Blind Decision-Feedback Interference Cancellation: A Systematic Approach

Shu Wang, Sang G. Kim, Li-H. Sun, Hobin Kim,
Suk W. Lee, Young C. Yoon, S. R. Subramanya and Byung K. Yi
LGE Mobile Research (LGEMR), San Diego, CA 92131

***Abstract*—Interference cancellation is one of the multiuser detection strategies for suppressing interference effects and consequently improving system performance. In this paper, a blind decision feedback interference cancellation framework, as well as several implementations using least squares, maximum likelihood and minimum mean squared error criteria, are proposed for solving the CDMA near-far problem. Compared with existing blind detectors, the proposed framework requires a minimum number of previously received signals and no subspace separation or sequence estimation operation. The computation complexity and detection delay can therefore be much reduced. Theoretical analysis and computer simulations are provided to demonstrate the performance of the proposed schemes.**

I. Introduction

Interference cancellation (IC) is the strategy for forming an estimate of various interference, including intersymbol interference (ISI), co-channel interference (CCI), adjacent channel interference (ACI), etc., and subtracting it from received signals before detection. Compared with other detection strategies, interference cancellation focuses more on interference estimation and different interference estimation methods may lead to different interference cancellation schemes [1, 2] such as successive cancellation [3], multistage detection [4], decision-feedback interference cancellation [5, 6], etc. Decision-feedback interference cancellation (DFIC), including minimum mean squared error (MMSE) decision-feedback detection [5] and decorrelating decision-feedback detection [6], is the decision-driven detection scheme that combines several features of successive interference cancellation and multistage detection [1]. Recent research has been devoted to semiblind/blind implementation of interference cancellation as well as other multiuser detectors [7, 8, 9, 10] for the practical applications where only desired users's information is available. For most semiblind/blind implementations, many adaptive filter techniques, e.g., Wiener filtering [7], Kalman filtering [10] and subspace [9] techniques, are among the most popular approaches. However, these approaches are known to be too complicated or slow for many dynamic high-data rate situations.

Decision-feedback techniques have been intensively discussed for channel equalization. In single-user decision-feedback equalization, previous decision outputs are feeded back for eliminating ISI and detecting the current symbol. It is known to have the complexity close to linear equalization while its performance is close to maximum likelihood equalization. Similarly in multiuser DFIC, previous decision outputs as well as other users' decision outputs are utilized for helping detect desired users's current information [7, 8, 9, 1]. In conventional DFIC [1], it is shown that other user's current decision outputs are enough for detecting desired information providing all users' signal signatures are known. In blind implementations of DFIC as well as other ICs, previous received signals and decision outputs are reused to separate signal subspaces or adapt filters for interference estimation [8, 9]. The problem with existing DFIC approaches is that either subspace separation or filter adapt procedure isn't trivial and may not be fast enough for fast-fading channels.

In order to solve the near-far problem with minimum prior knowledge and computation complexity [11, 12, 13], we provide an alternative blind DFIC framework, which requires a small amount of previously received signals for estimating interference and detecting desired signals. Different to existing approaches, a minimum number of previously received symbols are required in addition to desired user(s)' signatures and timing. No other users' signal signatures or signal subspaces separation is necessary here. Hence both the complexity and detection delay are much reduced. This makes it an attractive candidate for interference cancellation in high data rate systems. Theoretical analysis and computer simulations are finally presented to demonstrate the performance of these blind detectors. The proposed framework and approaches can be easily applied for asynchronous CDMA [12].

II. System Model And Problem Description

We consider a widely-discussed conventional single-cell forward-link DS/CDMA model here [1, 13]. There are K active users in the cell and the data $\{b_k$:

$k = 1, 2, \ldots K\}$ are individually spread using different spreading sequences and synchronously transmitted to these users through multipath channel. The user k's RAKE output $r(t)$ is sampled at $f_s = 1/T_s$ and can be written by

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

where $\mathbf{S} = [\mathbf{s}_1\ \mathbf{s}_2\ \ldots\ \mathbf{s}_K]$ is the received signal signature matrix including possible ISI and MAI information, $\mathbf{A} = \mathrm{diag}\left([A_1\ A_2\ \ldots\ A_k]\right)$ is the amplitude diagonal matrix of the amplitudes $\{A_k : k = 1, 2, \ldots K\}$ and $L = T/T_s$ is the number of samples per symbol, which usually is not 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]. Interference cancellation is one of the receiver techniques for solving this problem.

