Semi-Blind Adaptive Multiuser Detection For Asynchronous CDMA

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***Abstract*—In this paper, we proposed a semiblind multiuser detection framework for asynchronous CDMA. Compared with most exsting semiblind/blind detectors, the proposed framework requires a minimum number of previously received signals, which is about the number of interfering signals, and no detection filter converging or subspace separation precedure. The computation complexity and detection delay are therefore much reduced. In this framework, a semiblind multiuser signal model is used instead of the widely-discussed conventional multiuser model or subspace-based parametric multiuser signal model. Following this framework, two optimal semiblind linear detectors are developed using the minimum variance unbiased estimation (MVU) and minimum mean squared error (MMSE) estimation criteria. Meanwhile, a multi-window scheme is proposed for simultaneously detecting several bits and a recursively adaptive procedure is developed for further lessening the complexity. After these, the asymptotic multiuser efficiency (AME) of the proposed framework, the comparsion between the employed semiblind multiuser signal model and the conventional signal model, and several estimation bounds are discussed. Computer simulations are presented to support the performance of the proposed semiblind multiuser detection schemes too.**

I. Introduction

Multiuser detection strategy is a method for minimizing the effect of multiple access interference (MAI) and solving the near-far problem without a significant reduction in the signal energies of the strong users in order for the weaker users to achieve reliable communication. It has been extensively investigated over the past several years, since MAI is the dominant impairment for CDMA systems and exists even in perfect power-controlled CDMA systems [1, 2, 3, 4, 5, 6, 7, 8]. Most multiuser detection schemes are based on the conventional multiuser signal model and then detect desired users' bits using statistical signal estimation techniques, which include the minimum bit-error rate (MBER) [1, 2], least-square (LS) errors [3], MMSE [3, 4, 5] and minimum output energy (MOE) [5] criteria. In the conventional signal model, received signals and multiuser receivers are represented by involved users' amplitudes, timing and spreading signatures, which are difficult to be known priorly by most semiblind/blind detectors. On the other hand, the converging and training procedure employed by many semiblind/blind multiuser detectors for discovering interference structure normally cost multiuser receivers lots of time and computation resource. Recently, there are lots of attentions focused on subspace-based signal models, in which each received signal is taken as a combination of the bases of signal and noise subspaces [9, 10, 11], and subspace-based multiuser detectors [6, 8]. Subspace-based multiuser detection essentially is a method for blindly reconstruct existing conventional detectors. Thought their performance can be well above many previous semiblind/blind approaches, subspace-based multiuser detectors need compute the covariance matrix of received signals and separate signal/noise subspace bases. This makes it difficult to be implemented in many practical situations, especially where the wireless channel and the number of users experience fast dynamic changes. Hence recent blind multiuser detection research is focused on reducing detection complexity and delay.

Though both the conventional multiuser signal model and subspace-based multiuser signal model provides a natural and straightforward description of received signals, most semiblind or blind detectors based on them are hard to be implemented in many practical applications since the signal bases used in these two models are unknown beforehand and it is nontrivial to estimate them by receivers. In order to detect desired user's information bits with minimum computation complexity and prior knowledge, we propose a semiblind multiuser signal model and a noval multiuser detection framework, which require only desired users' spreading sequence, amplitude, several previously received signals and possible channel noise variance, for asynchronous CDMA channel. Based on this framework, we develop two optimal semiblind linear multiuser detectors using minimum variance unbiased and minimum mean squared sestimation criteria instead of the least-sqaure criterion discussed in [12, 13]. In the proposed signal model and framework, each received asynchronous signal and semiblind receiver is taken as a combination of the desired user's spreading sequence, several previously received signals and noise. Therefore, there is no detection filter converging or subspace separation procedure required for interference signal structure discovery. The proposed semiblind schemes are simple and direct. They require a minimum number of previously received signals, which is about the number of interferring signals. A recursively adaptive implementation is developed for further reducing the complexity. At last, the comparasion between the proposed semiblind signal model and the conventional model, the asymptotic multiuser efficiency of the proposed framework, several estimation bounds and also computer simulations are presented to demonstrate their performance.

