Blind Adaptive Multiuser Detection

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***Abstract*—Most existing multiuser detectors are based on the conventional multiuser model and/or subspace parametric model and use statistical signal estimation techniques. In this paper, a new and simple blind multiuser detection model and framework are proposed for CDMA forward links. Based on this framework, several new blind multiuser detection schemes are developed using least squares (LS) estimation, best least unbiased (BLU) estimation, minimum mean-square error (MMSE) estimation criteria. They are simple and direct without any subspace separation or sequence/channel estimation operation. Compared with existing blind detection schemes, the proposed schemes require a minimum number of previously received signals. An adaptive scheme is developed for further reducing the complexity too. All these can be easily extended for CDMA reverse links. Theoretical analysis and computer simulations are finally provided to demonstrate the proposed schemes.**

I. Introduction

Multiuser detection strategy is a method for mitigating multiple access interference (MAI) effects with exploiting interference structure [1]. Recent research has been devoted to blind multiuser detection and subspace-based signature waveform estimation schemes for achieving better performance and higher capacity [2, 3, 4, 5, 6, 7, 8]. Blind multiuser detectors can achieve good performance with only the knowledge of the timing and signature waveform of desired user(s). This assumption also is much closer to practical applications. There are two popular approaches for designing blind multiuser detectors. One is to use the conventional multiuser signal model, where received signals and multiuser receivers are taken as linear combinations of actual spreading sequences and noise, and statistical signal estimation techniques for blind multiuser detection, e.g., the blind multiuser receiver design using Wiener filters [3] or Kalman filters [8] techniques. The other approach is based on parametric signal modelling and signal spectrum estimation, where received signals and multiuser receivers are taken as a linear combination of desired users' spreading sequences and the signal/noise subspace bases. Many subspace-based schemes are the examples of this approach, which essentially is a new approach for blindly reconstructing existing conventional multiuser detectors using subspace concept [6, 7]. One of the difficulties in implementing the above approaches is that the signal bases employed for designing blind multiuser receivers are mostly unknown beforehand and it is nontrivial to accurately estimate them out. Therefore the required computation resources are known to be too high for many practical applications especially when wireless channels and/or interfering signals experience fast dynamic change.

For solving these problems, we propose a blind multiuser signal model and bring a new and simple blind multiuser detection architecture in this paper, where multiuser receivers, as well as received signals, can be represented by only desired users' spreading sequences, several previously received signals and/or noise and therefore can be easily implemented in practices. In this proposed framework, we construct a blind spreading matrix for desired user(s). This spreading matrix may be different from user to user and fast changed from time to time. Based on this new blind multiuser signal model and detection framework, several blind multiuser detectors are developed using BLU and MMSE estimation criteria in addition to the LS-based schemes in [9, 10], where a closed semiblind approach is discussed. The proposed algorithms are simple and direct without any converging, estimation or subspace separation procedure as employed by many other semi-blind/blind detectors [5, 6]. Only the signatures and timing of desired users are required. Compared with existing blind detection schemes, they require a minimum number of previously received signals. An adaptive implementation is also provided to further reduce the computation complexity. Theoretical analysis and computer simulations are finally presented to demonstrate the performance of these blind detectors.

II. System Model And Problem Description

We consider forward-link transmissions in a single-cell DS/CDMA system. There are K active users over the multipath channel with P strong paths [1] and the channel is an additive white Gaussian noise (AWGN) channel. The baseband representation of the received sig-

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

nal due to user k is given by

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

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 $[0,\ T]$, $\tau_1 \leq \tau_2 \leq \ldots \leq \tau_P$, denotes P different transmission delays from the base station to user k and $A_k[n]$ is the amplitude of the received signal for user k at time $t = n$. The total baseband signal received by user k is

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

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]

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

where

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

is the intersymbol interference (ISI) to user k,

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

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. The user k's RAKE output can be sampled at $f_s = 1/T_s$ and straightforwardly expressed by

