Blind Multiuser Receiver Design

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***Abstract*— The multiuser signal model not only helps us understand signal structures but also plays a key role in multiuser receiver design. In this paper, we present an alternative multiuser signal model and discuss its applications for blind multiuser receiver design. At first, we compare it with the conventional signal model and signal subspace based signal model 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 after that. Through these, the trade-offs between the complexity and performance of blind multiuser receiver design can be revealed. Computer simulations are finally provided to demonstrate the performance and theoretic analysis.**

I. Introduction

Multiuser detection (MUD) is the strategy for mitigating multiple access interference (MAI) effects and solving the near-far problem with exploiting interference structure. MUD has been extensively investigated 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] and it is believed to be one of the critical techniques for mitigating MAI effects and 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 for reducing the computation complexity and prior knowledge [3], [4], [5], [6], [7], [8], [9]. Blind multiuser receivers can achieve good performance with the knowledge of only desired user's timing and signature waveform. This assumption also is much closer to practical applications where most interferences are unknown beforehand. However, most existing blind receivers are known to be too complicated for high-data-rate applications.

In the procedure of advanced multiuser receiver development, it is known that a proper received signal model can help us understand received signals as well as receiver design. There are two popular multiuser signal models which have been intensively 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., the blind receiver design with Wiener filter [3] and Kalman filter [6] techniques. Though the conventional signal model provides us a natural view of received signals, the involved signature waveforms or amplitudes information is unknown and it usually take the receiver lots of efforts to obtain it before detection. For compensating the weakness of the conventional signal model, the subspace signal model is proposed 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 received signals. Subspace signal mode can be taken as a result of parametric signal modelling and provides a in-depth comprehension of received signals. Though subspace-based approaches don't need explicitly estimate each user's signal signature and the initialization and adaptive speed are improved with good performance, the signal subspace formation procedure still is not trivial.

It is known that the conventional signal model provides us the foundation for both optimal and conventional multiuser receiver design and subspace signal model helps us understand signal underneath structure. However, neither of them is easy enough for developing the blind multiuser receivers for high-speed CDMA systems [2]. In order to solve the near-far problem with minimum prior knowledge and computation complexity, we propose a new blind multiuser model with directly connecting the current received signal and several previous received signal while no explicitly signal structure estimation. With this blind signal model and widely employed signal estimation criteria including least squares (LS), minimum mean-squared errors (MMSE) and maximum likelihood (ML), several noval blind multiuser receivers are developed. There is no statistical signal estimation or subspace separation procedure required. Only a minimum number of previously received signals and the desired user's signal signature waveform and timing are required. Hence the computation complexity and detection delay can be much reduced. After this, we compare the proposed blind signal model and receivers with the conventional signal model and subspace signal mode and their blind receivers. The trade-off between the performance and complexity in blind receiver development is discussed too. Computer simulations are finally provided.

II. Multiuser Signal Models

The forward-link transmissions in a single-cell DS/CDMA system with K active users is discussed here. The channel is multiplath channel with P strong paths [1] 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 pth path loss of user k's signal, $b_k[n]$ 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 $[0,\ T]$, $0 \le \tau_1 \le \tau_2 \le \ldots \le \tau_P$, denotes P different transmission delays from the base station to user k and $A_k[n]$ is the received signal amplitude for user k at time $t = nT$, which depends on the possible channel statistics. The total baseband signal received by user k is

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

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 [2]

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

where

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

is the intersymbol interference (ISI) to user k,

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

is the MAI to user k, β_{qk} is the weight of the qth RAKE finger with $\sum_{q=1}^{P} \beta_{qk} \alpha_{qk} = 1$ and $\tau_{q1} = \tau_q - \tau_1$ is the propagation delay difference between the 1st path and pth path. $\otimes$ denotes the convolutional product. $n(t)$ is AWGN with variance σ^2. Because of $m_{\mathrm{MAI}}(t)$ existing in the received signal $r(t)$, the performance of conventional matched filter receiver suffers from the so-called near-far problem [1]. Multiuser detection is one of the receiver techniques for solving this problem.