II. Data Model and Problem Description

At first, the conventional K-user asynchronous multiuser model is presented [7]. The baseband representation of the received signal due to the kth user is given by

$$r_k(t) \quad = \quad \sum_{i=-\infty}^{+\infty} A_k b_k[i] s_k(t - iT_c - \tau_k) \qquad (1)$$

where $b_k[i]$ is the ith bit sent by the kth user. We assume that $\{b_k[i]\}$ are independent and identically distributed random variables with $\mathrm{E}\{b_k[i]\} = 0$ and $\mathrm{E}\left\{|b_k[i]|^2\right\} = 1$. $s_k(t)$ denotes the normalized signal waveform of the kth user during the interval $[(n-1)T,\ nT]$, τ_k denotes the transmission delay from the kth user to the base station and A_k is the amplitude of the received signal of the kth user. The baseband signal at the input of the receiver at the mobile station is

$$r(t) \quad = \quad \sum_{k=1}^{K} r_k(t) + n(t) \qquad (2)$$

where $n(t)$ is additive white Gaussian noise (AWGN) with power spectral density σ_n^2.

The received signal is synchronized for each user individually, passed through the corresponding chip matched filter (CMF) and sampled at least at the chip rate $1/T_c$. The vertor of the output samples of the CMF for kth user in the nth symbol interval can be expressed as

$$\mathbf{r}_k[n] = [\, r_k(nT + T_c + \tau_k) \quad \ldots \quad r_k(nT + LT_c + \tau_k)\,]^{\mathrm{T}} \ . \qquad (3)$$

Prior to developing our semi-blind decorrelating detectors, we review the classic single-truncated-window decorrelating detector, in which the system is assumed to be chip-synchronous and the observation window is restricted to one symbol interval [7]. Without loss of generality, we consider the detection of the first user while the other users' signals are treated as interference. A typical interferer has two consecutive symbols interfering with the symbol of user 1 so that the received signal $\mathbf{r}$ can be conventionally and straightforwardly expressed by

$$\begin{aligned}\mathbf{r}_1 &= A_1 b_1[n]\mathbf{s}_1 + \sum_{k=2}^{K} A_k \{b_k[n-1]\mathbf{s}_{k-} + b_k[n]\mathbf{s}_{k+}\} + \mathbf{n} \\ &= \mathbf{S}_1 \mathbf{A}_1 \mathbf{b}_1 + \mathbf{n}\end{aligned} \qquad (4)$$

where $\mathbf{s}_{k-}$ and $\mathbf{s}_{k+}$ are effective signature sequences or partial signature sequences that are completely determined by the spreading sequences $\mathbf{s}_k$ and the delays relative to the first user $\tau_{k1} = \tau_k - \tau_1$, $\mathbf{n}$ is an L-dimension Gaussian vector with independent σ_n^2-variance components, where $L \geq 2K - 1$, and

$$\mathbf{S}_1 = [\, \mathbf{s}_1 \quad \mathbf{s}_{2-} \quad \mathbf{s}_{2+} \quad \ldots \quad \mathbf{s}_{K-} \quad \mathbf{s}_{K+}\,] \ , \qquad (5)$$

$$\mathbf{A}_1 = \mathrm{diag}\{\, A_1 \quad A_2 \quad A_2 \quad \ldots \quad A_K \quad A_K\,\} \ , \qquad (6)$$

$$\mathbf{b}_1 = [\, b_1[n] \quad b_2[n-1]\; b_2[n] \quad \ldots \quad b_K[n-1]\; b_K[n]\,]^{\mathrm{T}} . \qquad (7)$$

The classic single-truncated-window decorrelating detector actually performs the following operation

$$\hat{\mathbf{b}}_1 \quad = \quad \mathrm{sgn}\left\{\mathbf{S}_1^{+}\mathbf{r}_1\right\} \qquad (8)$$

where $[\cdot]^{+}$ denotes generalized inverse. The single-truncated-window decorrelating detector is designed to completely eliminate MAI caused by other users, which is achieved at the expense of enhancing the ambient noise. There are some desirable features of this multiuser detector. It can readily be decentralized in the sense that the demodulation of each user can be implemented completely independently. It does not require knowledge of the received amplitudes of all users but $\mathbf{S}_1^{+}$, which makes it hard to be directly implemented in many practical situtations, and the delays of all users. Also since each interferring signal's spreading sequence is separated into two subsequences in $\mathbf{S}$, the sequence engergy or values are spared into a double-size matrix $\mathbf{S}_1$, where $\eta_1 = K/(2K-1)$, which is only about one half when K is large enough, of elements are nonzero. Therefore, $\mathbf{S}_1^{+}$ is prone to be singular and the performance of the single-window decorrelating detector is less than the compelete decorrelating detector [7].