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

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

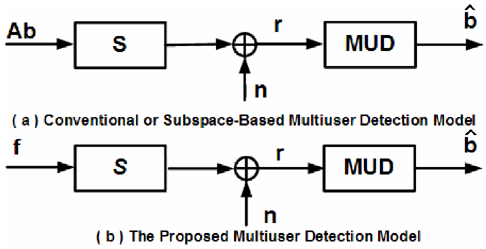

Fig. 1. Multiuser detection models.

where $\mathbf{S} = [\mathbf{s}_1\ \mathbf{s}_2\ \ldots\ \mathbf{s}_K]$ is the received spreading sequence matrix combined with both 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.

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 the receiver technique for solving this problem and most multiuser detectors are firstly developed using the conventional system model like (6). These are well documented in [1]. One of the difficulties in developing blind multiuser detectors using (6) is that the $\mathbf{S}$ is hard to be known beforehand. And it normally takes much effort to determine it later. The similar situation can also be met in developing blind detectors using the parametric subspace signal model proposed in [6].

III. Blind Multiuser Detection Framework

Instead of using the conventional signal model or the parametric subspace signal model, we develop a new blind multiuser signal model shown in Fig. 1, which uses a blind but "faked" spreading matrix $\boldsymbol{\mathcal{S}}$ for desired user(s). We call $\boldsymbol{\mathcal{S}}$ the blind but "faked" spreading matrix because 1) it is composed by only desired users' spreading sequences and previously received signals and 2) it isn't the original one but works like the original one. Without loss of the generality, only the bits sent for first G users are considered here and the $L \times M$ blind spreading sequence matrix $\boldsymbol{\mathcal{S}}$ is defined by

$$\boldsymbol{\mathcal{S}} = [\,\mathbf{s}_1 \quad \ldots \quad \mathbf{s}_G \quad \mathbf{r}_1 \quad \mathbf{r}_2 \quad \ldots \quad \mathbf{r}_{M-G}\,] \quad (7)$$

where $\mathbf{s}_g$, $g = 1,\ 2,\ \ldots,\ G$, denote the group of G spreading waveforms which are already known to user 1. $\mathbf{r}_m$, $m = 1,\ 2,\ \ldots,\ M - G$, are $M - G$ previously received independent signal vectors. $K \leq M \leq L$. Obviously $M = K$ is the minimum number for blind multiuser detector to unambiguously distinguish different interfering signals. And if $M > L$, blind multiuser receiver will not be unique since there will be more variables than available equations. The relationship between the proposed blind spreading matrix $\boldsymbol{\mathcal{S}}$ and the original spreading matrix $\mathbf{S}$ can be given by

$$\boldsymbol{\mathcal{S}} = \mathbf{SB} + \mathbf{N} \quad (8)$$

where the first G columns of $\boldsymbol{\mathcal{S}}$ and $\mathbf{S}$ are same,

$$\mathbf{B} = \begin{bmatrix} \mathbf{I} & \bar{\mathbf{D}} \\ \mathbf{0} & \tilde{\mathbf{D}} \end{bmatrix} = \begin{bmatrix} \mathbf{E} & \bar{\mathbf{D}} \\ & \tilde{\mathbf{D}} \end{bmatrix} = \begin{bmatrix} & \mathbf{G} & \\ \mathbf{0} & & \tilde{\mathbf{D}} \end{bmatrix} \quad (9)$$

is the $K \times M$ data matrix associated with $\boldsymbol{\mathcal{S}}$. $\mathbf{E} = [\,\mathbf{I} \quad \mathbf{0}\,]^{\mathrm{T}}$, $\mathbf{G} = [\,\mathbf{I} \quad \bar{\mathbf{D}}\,]$ is the $G \times M$ matrix composed by known data in $\boldsymbol{\mathcal{S}}$. rank$\{\tilde{\mathbf{D}}\} = K - G$ and rank$\{\mathbf{B}\} \le K$. Combining (6) and (7), the received signal vector $\mathbf{r}$ in (6) can be expressed as the linear combination of the columns in $\boldsymbol{\mathcal{S}}$ instead of $\mathbf{S}$, which is written by