A. Conventional Signal Model

After RAKE combining, the user 1's output can be sampled at $f_s = 1/T_s$ and directly expressed by [3]

$$\begin{aligned} \mathbf{r} &= \left[\, r(nT + T_s + \tau_1) \quad \ldots \quad r(nT + LT_s + \tau_1) \,\right]^{\mathrm{T}} \\ &= \sum_{k=1}^{K} A_k b_k \mathbf{s}_k + \mathbf{n} \\ &= \mathbf{SAb} + \mathbf{n} \end{aligned} \tag{6}$$

where $\mathbf{S} = [\mathbf{s}_1\ \mathbf{s}_2\ \ldots\ \mathbf{s}_K]$ is the received spreading signature matrix combined with inter-chip interference (ICI), inter-symbol interference (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 (6), which is named conventional multiuser signal model. They are well documented in [1]. One of the major problems using (6) is $\{\mathbf{s}_k,\ A_k : k \ne 1\}$ or possible timing is unknown at receiver. This may make multiuser receiver design complicated.

B. Subspace Signal Model

It is known that it is hard to accurately estimate the $\{\mathbf{s}_k : k \ne 1\}$ in (6) in order to directly apply the well-developed optimum or conventional multiuser detection schemes. Another approach is to use subspace-based signal model and signal processing techniques for re-construct the conventional detectors [5]. In the subspace signal model, $\mathbf{r}$ is modelled by the combination of the signal subspace bases $\{\mathbf{u}_{sk} : 1 \le k \le K\}$:

$$\mathbf{r} = \mathbf{U}_s \boldsymbol{\phi} + \mathbf{n} \tag{7}$$

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

$$\boldsymbol{\phi} = \mathbf{\Phi A b} \tag{8}$$

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

$$\mathbf{S} = \mathbf{U}_s \mathbf{\Phi}\ . \tag{9}$$

[1] Strong paths are those to be explicitly combined by RAKE receiver.

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

[3] Without loss of the generality, we name the first user as the desired user.

One of the major advantages of the subspace signal model (7) is that the signal subspace bases $\{\mathbf{u}_{sk} : 1 \leq k \leq K\}$ are much easier to be estimated than the actual signal signature waveforms so that the blind receiver design can be much simplified. These signal bases can be estimated applying subspace decomposition on the autocorrelation matrix $\mathbf{R}$:

$$\begin{aligned} \mathbf{R} &= \mathrm{E}\{\mathbf{r}\mathbf{r}^{\mathrm{T}}\} \\ &= \begin{bmatrix} \mathbf{U}_s & \mathbf{U}_n \end{bmatrix} \begin{bmatrix} \boldsymbol{\Lambda}_s & \\ & \boldsymbol{\Lambda}_n \end{bmatrix} \begin{bmatrix} \mathbf{U}_s^{\mathrm{T}} \\ \mathbf{U}_n^{\mathrm{T}} \end{bmatrix} . \end{aligned} \tag{10}$$

where $\mathbf{U}_n$ denotes the noise subspace bases and $[\cdot]^{\mathrm{T}}$ denotes the transportation operation.

C. The Proposed Blind Signal Model

As we can see, one of the difficulties in using the conventional signal model or subspace signal model for blind receiver design is the signal signatures $\{\mathbf{s}_k : k \neq 1\}$ in (6) or the signal subspace matrix $\mathbf{U}_s$ in (7) are unknown beforehand. Instead we propose a known blind signature matrix $\boldsymbol{\mathcal{S}}$

$$\begin{aligned} \boldsymbol{\mathcal{S}} &= \begin{bmatrix} \mathbf{s}_1 & \mathbf{r}_1 & \mathbf{r}_2 & \dots & \mathbf{r}_{M-1} \end{bmatrix} \\ &= \mathbf{SD} + \mathbf{N} \end{aligned} \tag{11}$$