III. Blind Interference Cancellation

Without loss of the generality, the signals for the first G desired users will be detected here with $\mathbf{S}_1 = [\,\mathbf{s}_1 \quad \mathbf{s}_2 \quad \ldots \quad \mathbf{s}_G\,]$ known beforehand. Before this, we assemble M previously received and detected signal vectors into

$$\begin{aligned}\boldsymbol{\mathcal{S}} &= \left[\,\mathbf{r}[n-1] \quad \mathbf{r}[n-2] \quad \ldots \quad \mathbf{r}[n-M]\,\right] \\ &= \mathbf{SAB} + \mathbf{N} \\ &= \mathbf{S}_1\mathbf{A}_1\mathbf{B}_1 + \mathbf{S}_2\mathbf{A}_2\mathbf{B}_2 + \mathbf{N}\end{aligned} \tag{2}$$

where $\mathbf{B} = \left[\mathbf{B}_1^{\mathrm{H}}\ \mathbf{B}_2^{\mathrm{H}}\right]^{\mathrm{H}}$ is the data matrix for $\boldsymbol{\mathcal{S}}$, $\mathbf{S}_2$ is the original interfering signals' signatures, $\mathbf{A}_1$, $\mathbf{A}_2$, $\mathbf{B}_1$ and $\mathbf{B}_2$ are the amplitude matrices and data matrices for desired users and interfering users, respectively. Obviously The minimum number of received signals a receiver requires for possibly distinguishing all $K-G$ interfering users is $M = K-G$ and the rank of $\mathbf{B}_2$ is $r\left(\mathbf{B}_2\right) = K-G$ at this time. With (2), the interference subspace can be approximated by $\bar{\mathbb{S}}_1 = \mathrm{span}\left\{\mathbf{s}_m | m = G+1, \ldots K\right\} \approx \mathrm{span}\left\{\boldsymbol{\mathcal{S}} - \mathbf{S}_1\mathbf{A}_1\mathbf{B}_1\right\}$ providing the signal-to-noise ratio (SNR) is high enough. And the MAI $\mathbf{m}$ can be rewritten by

$$\begin{aligned}\mathbf{m} &= \mathbf{S}_2\mathbf{A}_2\mathbf{b}_2 \\ &= \left(\boldsymbol{\mathcal{S}} - \mathbf{S}_1\mathbf{A}_1\mathbf{B}_1 - \mathbf{N}\right)\mathbf{B}_2^{+}\mathbf{b}_2 \\ &= \boldsymbol{\mathcal{S}}\mathbf{f} - \mathbf{S}_1\mathbf{D}_1\mathbf{f} + \tilde{\mathbf{n}}\end{aligned} \tag{3}$$

where $\mathbf{f} = \mathbf{B}_2^{+}\mathbf{b}_2$ denotes a projection of $\mathbf{m}$ onto the interfering subspace of $\mathbf{S}_2\mathbf{A}_2\mathbf{B}_2$, $\mathbf{D}_1 = \mathbf{A}_1\mathbf{B}_1$ and $\tilde{\mathbf{n}} = -\mathbf{N}\mathbf{B}_2^{+}\mathbf{b}_2$.