$$\mathbf{r} \quad = \quad \boldsymbol{\mathcal{S}}\mathbf{f} + \bar{\mathbf{n}} \quad (10)$$

where the $M \times 1$ vector $\mathbf{f}$ is termed the detection vector defined by

$$\mathbf{f} \quad = \quad \mathbf{B}^{+}\bar{\mathbf{b}} \quad (11)$$

where $[\cdot]^{+}$ denotes the general inverse operator and $\bar{\mathbf{b}} = \mathbf{A}\mathbf{b}$. $\bar{\mathbf{n}}$ is the new $L \times 1$ noise vector defined by

$$\bar{\mathbf{n}} \quad = \quad \mathbf{n} - \mathbf{N}\mathbf{B}^{+}\bar{\mathbf{b}} \quad (12)$$

With (11), the bit b_1 sent for user 1 can be detected using the following equations:

$$\hat{\mathbf{b}}_1 = [\,\hat{b}_1 \quad \hat{b}_2 \quad \ldots \quad \hat{b}_G\,]^{\mathrm{T}} = \mathrm{sgn}\{\mathbf{G}\mathbf{f}\} \quad , \quad (13)$$

$$\hat{\mathbf{a}}_1 = [\,\hat{A}_1 \quad \hat{A}_2 \quad \ldots \quad \hat{A}_G\,]^{\mathrm{T}} = |\mathbf{G}\mathbf{f}| \ . \quad (14)$$

The detection of user 1 now becomes how to efficiently estimate $\mathbf{f}$ and update $\boldsymbol{\mathcal{S}}$ or $\mathbf{G}$. In the following, we discuss various algorithms for estimating $\mathbf{f}$ and detecting $\mathbf{b}_1$. An adaptive implementation will be presented in Section V.

IV. Blind Multiuser Detectors

A. Least Squares Detection

At first, we assume that the measurements of $\boldsymbol{\mathcal{S}}$ are assumed to be free of error. All errors are confined to the received vector $\mathbf{r}$. Hence, the detection vector can be estimated with solving the following equation [11, 12]

$$\mathbf{f}_{\mathrm{LS}} \quad = \quad \arg\min_{\mathbf{x}} \|\mathbf{r} - \boldsymbol{\mathcal{S}}\mathbf{x}\|_2 \quad = \quad \boldsymbol{\mathcal{S}}^{+}\mathbf{r} \quad (15)$$

and the bit vector for the first G users can be detected by

$$\hat{\mathbf{b}}_1 \quad = \quad \mathrm{sign}\{\mathbf{G}\boldsymbol{\mathcal{S}}^{+}\mathbf{r}\} \quad (16)$$

B. Total Least Squares Detection

It assumes $\boldsymbol{\mathcal{S}}$ to be error-free in the previous LS estimation. This assumption is not entirely accurate with $\boldsymbol{\mathcal{S}}$ because of $\mathbf{N}$. Problem (15) can then be transformed into the TLS problem:

$$\begin{bmatrix} \boldsymbol{\mathcal{S}}_{\mathrm{TLS}} \\ \mathbf{f}_{\mathrm{TLS}} \end{bmatrix} = \arg\min_{\bar{\boldsymbol{\mathcal{S}}},\, \mathbf{x}} \left\| \begin{bmatrix} \boldsymbol{\mathcal{S}} \\ \mathbf{r} \end{bmatrix} - \begin{bmatrix} \bar{\boldsymbol{\mathcal{S}}} \\ \bar{\boldsymbol{\mathcal{S}}}\mathbf{x} \end{bmatrix} \right\|_2 \ . \quad (17)$$