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

$$\mathbf{D} = \begin{bmatrix} 1 & \bar{\mathbf{d}}^{\mathrm{T}} \\ \mathbf{0} & \tilde{\mathbf{D}} \end{bmatrix} = \begin{bmatrix} \mathbf{e} & \begin{matrix} \bar{\mathbf{d}}^{\mathrm{T}} \\ \tilde{\mathbf{D}} \end{matrix} \end{bmatrix} = \begin{bmatrix} \mathbf{g}^{\mathrm{T}} \\ \mathbf{0} \quad \tilde{\mathbf{D}} \end{bmatrix} \tag{12}$$

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

$$\mathbf{r} = \boldsymbol{\mathcal{S}}\mathbf{f} + \tilde{\mathbf{n}} \tag{13}$$

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

$$\mathbf{f} = \mathbf{D}^{+}\mathbf{A}\mathbf{b} \ , \tag{14}$$

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

$$\tilde{\mathbf{n}} = \mathbf{n} - \mathbf{N}\mathbf{D}^{+}\mathbf{A}\mathbf{b} \tag{15}$$

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

Different to the models in (6) and (7), the key component $\boldsymbol{\mathcal{S}}$ in (13) is known beforehand. This makes this model ready for designing new blind multiuser receivers from the beginning. After we estimate $\mathbf{f}$ with conventional signal estimation techniques, the detection of user 1's information can easily be done with knowing $d_1 = A_1 b_1$, which can be estimated by

$$\hat{d}_1 = \mathbf{g}^{\mathrm{T}}\mathbf{f} \ . \tag{16}$$

III. Blind Multiuser Receiver

In the 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 (13), we use conventional multiuser detection techniques for blind receiver design.

A. Conventional Blind Multiuser Detection

With the conventional signal model in (6), 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 know to be computation-intensive since the signal waveform estimation itself is not simple [4]. The other one is to use adaptive filter techniques with some signal processing criteria. Under this direction, there are well-known minimum output energy (MOE) detector, blind MMSE detector and blind Kalman detector [3], [1], [6]. However, these blind detectors are known to be slow in their adaptive procedures.

B. Subspace-Based Blind Multiuser Detection

With the subspace signal mode in (7), the first step usually is to separate signal/noise subspaces and estimate $\mathbf{U}_s$ using (10). After this, the least-square-based decorrelating detector is given by [5]

$$\mathbf{d}_{\mathrm{DD1}} = \frac{1}{\mathbf{s}_1^{\mathrm{T}}\mathbf{U}_s\left(\boldsymbol{\Lambda}_s - \sigma\mathbf{I}\right)^{-1}\mathbf{U}_s^{\mathrm{T}}\mathbf{s}_1} \mathbf{s}_1^{\mathrm{T}}\mathbf{U}_s \left(\boldsymbol{\Lambda}_s - \sigma\mathbf{I}\right)^{-1} \mathbf{U}_s^{\mathrm{T}}\mathbf{r} \tag{17}$$

and the MMSE detector can be expressed by

$$\mathbf{d}_{\mathrm{MMSE1}} = \frac{1}{\mathbf{s}_1^{\mathrm{T}}\mathbf{U}_s\boldsymbol{\Lambda}_s^{-1}\mathbf{U}_s^{\mathrm{T}}\mathbf{s}_1} \mathbf{s}_1^{\mathrm{T}}\mathbf{U}_s\boldsymbol{\Lambda}_s^{-1}\mathbf{U}_s^{\mathrm{T}}\mathbf{r} \tag{18}$$

C. New Blind Multiuser Detection Approaches

It shows that one of the key components in the proposed blind receiver design framework is the estimation of $\mathbf{f}$. After this $\mathbf{d}_1$ can be estimated with (16).