III. Semi-blind Signal Model And Framework

In order to do multiuser detection without estimating the received signal presentation bases, we extend the synchronous semiblind detection idea in [12, 13] and define a new asynchronous $PL \times M$ semi-blind signal signature matrix $\boldsymbol{\mathcal{S}}$ for user 1. The signature matrix $\boldsymbol{\mathcal{S}}$ will be used as a set of signal bases for representing received siganls and written by

$$\begin{aligned} \boldsymbol{\mathcal{S}} &= [\,\mathbf{I}_P \otimes (A_1\mathbf{s}_1) \quad \bar{\mathbf{r}}_1 \quad \bar{\mathbf{r}}_2 \quad \ldots \quad \bar{\mathbf{r}}_{M-P}\,] \\ &= \mathbf{S}\bar{\mathbf{A}}\mathbf{B} + \bar{\mathbf{N}} \end{aligned} \tag{9}$$

where the $PL \times (PK + K - 1)$ matrix

$$\mathbf{S} = [\,\bar{\mathbf{S}}_1 \quad \bar{\mathbf{S}}_2 \quad \bar{\mathbf{S}}_3 \quad \ldots \quad \bar{\mathbf{S}}_K\,] \tag{10}$$

is a multi-window version of the original signature matrix $\mathbf{S}_1$ with

$$\bar{\mathbf{S}}_1 = \mathrm{diag}\{\,\mathbf{s}_1 \quad \mathbf{s}_1 \quad \ldots \quad \mathbf{s}_1\,\}_{PL\times P} \tag{11}$$

and

$$\bar{\mathbf{S}}_k = \mathrm{diag}\{\,\mathbf{s}_{k_-} \quad \mathbf{s}_k \quad \ldots \quad \mathbf{s}_k \quad \mathbf{s}_{k_+}\,\}_{PL\times (P+1)}\ , \tag{12}$$

the $(PK + K - 1) \times (PK + K - 1)$ diagonal matrix

$$\bar{\mathbf{A}} = \mathrm{diag}\{\,\bar{\mathbf{A}}_1 \quad \bar{\mathbf{A}}_2 \quad \ldots \quad \bar{\mathbf{A}}_K\,\} \tag{13}$$

denotes a multi-window amplitude diagonal matrix with

$$\bar{\mathbf{A}}_1 = \mathrm{diag}\{\,A_1 \quad A_1 \quad \ldots \quad A_1\,\}_{P\times P} \tag{14}$$

and

$$\bar{\mathbf{A}}_k = \mathrm{diag}\{\,A_k \quad A_k \quad \ldots \quad A_k\,\}_{(P+1)\times (P+1)}\ , \tag{15}$$

$\bar{\mathbf{r}}_i$ are several previously received vectors of length P symbols,

$$\mathbf{B} = \begin{bmatrix} \mathbf{G} \\ \mathbf{0} \quad \tilde{\mathbf{D}} \end{bmatrix} = \begin{bmatrix} \mathbf{I}_P & \bar{\mathbf{D}} \\ \mathbf{0} & \tilde{\mathbf{D}} \end{bmatrix}, \tag{16}$$

with the $PL \times (M - P)$ multi-window bits matrix $\mathbf{D} = [\bar{\mathbf{D}}^{\mathrm{T}}\ \tilde{\mathbf{D}}^{\mathrm{T}}]^{\mathrm{T}}$, in which $\bar{\mathbf{D}}$ is a known $(M - P) \times P$ vector consisting of previously detected bits for the desired user. $\mathrm{rank}\{\mathbf{B}\} \leq PK + K - 1$ and $\mathrm{rank}\{\tilde{\mathbf{D}}\} \leq PK + K - P - 1$. The $PL \times M$ matrix $\bar{\mathbf{N}} = [\mathbf{0}\ \tilde{\mathbf{N}}]$ denotes the multi-window noise matrix. $\otimes$ denotes the Kronecker product and we maintain $PK + K - 1 \leq M \leq PL$. $M = PK + K - 1$ is the minimum number for indentifying $\mathbf{S}$ from $\boldsymbol{\mathcal{S}}$.

