a constant and $\mathbf{e} = \mathbf{r} - \boldsymbol{\mathcal{S}}\mathbf{f}$. Provided $\boldsymbol{\mathcal{S}}$ is known, the closed-form CRLB expression of $\mathbf{f}$ is given by

$$\mathrm{CRLB}(\mathbf{f}|\boldsymbol{\mathcal{S}}) = \left(1 + \frac{M-1}{M-K}\right)\sigma^2(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}})^{+} \ . \qquad (27)$$

which is larger than the result in (24) and shows that accuracy of estimating $\mathbf{f}$ can be improved by increasing M.

E. Bit-Error Rate

With decorrelating detection and BPSK modulation, the bit-error rate (BER) for user k is

$$P_{ek,\mathrm{DD}} = Q\left(\frac{A_k}{\sigma\sqrt{\left[\mathbf{R}_{\mathbf{S}}^{+}\right]_{kk}}}\right) \ . \qquad (28)$$

Similarly, for the blind LS multiuser receiver, the detection BER can be written as

$$P_{e1,\mathrm{LS}} = Q\left(\frac{\sqrt{\frac{M}{2M+K-1}}}{\sqrt{\left[\left(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}}\right)^{+}\right]_{11}}}\frac{A_1^2}{\sigma}\right) \qquad (29)$$

which is larger than (28) due to the noise enhancement effect shown in (23).

F. Asymptotic Multiuser Efficiency

A commonly used performance measure for a multiuser detector is asymptotic multiuser efficiency (AME), which measures the exponential decay rate of the error probability as the background noise approaches zero, and near-far resistance, which is the infimum of AME [1]. The AME of the conventional decorrelating detection approach is

$$\eta_k = \left[\mathbf{R}_{\mathbf{S}}^{+}\right]_{kk}^{-1} \qquad (30)$$

and the AME of the proposed LS scheme is

$$\bar{\eta}_1 = \frac{M}{2M+K-1}\left[\mathbf{R}_{\boldsymbol{\mathcal{S}}}^{+}\right]_{11}^{-1} \qquad (31)$$

where $\mathbf{R}_{\boldsymbol{\mathcal{S}}} = \boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}}$. Because of the noise enhancement shown in (23), we see that there is a degradation by a factor $\frac{M}{2M+K-1}$ in the AME.

VI. Computer Simulations

A single-cell DS/CDMA synchronous multiuser system is simulated. The spreading sequences are random sequences with $L = 64$. In the simulations, previous amplitude estimates are used for the next detection. In Fig. 1, there are 16 users and $M = 32$. From the figure, where the interference is low, the performance of the blind MMSE detector has the best performance since it takes advantage of noise estimation. The LS detector and ML detector are the same and thus have the same performance. From Fig. 2, the blind MMSE, LS and ML detectors have similar performance when the interference is strong. In Fig. 3, there are two active users simulated

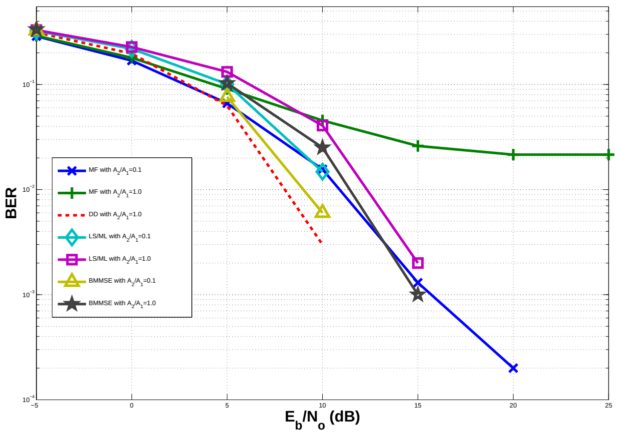

Fig. 1. The BER of various schemes with low interference against SNR with $L = 64$, $M = 32$ and $K = 16$.