With (3), it shows that $\mathbf{m}$ can be estimated providing $\mathbf{f}$ is known. In order to estimate $\mathbf{f}$, we perform QR-decomposition on $\mathbf{S}_1$ so that [14, 1]

$$\mathbf{S}_1 = \mathbf{Q}_1\mathbf{R}_1 = \mathbf{Q}_{11}\mathbf{R}_{11}\ , \tag{4}$$

where $\mathbf{Q}_1 = [\mathbf{Q}_{11}\ \mathbf{Q}_{12}] \in \mathbb{R}^{L\times L}$ is orthogonal and $\mathbf{R}_1 = [\mathbf{R}_{11}^{\mathrm{H}}\ \mathbf{0}^{\mathrm{H}}]^{\mathrm{H}} \in \mathbb{R}^{L\times G}$, and apply $\mathbf{Q}_{12}^{\mathrm{H}}$ on (3) to get

$$\mathbf{Q}_{12}^{\mathrm{H}}\mathbf{m} = \mathbf{Q}_{12}^{\mathrm{H}}\boldsymbol{\mathcal{S}}\mathbf{f} + \mathbf{Q}_{12}^{\mathrm{H}}\tilde{\mathbf{n}}\ . \tag{5}$$

Since

$$\mathbf{Q}_{12}^{\mathrm{H}}\mathbf{r} = \mathbf{Q}_{12}^{\mathrm{H}}\mathbf{m} + \mathbf{Q}_{12}^{\mathrm{H}}\mathbf{n}\ , \tag{6}$$

$\mathbf{f}$ can be estimated from

$$\mathbf{Q}_{12}^{\mathrm{H}}\mathbf{r} = \mathbf{Q}_{12}^{\mathrm{H}}\boldsymbol{\mathcal{S}}\mathbf{f} + \mathbf{Q}_{12}^{\mathrm{H}}\bar{\mathbf{n}}\ , \tag{7}$$

where $\bar{\mathbf{n}} = \tilde{\mathbf{n}} + \mathbf{n}$.

After $\mathbf{f}$ is estimated, $\mathbf{m}$ can be estimated using (3) and extracted from $\mathbf{r}$ so that the desired information vector $\mathbf{b}_1$ as well as $\mathbf{A}_1$ can be detected and estimated from

$$\mathbf{S}_1\mathbf{d}_1 \approx \mathbf{r} - \left(\boldsymbol{\mathcal{S}} - \mathbf{S}_1\hat{\mathbf{D}}_1\right)\hat{\mathbf{f}}\ , \tag{8}$$

where $\mathbf{d}_1 = \mathbf{A}_1\mathbf{b}_1$, $\hat{\mathbf{D}}_1$ denotes previous detection outputs from $\boldsymbol{\mathcal{S}}$ and $\hat{\mathbf{f}}$ denotes an estimate of $\mathbf{f}$. This can be done using either Viterbi algorithm or other sub-optimal detection schemes. This can be shown in Fig. 1. Since the previous decision outputs $\hat{\mathbf{D}}_1$ are used for estimating $\mathbf{m}$ and $\mathbf{A}_1$ and detecting $\mathbf{b}_1$, this framework is named blind decision-feedback interference cancellation. Though this framework is presented as a two-stage approach here, it can be implemented in a joint detection fashion with simultaneously estimating $\mathbf{d}_1$ and $\mathbf{f}$.

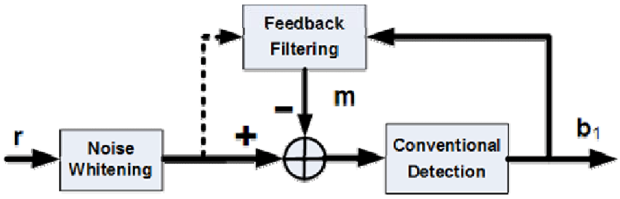

Fig. 1. A decision feedback interference cancellation block diagram

A. *Least Squares Interference Cancellation*

In classic least squares estimations, the observation matrix is assume to be error-free so that all estimation errors are supposed to come from $\mathbf{r}$. This can be expressed by [14]

$$\begin{bmatrix}\hat{\mathbf{d}}_{1\mathrm{LS}} \\ \mathbf{f}_{\mathrm{LS}}\end{bmatrix} = \arg\min_{\mathbf{x}} \|\mathbf{r} - \mathbf{Gx}\|_2 \tag{9}$$

where

$$\mathbf{G} = \left[\,\mathbf{S}_1 \quad \left(\boldsymbol{\mathcal{S}} - \mathbf{S}_1\mathbf{D}_1\right)\right]\ . \tag{10}$$