Let $\boldsymbol{\mathcal{S}} = \mathbf{U}'\boldsymbol{\Sigma}'\mathbf{V}'^{\mathrm{T}}$ and $[\boldsymbol{\mathcal{S}}\ \mathbf{r}] = \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^{\mathrm{T}}$ be the SVD of $\boldsymbol{\mathcal{S}}$ and $[\boldsymbol{\mathcal{S}}\ \mathbf{r}]$, respectively. If $\sigma'_K > \sigma_{K+1}$, TLS estimation of $\mathbf{f}$ then is [11, 12]

$$\mathbf{f}_{\mathrm{TLS}} = \left(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}} - \sigma_{K+1}^2\mathbf{I}\right)^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{r} \quad (18)$$

and the bit vector for the first G users can be detected by

$$\hat{\mathbf{b}}_1 \quad = \quad \mathrm{sign}\left\{\mathbf{G}(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}} - \sigma_{K+1}^2\mathbf{I})^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{r}\right\} \quad (19)$$

C. Mixed LS/TLS Detection

Though there exists a noise or error matrix $\mathbf{N}$ in $\boldsymbol{\mathcal{S}}$, its first G columns are exactly known to be noise-free or error-free. Hence, to maximize the estimation accuracy of the detection vector $\mathbf{f}$, it is natural to require the corresponding columns of $\boldsymbol{\mathcal{S}}$ to be unperturbed since they are known exactly. Problem (15) and (17) can then be transformed into the following MLS problem:

$$\begin{bmatrix} \boldsymbol{\mathcal{S}}_{\mathrm{MLS}} \\ \mathbf{f}_{\mathrm{MLS}} \end{bmatrix} = \arg\min_{\bar{\boldsymbol{\mathcal{S}}},\, \mathbf{x}} \left\| \begin{bmatrix} \tilde{\boldsymbol{\mathcal{S}}} \\ \mathbf{r} \end{bmatrix} - \begin{bmatrix} \bar{\boldsymbol{\mathcal{S}}} \\ [\mathbf{s}_1\ \bar{\boldsymbol{\mathcal{S}}}]\mathbf{x} \end{bmatrix} \right\|_2 \ . \quad (20)$$

Perform the Householder transformation $\mathbf{Q}$ on the matrix $[\,\boldsymbol{\mathcal{S}} \quad \mathbf{r}\,]$ so that

$$\mathbf{Q}^{\mathrm{T}}[\,\mathbf{s}_1 \quad \ldots \quad \mathbf{s}_G \quad \bar{\boldsymbol{\mathcal{S}}} \quad \mathbf{r}\,] = \begin{bmatrix} \mathbf{R}_{11} & \mathbf{R}_{12} & \mathbf{r}_{1r} \\ \mathbf{0} & \mathbf{R}_{22} & \mathbf{r}_{2r} \end{bmatrix} \quad (21)$$

where $\mathbf{R}_{11}$ is a $G \times G$ up triangle matrix, $\mathbf{r}_{1r}$ is a $G \times 1$ vector and $\mathbf{r}_{2r}$ is a $(L - G) \times 1$ vector. Denote σ' as the smallest singular value of $\mathbf{R}_{22}$ and σ as the smallest singular value of $[\,\mathbf{R}_{22} \quad \mathbf{r}_{2r}\,]$. If $\sigma' > \sigma$, then the MLS solution uniquely exists and is given by [11]

$$\mathbf{f}_{\mathrm{MLS}} \quad = \quad \left(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}} - \sigma^2 \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{M-G} \end{bmatrix}\right)^{-1} \boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{r} \ . \quad (22)$$

and the bit vector for the first G users can be detected by

$$\hat{\mathbf{b}}_1 = \mathrm{sign}\left\{\mathbf{G}\left(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}} - \sigma^2 \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{M-G} \end{bmatrix}\right)^{-1} \boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{r}\right\} \quad (23)$$