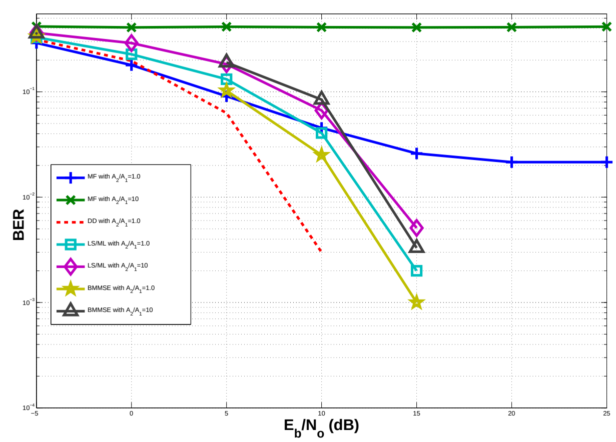

Fig. 2. The BER of various schemes with high interference against SNR with $L = 64$, $M = 32$ and $K = 16$.

with $M = 4$. The crosscorrelation between these two users is $\rho = 0.25$. We see that the performance of proposed schemes changes slightly as the near-far ratio changes. However, due to the noise enhancement we analyzed before and the fact that the conventional decorrelating detector has knowledge of all users' signature waveforms, the performance of the proposed detectors is not as good as the conventional decorrelating detector, which has the best near-far resistance.

VII. Conclusions

In this paper, we presented a novel approach for blind multiuser receiver design and compare it with the existing conventional receiver and subspace-based receiver designs in terms of geometric properties, asymptotic multiuser efficiency, near-far resistance, noise enhancement and the Cramér-Rao lower bound. The proposed model, which includes previous received signal vectors in the new signature matrix, requires no knowledge of other users' received signal information (either estimated or *a priori*) and compares reasonably well in terms of performance with the conventional decorrelating detector.

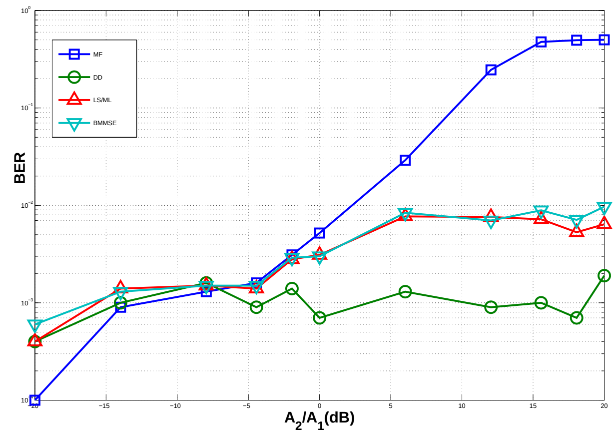

Fig. 3. The near-far resistance of various schemes. $\mathrm{SNR} = 10\mathrm{dB}$, $\rho = 0.25$, $M = 4$, $L = 64$ and $K = 2$.

References

[1] S. Verdu, *Multiuser Detection*. Cambridge University Press, 1998.

[2] J. G. Andrews, "Interference cancellation for cellular systems: A contemporary overview," *IEEE Wireless Communications*, pp. 19–29, April 2005.

[3] M. H. U. Madhow and S. Verdu, "Blind adaptive multiuser detection," *IEEE Trans. on Information Theory*, vol. 41, pp. 944–960, July 1995.

[4] M. Torlak and G. Xu, "Blind multiuser channel estimation in asynchronous cdma systems," *IEEE Trans. on Signal Processing*, vol. 45, pp. 137–147, January 1997.

[5] X. Wang and H. V. Poor, "Blind multiuser detection: A subspace approach," *IEEE Trans. on Information Theory*, vol. 44, pp. 677–691, March 1998.

[6] X. Zhang and W. Wei, "Blind adaptive multiuser detection based on kalman filtering," *IEEE Transactions on Signal Processing*, vol. 50, pp. 87–95, Jan. 2002.

[7] S. W. J. C. Jr. and H. Shen, "Semi-blind decorrelating detection for synchronous cdma," *IEEE Wireless Communications and Networking Conference (WCNC) 2003*, vol. 4, pp. 379–384, March 2003.

[8] S. W. et al., "Semi-blind adaptive multiuser detection for asynchronous cdma," in *2005 IEEE International Conference On Electro Information Technology (eit2005)*, (Lincoln, Nebraska), May 2005.

[9] S. W. et al., "Blind adaptive multiuser detection," *to be appeared in IEEE GlobeCom 2005*, November 2005.

[10] U. Madhow, "Blind adaptive interference suppression for direct-sequence cdma," *Proceedings of the IEEE*, vol. 86, pp. 2049–2069, October 1998.

[11] U. Madhow and M. Honig, "Mmse interference suppression for direct-sequence spread spectrum cdma," *IEEE Trans. on Communication*, vol. 42, pp. 3178–3188, December 1994.

[12] Y. C. Eldar, "On geometric properties of the decorrelator," *IEEE Communications Letters*, vol. 6, pp. 16–18, January 2002.

[13] R. R. Mller, "Applications of large random matrices in communications engineering," *http://citeseer.ist.psu.edu/652499.html*.