Using (4) and (9), the semiblind representation of the current received signal vector $\mathbf{r}$, which is of length P symbols, is given by

$$\begin{aligned} \mathbf{r} &= [\,\mathbf{r}_1[n]^{\mathrm{T}} \quad \mathbf{r}_1[n-1]^{\mathrm{T}} \quad \ldots \quad \mathbf{r}_1[n-P+1]^{\mathrm{T}}\,]^{\mathrm{T}} \\ &= \boldsymbol{\mathcal{S}}\mathbf{d} + \bar{\mathbf{n}} \end{aligned} \tag{17}$$

where the $M \times 1$ vector $\mathbf{d}$ denotes the new detection vector and is defined as

$$\mathbf{d} = \mathbf{B}^{+}\bar{\mathbf{b}}_1 \tag{18}$$

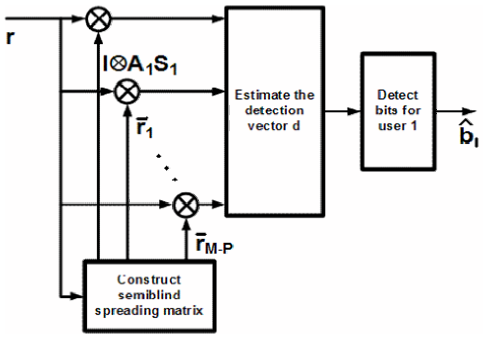

Fig. 1. The proposed semiblind Multiuser detection model and framework.

and $\bar{\mathbf{n}}$ is the new noise vector and defined as

$$\bar{\mathbf{n}} = \mathbf{n} - \bar{\mathbf{N}}\mathbf{B}^{+}\bar{\mathbf{b}}_1 \tag{19}$$

With (16) and (18), the bits vector $\bar{\mathbf{b}}$ which consists of P bits sent by user 1 at the consecutive symbol intervals $t = n - P + 1, n - P + 2, \ldots, n$ can be obtained by

$$\bar{\mathbf{b}}_1 = \mathbf{G}\mathbf{d}\ . \tag{20}$$

The proposed semiblind detection framework can be illustrated in Fig. 1.

IV. Semi-Blind Multiuser Detection

After defining the known semi-blind signature matrix $\boldsymbol{\mathcal{S}}$ in (9), the conventional signal model (4) is transformed into (17) with the desired bits vector $\mathbf{b}$ replaced by the detection vector $\mathbf{d}$ and the original noise vector $\mathbf{n}$ replace by $\bar{\mathbf{n}}$. On the other hand, the desired bits vector $\mathbf{b}$ can be detected using $\mathbf{d}$, $\mathbf{G}$ and (20). Now the question is how to efficiently estimate $\mathbf{d}$ in (17). In [12, 13], three LS-based approaches were proposed with different assumptions regarding the noise in $\boldsymbol{\mathcal{S}}$. In the following, we develop two new estimation schemes based on MUV and MMSE criteria using some statistical information regarding $\mathbf{d}$ and $\bar{\mathbf{n}}$.

A. Minimum Variance Unbiase Estimation

The optimal estimator which constrains the biase to be zero and minimizes the variance is termed MVU estimator. When MVU estimator

$$\mathbf{d}_{\mathrm{MVU}} = \mathbf{f}(\mathbf{r}) \tag{21}$$

exists, it may be found that attains the Cramer-Rao Lower Bound (CRLB) so that

$$\frac{\partial \ln Pr(\mathbf{r};\ \mathbf{d})}{\partial \mathbf{d}} = \mathbf{I}(\mathbf{d})\,[\mathbf{f}(\mathbf{r}) - \mathbf{d}]\ , \tag{22}$$

where $Pr(\mathbf{r};\ \mathbf{d})$ is the joint PDF of $\mathbf{r}$ and $\mathbf{d}$ and $\mathbf{I}(\mathbf{d})$ is the Fisher information matrix (FIM) defined by

$$\mathbf{I}(\mathbf{d}) = \mathrm{E}\left\{\left(\frac{\partial \ln Pr(\mathbf{r};\ \mathbf{d})}{\partial \mathbf{d}}\right)\left(\frac{\partial \ln Pr(\mathbf{r};\ \mathbf{d})}{\partial \mathbf{d}}\right)^{\mathrm{H}}\right\}\ . \tag{23}$$