Therefore the desired vector $\mathbf{d}_1$ can be estimated by

$$\begin{bmatrix}\hat{\mathbf{d}}_{1\mathrm{LS}} \\ \mathbf{f}_{\mathrm{LS}}\end{bmatrix} = \mathbf{G}^{+}\mathbf{r}. \tag{11}$$

where $[\cdot]^{+}$ denotes the general inverse operation.

B. *Mixed Least Squares Interference Cancellation*

In (9), it assumes that there exist errors or noises on both $\mathbf{S}_1$ and $(\boldsymbol{\mathcal{S}} - \mathbf{S}_1\mathbf{D}_1)$. Obviously this is not true since $\mathbf{S}_1$ is known to be noise-free. To maximize the accuracy of estimating $\mathbf{d}_1$, it is natural to require $\mathbf{S}_1$ to be unperturbed while keep $\mathbf{S}_2$ estimated. For this, $\mathbf{r}$ can be re-written as

$$\mathbf{r} \quad = \quad \mathbf{S}_1 \left(\mathbf{d}_1 + \mathbf{D}_1\hat{\mathbf{f}}\right) - \boldsymbol{\mathcal{S}}\hat{\mathbf{f}} + \bar{\mathbf{n}} \ . \tag{12}$$

The mixed least squares (MLS) interference cancellation can be written by

$$\left[\begin{array}{c} \hat{\mathbf{S}} \\ \left[\begin{array}{c} \hat{\mathbf{d}}_1 + \mathbf{D}_1\hat{\mathbf{f}} \\ \hat{\mathbf{f}} \end{array}\right]_{\mathrm{MLS}} \end{array}\right] = \arg\min_{\mathbf{Z}\ \mathbf{y}} \left\| \left[\begin{array}{c} \boldsymbol{\mathcal{S}} \\ \mathbf{r} \end{array}\right] - \left[\begin{array}{c} \mathbf{Z} \\ \left[\mathbf{S}_1\ \mathbf{Z}\right]\mathbf{y} \end{array}\right] \right\|_2 . \tag{13}$$

If $\sigma'_{K-G} > \sigma_{K-G+1}$, the MLS estimation of $\mathbf{f}$ is [14]

$$\mathbf{f}_{\mathrm{MLS}} = \left(\boldsymbol{\mathcal{S}}^{\mathrm{H}}\mathbf{Q}_{12}\mathbf{Q}_{12}^{\mathrm{H}}\boldsymbol{\mathcal{S}} - \sigma_{K-G+1}^2\mathbf{I}\right)^{-1} \boldsymbol{\mathcal{S}}^{\mathrm{H}}\mathbf{Q}_{12}\mathbf{Q}_{12}^{\mathrm{H}}\mathbf{r} \tag{14}$$

where σ'_{K-G} and σ_{K-G+1} are the $(K-G)$th and $(K-G+1)$th largest singular value of $\mathbf{Q}_{12}^{\mathrm{H}}\boldsymbol{\mathcal{S}}$ and $\mathbf{Q}_{12}^{\mathrm{H}}\left[\,\mathbf{r} \quad \boldsymbol{\mathcal{S}}\,\right]$. The MLS-IC $\hat{\mathbf{d}}_{1\mathrm{MLS}}$ can be expressed by

$$\hat{\mathbf{d}}_{1\mathrm{MLS}} \quad = \quad \mathbf{S}_1^{+}\mathbf{r} - \mathbf{S}_1^{+}\left(\boldsymbol{\mathcal{S}} - \mathbf{S}_1\mathbf{D}_1\right)\mathbf{f}_{\mathrm{MLS}} \tag{15}$$