D. Best Linear Unbiased Detection

We assume the linear structure

$$\mathbf{f}_{\mathrm{BLU}} \quad = \quad \mathbf{W}_{\mathrm{BLU}}^{\mathrm{T}}\mathbf{r} \quad (24)$$

for this so-called best linear unbiased estimator (BLUE), which is equal to the optimal minimum variance unbiased estimator (MVUE) in linear signal models if the data are truly Gaussian. Matrix $\mathbf{W}_{\mathrm{BLU}}$ is designed such that: 1) $\boldsymbol{\mathcal{S}}$ must be deterministic, 2) $\bar{\mathbf{n}}$ must be zero mean with positive definite known covariance matrix $\mathbf{C}_{\bar{\mathbf{n}}}$, 3) $\mathbf{f}_{\mathrm{BLU}}$ is an unbiased estimator of $\mathbf{f}$, 4) and the error variance for each of the M parameters is minimized as

$$\mathbf{W}_{\mathrm{BLU}} \;=\; \min_{\mathbf{W}_{\mathbf{f}}} \mathrm{var}\left\{\mathbf{W}_{\mathbf{f}}^{\mathrm{T}}\mathbf{r}\right\} \;. \tag{25}$$

The resulting best linear unbiased estimator is (Gauss-Markov Theorem):

$$\mathbf{f}_{\mathrm{BLU}} \;=\; (\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{C}_{\tilde{\mathbf{n}}}^{-1}\boldsymbol{\mathcal{S}})^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{C}_{\tilde{\mathbf{n}}}^{-1}\mathbf{r}\,. \tag{26}$$

The covariance matrix of $\mathbf{f}_{\mathrm{BLU}}$ given by

$$\mathbf{C}_{\mathbf{f}_{\mathrm{BLU}}} \;=\; (\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{C}_{\tilde{\mathbf{n}}}^{-1}\boldsymbol{\mathcal{S}})^{-1} \;. \tag{27}$$

Though the PDF of $\mathbf{B}$ may be determined, the PDF of $\mathbf{B}^{+}$ is largely unknown. However, with Girko's Law, when $\alpha = (K-G)/(M-G)$ is fixed, K, $M \to \infty$, the diagonal element of $\frac{1}{M-G}\tilde{\mathbf{D}}^{+}\tilde{\mathbf{b}}\tilde{\mathbf{b}}^{\mathrm{T}}\tilde{\mathbf{D}}^{+\mathrm{T}}$ may be approximated by [13]

$$\lim \frac{1}{M-G}\left[\tilde{\mathbf{D}}^{+}\tilde{\mathbf{b}}\tilde{\mathbf{b}}^{\mathrm{T}}\tilde{\mathbf{D}}^{+\mathrm{T}}\right]_{ii}^{-1} \;=\; 1-\alpha \;. \tag{28}$$

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

$$\mathbf{C}_{\mathbf{f}} \;=\; \begin{bmatrix} \frac{2M-K-G}{M-K}\mathbf{A}_1^2 & \mathbf{0}^{\mathrm{T}} \\ \mathbf{0} & \frac{1}{M-K}\mathbf{I} \end{bmatrix} , \tag{29}$$

where $\mathbf{A}_1 = \mathrm{diag}\{\mathbf{a}_1\}$,

$$\mathbf{C}_{\tilde{\mathbf{n}}} \;=\; \sigma^2\frac{2M-K-G}{M-K}\mathbf{I} \tag{30}$$

and the bit vector for the first G users can be detected by

$$\hat{\mathbf{b}}_1 \;=\; \mathrm{sign}\left\{\mathbf{G}(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}})^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{r}\right\} \tag{31}$$