With the blind signal model in (13), one possible approach is firstly to estimate the detection vector $\mathbf{f}$. Obviously different signal estimation criteria may lead to different solutions. If the LS criterion is direct applied here, the traditional LS estimation of $\mathbf{f}$ can be expressed by

$$\mathbf{f}_{\mathrm{LS}} = \arg\min_{\mathbf{x}} \|\mathbf{r} - \boldsymbol{\mathcal{S}}\mathbf{x}\|_2 = \boldsymbol{\mathcal{S}}^{+}\mathbf{r} \tag{19}$$

with the assumption that $\boldsymbol{\mathcal{S}}$ is error-free.

If $\boldsymbol{\mathcal{S}}$ is assumed to be error-polluted in the above LS estimation problem (19), we have the total least squares (TLS) problem

$$\begin{bmatrix} \boldsymbol{\mathcal{S}}_{\mathrm{TLS}} \\ \mathbf{f}_{\mathrm{TLS}} \end{bmatrix} = \arg\min_{\bar{\boldsymbol{\mathcal{S}}},\ \mathbf{x}} \left\| \begin{bmatrix} \boldsymbol{\mathcal{S}} \\ \mathbf{r} \end{bmatrix} - \begin{bmatrix} \bar{\boldsymbol{\mathcal{S}}} \\ \bar{\boldsymbol{\mathcal{S}}}\mathbf{x} \end{bmatrix} \right\|_2 . \tag{20}$$

With solving (20), the TLS estimation of $\mathbf{f}$ can be written by

$$\mathbf{f}_{\mathrm{TLS}} = \left(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}} - \sigma_{K+1}^2\mathbf{I}\right)^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{r} \ , \quad (21)$$

where σ_{K+1} is the $K+1$th smallest singular value of $[\boldsymbol{\mathcal{S}}\ \mathbf{r}]$ and is assumed to be not greater than the kth largest singular value of $\boldsymbol{\mathcal{S}}$.

If only the first column of the $\boldsymbol{\mathcal{S}}$ in (19) is assumed to be error-free, we have the mixed least-square (MLS) problem:

$$\begin{bmatrix}\boldsymbol{\mathcal{S}}_{\mathrm{MLS}} \\ \mathbf{f}_{\mathrm{MLS}}\end{bmatrix} = \arg\min_{\bar{\boldsymbol{\mathcal{S}}},\ \mathbf{x}} \left\| \begin{bmatrix}\tilde{\boldsymbol{\mathcal{S}}} \\ \mathbf{r}\end{bmatrix} - \begin{bmatrix}\bar{\boldsymbol{\mathcal{S}}} \\ [\mathbf{s}_1\ \bar{\boldsymbol{\mathcal{S}}}]\mathbf{x}\end{bmatrix} \right\|_2 \ , \quad (22)$$

With solving (22), the MLS estimation of $\mathbf{f}$ can be written by

$$\mathbf{f}_{\mathrm{MLS}} = \left(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}} - \sigma^2\begin{bmatrix}\mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{M-G}\end{bmatrix}\right)^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{r} \ , \quad (23)$$

where σ is the smallest singular value of $[\boldsymbol{\mathcal{S}}\ \mathbf{r}]$.

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

$$\mathbf{f}_{\mathrm{MVU}} = \left(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{R}_{\tilde{\mathbf{n}}}^{-1}\boldsymbol{\mathcal{S}}\right)^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{R}_{\tilde{\mathbf{n}}}^{-1}\mathbf{r} \ . \quad (24)$$

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

$$\begin{aligned}\mathbf{f}_{\mathrm{MMSE}} &= \arg\min_{\hat{\mathbf{f}}} \mathrm{E}\|\hat{\mathbf{f}} - \mathbf{f}\|_2^2 \\ &= \left(\mathbf{R}_{\mathbf{f}}^{-1} + \boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{R}_{\tilde{\mathbf{n}}}^{-1}\boldsymbol{\mathcal{S}}\right)^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{R}_{\tilde{\mathbf{n}}}^{-1}\mathbf{r}\end{aligned} \ . \quad (25)$$

IV. Performance Analysis and Comparison

A. Comparison with Existing Blind Detectors

The 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 signal for signal detection and its complexity is closed to conventional detectors while other blind approaches typically requires a lots more than L signals [10], [5], [6].