C. *Maximum Likelihood Interference Cancellation*

In maximum likelihood interference cancellation (ML-IC), $\mathbf{d}_1$ is estimated with maximizing the probability density function (PDF) $p(\mathbf{r};\ \mathbf{d}_1,\ \mathbf{f})$. It is known that ML estimator asymptotically is the minimum variance unbiased (MVU) estimator though it is not optimal in general. For the linear Gaussian signal model in (8), ML-IC can be written by

$$\left[\begin{array}{c} \hat{\mathbf{d}}_{1\mathrm{ML}} \\ \mathbf{f}_{\mathrm{ML}} \end{array}\right] \quad = \quad \arg\min_{\mathbf{x}} \left\{\delta^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}\delta\right\} \tag{16}$$

where the estimation error vector

$$\delta \quad = \quad \mathbf{r} - \mathbf{G}\mathbf{x} \ . \tag{17}$$

Therefore the ML estimation of $\mathbf{d}_1$ can be given by

$$\left[\begin{array}{c} \hat{\mathbf{d}}_{1\mathrm{ML}} \\ \mathbf{f}_{\mathrm{ML}} \end{array}\right] \quad = \quad \left(\mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}\mathbf{G}\right)^{-1}\mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}^{-1}\mathbf{r} \ . \tag{18}$$

D. *Mini. Mean-Square Error Interference Cancellation*

With MMSE criterion, $\mathbf{d}_1$ is estimated with minimizing the Bayesian mean squared error (BMSE):

$$\mathbf{e}_{\mathrm{BMSE}} \quad = \quad \mathrm{E}\left\| \left[\begin{array}{c} \hat{\mathbf{d}}_1 \\ \hat{\mathbf{f}} \end{array}\right] - \left[\begin{array}{c} \mathbf{d}_1 \\ \mathbf{f} \end{array}\right] \right\|_2^2 . \tag{19}$$

The MMSE estimation can then be written by

$$\left[\begin{array}{c} \hat{\mathbf{d}}_{1\mathrm{MMSE}} \\ \mathbf{f}_{\mathrm{MMSE}} \end{array}\right] = \arg\min_{\mathbf{x}} \mathrm{E}\left\|\mathbf{r} - \mathbf{G}\mathbf{x}\right\|_2 \tag{20}$$

and, if $\mathbf{r}$, $\mathbf{d}_1$ and $\mathbf{f}$ are jointly Gaussian, it can be solved by

$$\left[\begin{array}{c} \hat{\mathbf{d}}_{1\mathrm{MMSE}} \\ \mathbf{f}_{\mathrm{MMSE}} \end{array}\right] \quad = \quad \left(\mathbf{R}_{\mathbf{x}} + \mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}\mathbf{G}\right)^{-1}\mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}^{-1}\mathbf{r} \tag{21}$$

where

$$\mathbf{R}_{\mathbf{x}} \quad = \quad \mathrm{E}\left\{ \left[\begin{array}{cc} \mathbf{d}_1\mathbf{d}_1^{\mathrm{H}} & \mathbf{d}_1\mathbf{f}^{\mathrm{H}} \\ \mathbf{f}\mathbf{d}_1^{\mathrm{H}} & \mathbf{f}\mathbf{f}^{\mathrm{H}} \end{array}\right] \right\} . \tag{22}$$

IV. Implementation Issues

A. *Adaptive Detection*

When transmitted signals experience fast fading channels, it is better for the receiver to response fast enough to follow time-varying channel distortions so that it may correctly detect desired information. With (2) and (8), it shows that the proposed DFIC framework requires $\boldsymbol{\mathcal{S}}$, which consists of M previously received symbols, for the next detection so that it may be able to fast track channel. Since its adaptive implementation typically involves the inverse of $\mathbf{G}^{\mathrm{H}}\mathbf{G}$ in (11), $\mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}\mathbf{G}$ in (18), etc., one of the possible approaches is to follow the well-known Sherman-Morrison-Woodbury matrix inverse lemma [15, 13]. For example, if we define

$$\boldsymbol{\Phi}[n] \quad = \quad \mathbf{G}^{\mathrm{H}}[n]\mathbf{G}[n] \ , \tag{23}$$

where $\mathbf{G}[n]$ denotes the instance of $\mathbf{G}$ at $t = n$, so that $\boldsymbol{\Phi}[n+1]$ can be rewritten by

$$\boldsymbol{\Phi}[n+1] \quad = \quad \boldsymbol{\Phi}[n] + \mathbf{u}[n]\mathbf{u}^{\mathrm{H}}[n] \ . \tag{24}$$