Though the determination of the optimal MVU estimator is generally a difficult, it can be evident with linear constraint. The MVU estimator for $\mathbf{d}$ then is [14]

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

The covariance matrix of $\mathbf{d}_{\mathrm{MVU}}$ given by

$$\mathbf{C}_{\mathbf{d}_{\mathrm{MVU}}} = (\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{C}_{\tilde{\mathbf{n}}}^{-1}\boldsymbol{\mathcal{S}})^{-1}\ . \quad (25)$$

Though the PDF of $\mathbf{B}$ may be determined, the PDF of $\mathbf{B}^{+}$ is largely unknown. This makes it is hard to calculate the closed-form solution of $\mathbf{C}_{\mathbf{d}}$ and $\mathbf{C}_{\tilde{\mathbf{n}}}$. However, with Girko's Law, when $\alpha = (PK+K-2)/(M-1)$ is fixed, K, $M \to \infty$, the diagonal element of $\frac{1}{M-1}\tilde{\mathbf{D}}^{+}\tilde{\mathbf{b}}\tilde{\mathbf{b}}^{\mathrm{T}}\tilde{\mathbf{D}}^{+\mathrm{T}}$ may be approximated by [15, 16]

$$\lim \tfrac{1}{M-1}\left[\tilde{\mathbf{D}}^{+}\tilde{\mathbf{b}}\tilde{\mathbf{b}}^{\mathrm{T}}\tilde{\mathbf{D}}^{+\mathrm{T}}\right]_{ii}^{-1} = 1-\alpha\ . \quad (26)$$

So, $\mathbf{C}_{\mathbf{d}}$ can be decided by

$$\mathbf{C}_{\mathbf{d}} = \begin{bmatrix} \frac{2M-PK-K}{M-PK-K+1} & \mathbf{0}^{\mathrm{T}} \\ \mathbf{0} & \frac{1}{M-PK-K+1}\mathbf{I} \end{bmatrix}\ , \quad (27)$$

and

$$\mathbf{C}_{\tilde{\mathbf{n}}} = \sigma^{2}\tfrac{2M-PK-K}{M-PK-K+1}\mathbf{I} \quad (28)$$

and the bit vector for user 1 can be detected by

$$\hat{\mathbf{b}}_{1} = \mathrm{sign}\left\{\mathbf{G}(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}})^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{r}\right\} \quad (29)$$

Now we can see that the proposed MVU detector in 29 actually has almost the same with the LS detector proposed in [12, 13].

B. Minimum Mean Square Estimation

Though the optimal Bayesian estimators are difficult to determine in close form or too computationally intensive to implement in general, they can be found under the jointly Gaussian assumption and linear constrain. This class of MMSE estimators are generically termed Wiener filter. Given measurements $\mathbf{r}$, the MMSE estimator of $\mathbf{d}$, $\mathbf{d}_{\mathrm{MMSE}} = f(\mathbf{r})$, minimizes the mean-squared error $J_{\mathrm{MMSE}} = E\{||\mathbf{d}-\hat{\mathbf{d}}||_2^2\}$. The function $f(\mathbf{r})$ may be nonlinear or linear and its exact structure is determined by minimizing J_{MSE}. When $\mathbf{d}$ and $\mathbf{r}$ are jointly Gaussian, the linear estimator $\mathbf{W}_{\mathrm{MMS}}$ that minimizes the mean-sqared error is (Bayesian Gauss-Markov Theorem)

$$\mathbf{d}_{\mathrm{MMS}} = (\mathbf{C}_{\mathbf{d}}^{-1}+\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{C}_{\tilde{\mathbf{n}}}^{-1}\boldsymbol{\mathcal{S}})^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{C}_{\tilde{\mathbf{n}}}^{-1}\mathbf{r} \quad (30)$$

and its performance is measured by the covariance matrix of the error $\epsilon = \mathbf{d}-\hat{\mathbf{d}}$ given by

$$\mathbf{C}_{\epsilon} = \left(\mathbf{C}_{\mathbf{d}}^{-1}+\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{C}_{\tilde{\mathbf{n}}}^{-1}\boldsymbol{\mathcal{S}}\right)^{-1}\ . \quad (31)$$