B. Geometrical Interpretation

It is known that conventional decorrelating detector can be interpolated 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 $\mathbb{S}_1 = \mathrm{span}\{\mathbf{s}_1\}$ [11] while conventional or blind MMSE detection can be taken as a balance between single-user matched filter and decorrelating detector. Subspace-based decorrelating detector and MMSE detector have the same geometrical interpretation with the conventional detectors, respectively.

In the proposed blind least-square receiver, 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 $\tilde{\mathbb{S}}_1 = \mathrm{span}\{\mathbf{r}_m : k = 1,\ 2,\ \ldots,\ M-1\}$, instead of $\bar{\mathbb{S}}_1$, along the orthogonal complement of $\mathbb{S}_1$. 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 (16).

C. Noise Enhancement

It is known that there is a noise enhancement issue in the LS-based conventional decorrelating detection. With conventional decorrelating detection, the output signal-to-noise ratio (SNR) for user k is decreased by $[\mathbf{R}_{\mathbf{s}}^{+}]_{kk}^{-1}$. With the proposed blind LS multiuser receiver, there is another noise enhancement issue. Following Girko's law, providing $\alpha = \frac{K-1}{M}$ 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 $K,\ M \to \infty$ [12]. And the autocorrelation matrix of $\tilde{\mathbf{n}}$ can be expressed by

$$\mathbf{R}_{\tilde{\mathbf{n}}} = \tfrac{2M+K-1}{M}\sigma^2\mathbf{I} \ . \quad (26)$$

It shows that the noise variance is increased by $\frac{2M+K-1}{M}$.

D. Cramér-Rao Lower Bound

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

$$\mathrm{CRLB}(\mathbf{d} \mid \mathbf{S}) = \sigma^2\left(\mathbf{S}^{\mathrm{T}}\mathbf{S}\right)^{-1} \ . \quad (27)$$

It shows that the conventional decorrelating detection can achieve maximum likelihood sense if the amplitude $\mathbf{A}$ is unknown. For the blind signal model, if the blind spreading matrix $\boldsymbol{\mathcal{S}}$ is known beforehand, we first define the parameter vector $\psi = \left[\tilde{\sigma}^2\ \mathbf{f}^{\mathrm{T}}\right]^{\mathrm{T}}$, where $\tilde{\sigma}^2 = (1 + \frac{M-1}{M-K})\sigma^2$, for computing the FIM

$$\mathbf{I}(\phi) = \mathrm{E}\left\{\left(\tfrac{\partial \ln \mathcal{L}}{\partial \psi}\right)\left(\tfrac{\partial \ln \mathcal{L}}{\partial \psi}\right)^{\mathrm{T}}\right\} \quad (28)$$

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

$$\ln\mathcal{L} = C - L\ln\tilde{\sigma}^2 - \tfrac{1}{2\tilde{\sigma}^2}\parallel \mathbf{e} \parallel_2^2 \ , \quad (29)$$

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

$$\mathrm{CRLB}(\mathbf{f} \mid \boldsymbol{\mathcal{S}}) = (1 + \tfrac{M-1}{M-K})\sigma^2(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}})^{+} \ . \quad (30)$$

It shows that the accuracy of estimating $\mathbf{f}$ may increase with increasing M.

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.