E. Minimum Mean Squared Error Detection

Given measurements $\mathbf{r}$, the MMSE estimator of $\mathbf{f}$, $\mathbf{f}_{\mathrm{MMSE}} = f(\mathbf{r})$, minimizes the MSE $J_{\mathrm{MSE}} = E\{||\mathbf{f}-\hat{\mathbf{f}}||_2^2\}$. When $\mathbf{f}$ and $\mathbf{r}$ are jointly Gaussian, the linear estimator $\mathbf{W}_{\mathrm{MMSE}}$ that minimizes the MSE J_{MSE} is (Bayesian Gauss-Markov Theorem)

$$\mathbf{f}_{\mathrm{MMS}} \;=\; (\mathbf{C}_{\mathbf{f}}^{-1}+\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{C}_{\tilde{\mathbf{n}}}^{-1}\boldsymbol{\mathcal{S}})^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{C}_{\tilde{\mathbf{n}}}^{-1}\mathbf{r}\,, \tag{32}$$

which is also termed Wiener filter, and the bit vector for the first G users can be detected by

$$\hat{\mathbf{b}}_1 = \mathrm{sign}\left\{\mathbf{G}(\mathbf{C}_{\mathbf{f}}^{-1}+\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{C}_{\tilde{\mathbf{n}}}^{-1}\boldsymbol{\mathcal{S}})^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{T}}\mathbf{C}_{\tilde{\mathbf{n}}}^{-1}\mathbf{r}\right\} \tag{33}$$

V. Adaptive Implementation

In Fig. 2, an adaptive structure of the presented blind multiuser detection scheme is presented for time-variant channels. Following the well-known Woodbury matrix inverse lemma [12], an adaptive implementation of

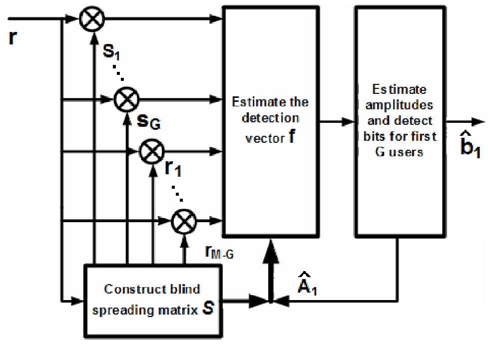

Fig. 2. The proposed adaptive blind multiuser detection structure.

the proposed LS and BLU blind detector can be expressed by

$$\hat{\mathbf{b}}_1(n) \;=\; \mathrm{sign}\left\{\mathbf{G}(n)\boldsymbol{\mathcal{C}}_{\mathcal{S}}^{+}(n)\boldsymbol{\mathcal{S}}^{\mathrm{T}}(n)\mathbf{r}(n)\right\} \tag{34}$$

$$\boldsymbol{\mathcal{C}}_{\mathcal{S}}^{+}(n) = \boldsymbol{\mathcal{C}}_{\mathcal{S}}^{+}(n-1) - \frac{\boldsymbol{\mathcal{C}}_{\mathcal{S}}^{+}(n-1)\mathbf{u}(n-1)\mathbf{u}^{\mathrm{T}}(n-1)\boldsymbol{\mathcal{C}}_{\mathcal{S}}^{+}(n-1)}{1+\mathbf{u}^{\mathrm{T}}(n-1)\boldsymbol{\mathcal{C}}_{\mathcal{S}}^{+}(n-1)\mathbf{u}(n-1)} \tag{35}$$

where

$$\boldsymbol{\mathcal{C}}_{\mathcal{S}}(n) \;=\; \boldsymbol{\mathcal{S}}(n)^{\mathrm{T}}\boldsymbol{\mathcal{S}}(n) \tag{36}$$

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

$$\mathbf{u}(n-1)\mathbf{u}^{\mathrm{T}}(n-1) \;=\; \boldsymbol{\mathcal{C}}_{\mathcal{S}}(n) - \boldsymbol{\mathcal{C}}_{\mathcal{S}}(n-1) \tag{37}$$