The bit vector for user 1 can be detected by

$$\hat{\mathbf{b}}_{1} = \mathrm{sign}\left\{\mathbf{G}(\mathbf{C}_{\mathbf{d}}^{-1}+\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{C}_{\tilde{\mathbf{n}}}^{-1}\boldsymbol{\mathcal{S}})^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{C}_{\tilde{\mathbf{n}}}^{-1}\mathbf{r}\right\}\ . \quad (32)$$

Combined with (27) and (28), $\hat{\mathbf{b}}_1$ can be further simplified as

$$\hat{\mathbf{b}}_{1} = \mathrm{sign}\left\{\mathbf{G}\left(\mathcal{C}\sigma^{\mathbf{2}}+\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}}\right)^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{r}\right\} \quad (33)$$

where

$$\mathcal{C} = \begin{bmatrix} 1 & \mathbf{0}^{\mathrm{T}} \\ \mathbf{0} & (2M-PK-K)\mathbf{I} \end{bmatrix}\ . \quad (34)$$

V. Adaptive Implementation

Following the well-known Sherman-Morrison-Woodbury matrix inverse lemma [17], an adaptive implementation of the proposed MVU semiblind detector can be expressed by

$$\hat{\mathbf{b}}_{1}(n) = \mathrm{sign}\left\{\mathbf{G}(n)\boldsymbol{\mathcal{C}}_{\mathcal{S}}^{+}(n)\boldsymbol{\mathcal{S}}^{\mathrm{T}}(n)\mathbf{r}(n)\right\} \quad (35)$$

$$\begin{aligned}\boldsymbol{\mathcal{C}}_{\mathcal{S}}^{+}(n) = \boldsymbol{\mathcal{C}}_{\mathcal{S}}^{+}(n-1) - \big[\boldsymbol{\mathcal{C}}_{\mathcal{S}}^{+}(n-1)\mathbf{U}(n-1)\mathbf{U}^{\mathrm{T}}(n-1)\\ \boldsymbol{\mathcal{C}}_{\mathcal{S}}^{+}(n-1)\big]\left[\mathbf{I}+\mathbf{U}^{\mathrm{T}}(n-1)\boldsymbol{\mathcal{C}}_{\mathcal{S}}^{+}(n-1)\mathbf{U}(n-1)\right]^{-1}\end{aligned} \quad (36)$$

where

$$\boldsymbol{\mathcal{C}}_{\mathcal{S}}(n) = \boldsymbol{\mathcal{S}}(n)^{\mathrm{T}}\boldsymbol{\mathcal{S}}(n) \quad (37)$$

and $\mathbf{U}(n-1)$ is designed using SVD so that

$$\mathbf{U}(n-1)\mathbf{U}^{\mathrm{T}}(n-1) = \boldsymbol{\mathcal{C}}_{\mathcal{S}}(n)-\boldsymbol{\mathcal{C}}_{\mathcal{S}}(n-1) \quad (38)$$

VI. Performance Analysis

A. Multiuser Signal Model Comparasion

The comparison between the proposed asynchronous multiuser signal mode and the classic single-window signal model is given in Table 1.

B. Comparasion with The Classic Decorrelator

When $P = 1$, there is no noise in $\boldsymbol{\mathcal{S}}$ and $\mathbf{G}$ is accurately known beforehand, there is the following relationship between the user 1's BLU detector $\mathbf{w}_{\mathrm{BLU}}$ and the decorrelator $\mathbf{w}_{\mathrm{DD}}$.

$$\mathbf{w}_{\mathrm{BLU}} = \mathbf{G}(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}})^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}} = A_1^{-1}\mathbf{w}_{\mathrm{DD}} \quad (39)$$

On the other hand, $\mathbf{w}_{\mathrm{DD}}$ can be taken as a special case of $\mathbf{w}_{\mathrm{BLU}}$ with $\mathbf{B} = \mathbf{I}$ and $P = 1$.