E. Bit-Error Rate

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

$$P_{ek,\mathrm{DD}} = Q\left(\frac{A_k}{\sigma\left[\mathbf{R}_{\mathbf{S}}^{+}\right]_{kk}}\right). \tag{31}$$

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

$$P_{e1,\mathrm{LS}} = Q\left(\frac{\sqrt{\frac{M}{2M+K-1}}\,\frac{A_k}{\sigma}}{\left[\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}}\right]^{+}_{11}}\right). \tag{32}$$

F. Asymptotic Multiuser Efficiency

A commonly used performance measure for a multiuser detector is asymptotic multiuser efficiency (AME) and near-far resistance [1]. The AME of the conventional decorrelating detection approach is

$$\eta_k = \left[\mathbf{R}_{\mathbf{S}}^{+}\right]_{kk}^{-1} \tag{33}$$

and the AME of the proposed schemes is

$$\bar{\eta}_k = \frac{M}{2M+K-1}\left[\mathbf{R}_{\boldsymbol{\mathcal{S}}}^{+}\right]_{kk}^{-1} \tag{34}$$

where $\mathbf{R}_{\boldsymbol{\mathcal{S}}} = \boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}}$ and $[\cdot]_{kk}$ denotes the kth diagonal element of the matrix.

V. Computer Simulations

Single-cell DS/CDMA synchronous multiuser system is simulated here. The spreading sequence are random sequences with $L = 64$. In the simulations, previous amplitude estimation is used for the next detection. In Fig 1, there are 16 users and the group size $G = 3$ with M. From Subplot (a) in Fig. 1, it is interesting to see that the performance of the simplest blind LS detector has the best performance when SNR is greater than 14dB. From Subplot (b), it is very impressive to find that the performance of the blind LS detector still is very good. In Fig. 2, there are two active users simulated with $G = 1$ and $M = 40$. The crosscorrelation between these two users is $\rho = 0.28$. We can see that the performance of proposed schemes is stable against the change of the near-far ratio. However, due to the noise enhancement

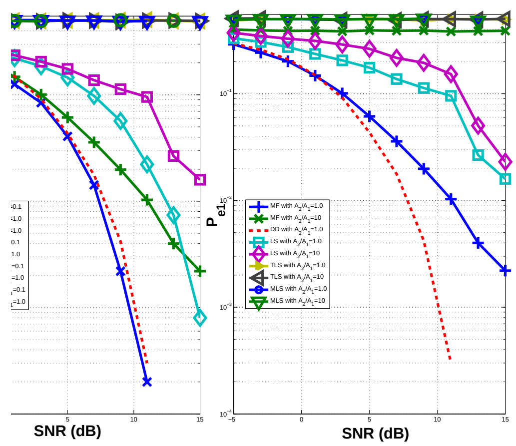

Fig. 1. The BER of various schemes against SNR. $K = 16$, $M = 40$ and $G = 4$.

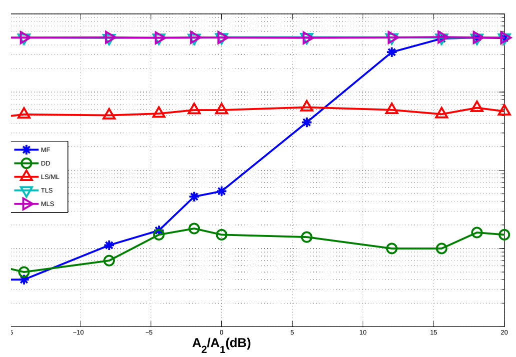

Fig. 2. The near-far resistance of various schemes. SNR = 10dB, $\rho = 0.28$, $M = 40$ and $K = 2$.

we analyzed before, their performance is not as good as the conventional decorrelating detector, which has the best near-far resistance.

VI. Conclusions

In this paper, we present a different approach for blind multiuser receiver design and side-by-side compare it with the existing conventional blind receiver and subspace-based receiver designs in terms of geometric properties, asymptotic multiuser efficiency and near-far resistance, noise enhancement, Cramér-Rao lower bound, etc., and discussed the trade-off between performance and complexity.

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