VI. Performance Analysis

A. AME and Near-Far Resistance

A commonly used performance measure for a multiuser detector is asymptotic multiuser efficiency (AME) and near-far resistance [1]. Since the proposed algorithms converges to the conventional decorrelating detector as $\sigma^2 \to 0$, their AME and near-far resistance are identical to the decorrelating detector:

$$\bar{\eta}_k \;=\; \frac{1}{\mathbf{R}_{kk}^{+}} \;. \tag{38}$$

B. CRLB for f Estimation

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

$$\mathbf{I}(\phi) \;=\; \mathrm{E}\left\{\left(\frac{\partial \ln\mathcal{L}}{\partial\phi}\right)\left(\frac{\partial \ln\mathcal{L}}{\partial\phi}\right)^{\mathrm{H}}\right\} \tag{39}$$

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

$$\ln\mathcal{L} \;=\; C - L\ln\bar{\sigma}^2 - \frac{1}{2\bar{\sigma}^2}\parallel \mathbf{e}\parallel_2^2 \;, \tag{40}$$

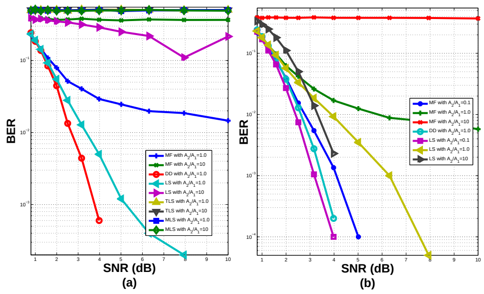

Fig. 3. (a) The performance of the proposed blind MUDs against SNR, $M = 12$. (b) The performance of the proposed blind LS detector, $M = 63$.

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

$$\mathrm{CRLB}(\mathbf{f} \mid \boldsymbol{\mathcal{S}}) = (1 + \tfrac{M-G}{M-K})\sigma^2(\boldsymbol{\mathcal{S}}^{\mathrm{T}}\boldsymbol{\mathcal{S}})^+ \ . \quad (41)$$

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

VII. Computer Simulations

There are $K = 10$ users with the group size $G = 3$ and the spreading sequences used in simulations are 64-chip ($L = 64$) random sequences. In the computer simulations, the previous amplitude estimation from (14) is directly use for the next detection without any amplitude filtering. From Subplot (a) in Fig. 3, it is interesting to see that the performance of the simplest LS detector has the best performance. From Subplot (b), it is very impressive to find that the performance of blind LS detector is very close to the conventional decorrelating detector whatever how strong the MAI is in our simulations when M is large enough. We then check the performance of the proposed LS blind detector against the amplitude estimation errors. From Fig. 4, we can see that the BER of the LS detector basically is unchanged against amplitude estimation error when SNR is large enough. From Fig. 5, we can see that the performance of the LS detector can be better providing M is larger enough. This confirms (30), which shows that the variance of $\bar{\mathbf{n}}$ decrease with increasing M.

VIII. Conclusions

In this paper, we proposed an alternative blind multiuser detection framework as well as several blind detectors. The proposed blind detectors are direct and simple without any channel or spreading sequence estimation or subspace separation operation.

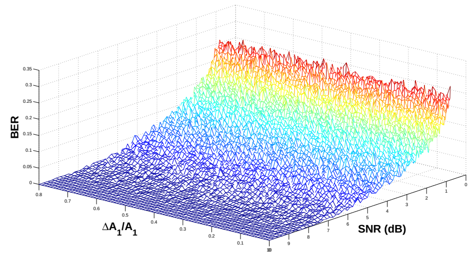

Fig. 4. The performance of the LS detector against amplitude estimation error $\Delta A_1/A_1$ and SNR, $M = 63$.

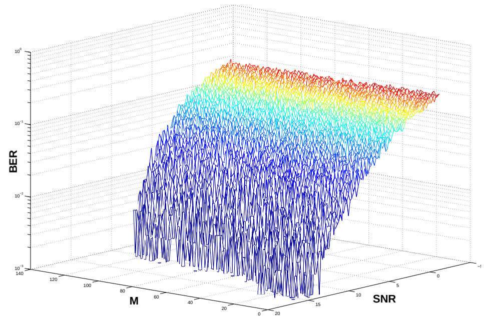

Fig. 5. The performance of the LS blind MUD against M and SNR.

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