Parameters	The proposed model	The conventional model
Common/Shared	dedicated	shared
Required Timing Information	only user 1	all users
Required Amplitude Information	only user 1	all users
Required Spreading Sequences	only user 1	all users
Input Vector	$\mathbf{r}\ -\ \mathbf{1}\times\mathrm{PL}$	$\mathbf{r_1}\ -\ \mathbf{1}\times\mathrm{L}$
Output Vector	$\bar{\mathbf{b}}_1\ -\ 1\times\mathrm{P}$	$\mathbf{b}_1\ -\ 1\times\mathrm{K}$
Num of Detected Bits	P	1
Spreading Matrix	$\boldsymbol{\mathcal{S}}\ -\ \mathrm{PL}\times\mathrm{M}$	$\mathbf{S}\ -\ \mathrm{L}\times\mathrm{K}$
Amplitude Matrix	N/A	$\mathbf{A}\ -\ \mathrm{K}\times\mathrm{K}$
Noise Vector	$\bar{\mathbf{n}}\ -\ 1\times\mathrm{PL}$	$\mathbf{n}\ -\ 1\times\mathrm{L}$

Table 1. The comparsion of the proposed semiblind multiuser signal model and the conventional signal model

C. The New Noise Vector $\tilde{\mathbf{n}}$

The mean of the semi-blind noise item $\tilde{\mathbf{n}}$ in (19) given by

$$\tilde{\mathbf{m}} \;=\; \mathrm{E}\{\tilde{\mathbf{n}}\} \;=\; 0 \tag{40}$$

The variance of $\tilde{\mathbf{n}}$ satisfies the following inequation

$$\left|\mathrm{E}\{(\tilde{\mathbf{n}}-\tilde{\mathbf{m}})^2\}\right|_\infty \leq \sigma_n^2 + (P+1)(K-1)\|\tilde{\mathbf{D}}^+\|_2^2\sigma_{\bar{n}}^2 \tag{41}$$

where $|\star|_\infty$ denotes the infinity norm of vector $\star$ and $\sigma_{\bar{n}}^2$ is the power of the noise item $\bar{\mathbf{N}}$ in the semi-blind signature matrix $\boldsymbol{\mathcal{S}}$.

D. AME and Near-Far Resistance

A commonly used performance measure for a multiuser detector is AME and near-far resistance [7]. Since the proposed algorithms converges to the conventional adecorrelating detector as $\sigma \rightarrow 0$, their AME and near-far resistance for user 1 is

$$\bar{\eta}_1 \;=\; [\mathbf{R}^+]_{11}^{-1} \;=\; \left[(\mathbf{S}^{\mathrm{T}}\mathbf{S})^+\right]_{11}^{-1}. \tag{42}$$

E. CRLB for $\mathbf{d}$ Estimation

The CRLB is given by the inverse of the FIM. Providing the blind spreading matrix $\boldsymbol{\mathcal{S}}$ is known beforehand, we first define the parameter vector $\phi = \left[\bar{\sigma}^2\ \mathbf{d}^{\mathrm{T}}\right]^{\mathrm{T}}$, where $\bar{\sigma}^2 = (1+\frac{M-1}{M-PK-K+1})\sigma^2$, for computing the FIM, which is defined by

$$\mathbf{I}(\phi) \;=\; \mathrm{E}\left\{\left(\frac{\partial \ln \Pr}{\partial \phi}\right)\left(\frac{\partial \ln \Pr}{\partial \phi}\right)^{\mathrm{H}}\right\} \tag{43}$$

where $\ln\Pr$ is the log-likelihood function given by

$$\ln\Pr \;=\; C - L\ln\bar{\sigma}^2 - \frac{1}{2\bar{\sigma}^2}\parallel \mathbf{e} \parallel_2^2\ , \tag{44}$$

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

$$\mathrm{CRLB}(\mathbf{d}\mid\boldsymbol{\mathcal{S}}) \;=\; (1+\frac{M-1}{M-PK-K+1})\sigma^2(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}})^+\ . \tag{45}$$

From (45), it shows that the accuracy of estimating $\mathbf{d}$ may increase with increasing M.

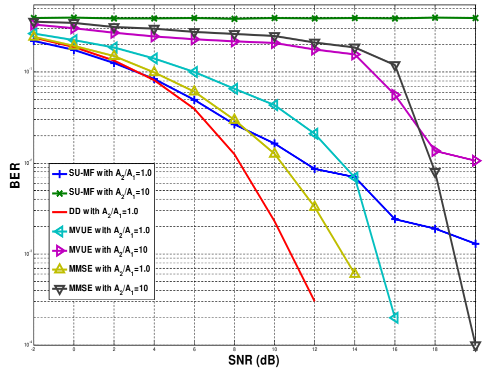

Fig. 2. The BER performance comparsion of the single-user matched filter, decorrelating detector and the proposed detectors.

VII. Computer Simulations

In this section, various computer simulation results are presented to demonstrate the performance of our proposed semiblind detectors. In our computer simulations, we assume a chip-level synchronized single base station system. In this system, there are $K = 10$ users sending asynchronous signals to the base station. The delays between interferring users and the first user are random variables between 1 and 63 chips. All spreading sequences are random sequences with the spreading gain $G = 64$. The size of the semiblind spreading matrix $\boldsymbol{\mathcal{S}}$ is 64×30 with $M = 30$. In Fig. 2, we compare the BER performance of the proposed semiblind detectors with the single-user matched filter (SU-MF) and decorrelating detector against changing SNR. It show that the performance of the conventional decorrelator and SU-MF are better than the proposed semiblind detectors when the near-far ratio is small, $A_1/A_2 = -0.1$. However, when MAI is strong and $A_2/A_1 = 10$, the SU-MF experiences the near-far problem and the performance of the proposed semiblind detectors are between the decorrelating detector and SU-MF. In Fig. 3, we examine the near-far resistance of the proposed semiblind detectors. We see that the near-far resistance of the MVUE detector is close to the

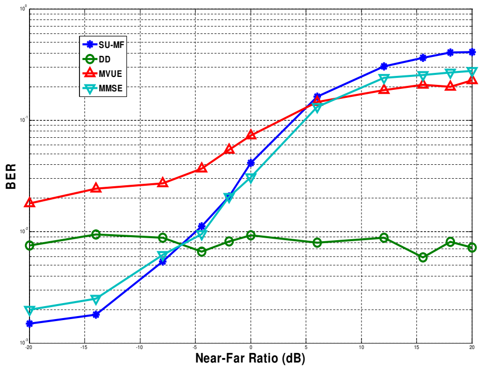

Fig. 3. The near-far resistance comparsion of the single-user matched filter, decorrelating detector and the proposed detectors. $SNR = 6dB$

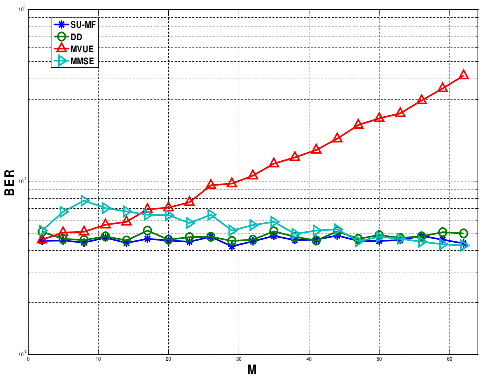

Fig. 4. The BER performance of the single-user matched filter, decorrelating detector and the proposed detectors with changing M. $P = 1$

decorrelating detector and the near-far resistance of the MMSE semiblind detector is close to the SU-MF when A_2/A_1 is small. When A_2/A_1 becomes large, the near-far resistance of both the MVUE and MMSE semiblind detectors are close the SU-MF. In Fig. 4 and 5, the BER performance of the proposed detectors are compared with the conventional detectors with changing the M and P individually. We see that the BER performance of the MVUE semiblind detector is going down and the BER performance of the MMSE semiblind detector is going up when M is increased. However, the BER performance of the MMSE semblind detector is going down while the BER performance of the MVUE detector is going up when P is increasd.

VIII. CONCLUSIONS

In this paper, a new semiblind multiuser detection framework and two semiblind detectors are proposed for asynchronous CDMA. Compared with most existing semiblind/blind multiuser detection schemes, the proposed schemes are simple and direct without any estimation or subspace separation operation and require a minimum number of previously received signals, as well as

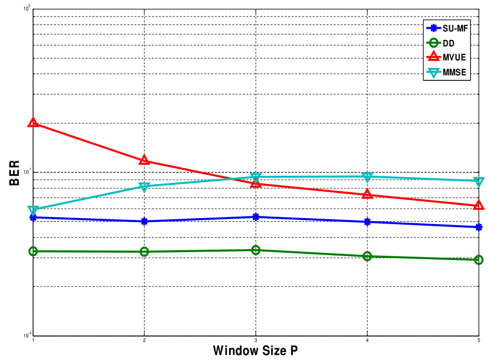

Fig. 5. The BER of the single-user matched filter, decorrelating detector and the proposed detectors with changing P. $M = 64$

desired user's spreading sequence, timing and amplitude. Their performance are comparable with the conventional single-window decorrelating detector.

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