The inverse of $\boldsymbol{\Phi}[n+1]$ can be recursively calculated by

$$\boldsymbol{\Phi}^{-1}[n+1] = \boldsymbol{\Phi}^{-1}[n] - \frac{\boldsymbol{\Phi}^{-1}[n]\mathbf{u}[n]\mathbf{u}^{\mathrm{H}}[n]\boldsymbol{\Phi}^{-1}[n]}{1+\mathbf{u}^{\mathrm{H}}[n]\boldsymbol{\Phi}^{-1}[n]\mathbf{u}[n]} \ . \tag{25}$$

B. *Iterative Detection*

The presented detection framework can be generalized by solving the following optimization problem:

$$\hat{\mathbf{d}}_1 \quad = \quad \min f\left(\boldsymbol{\mathcal{S}}, \hat{\mathbf{D}}_1, \mathbf{r}\right) \ , \tag{26}$$

which subject to some possible constraints, where the $f(\cdot)$ is the objective function. Iterative techniques are possible approaches for solving this optimization problem. Furthermore, (26) may be extended to

$$\hat{\mathbf{d}}_1 \quad = \quad \min f\left(\left[\boldsymbol{\mathcal{S}}\ \mathbf{r}\right], \left[\hat{\mathbf{D}}_1\ \hat{\mathbf{d}}_1\right], \mathbf{r}\right) \ . \tag{27}$$

Another possible iterative framework for solving (27) can be expressed by

$$\hat{\mathbf{d}}_1[n+1] \quad = \quad \min f\left(\left[\boldsymbol{\mathcal{S}}\ \mathbf{r}\right], \left[\hat{\mathbf{D}}_1\ \hat{\mathbf{d}}_1[n]\right], \mathbf{r}\right) \ . \tag{28}$$

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

Parameters	Conv. DF-IC	Blind MMSE	Subspace Approaches	Blind DF-IC
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	K	1	1	1
Complexity order	K	1	1	1

* For blind MMSE or subspace-based approaches, it typically requires many more than L signals for initialization.

V. Performance Analysis

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 [7, 9, 10].

B. *AME and Near-Far Resistance*

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

$$\bar{\eta}_k = \frac{1}{[\mathbf{R}^{+}]_{kk}} . \qquad (29)$$

C. *On the new noise vector* $\bar{\mathbf{n}}$

Though it is easy to verify that $\mathrm{E}\{\bar{\mathbf{n}}\} = \mathbf{0}$, the covariance matrix of $\bar{\mathbf{n}}$ is not easy to be decided because of the unknown PDF of $\mathbf{B}_2^{+}$. Following Girko's law, providing $\alpha = (K-G)/M$ is fixed, the diagonal element of $\frac{1}{M}\left(\mathbf{B}_2^{+}\mathbf{b}_2\right)\left(\mathbf{B}_2^{+}\mathbf{b}_2\right)^{\mathrm{H}}$ can be approximated to be $1-\alpha$ with K, $M \rightarrow \infty$ [16]. And the covariance matrix of $\bar{\mathbf{n}}$ can be expressed by

$$\mathbf{R}_{\bar{\mathbf{n}}} = \frac{2M+K-G}{M}\sigma^2\mathbf{I} . \qquad (30)$$

D. *CRLB for* $\mathbf{d}_1$ *and* $\mathbf{f}$ *Estimation*

The Cramér-Rao Lower Bound (CRLB) is given by the inverse of the Fisher information matrix (FIM). Providing $\boldsymbol{\mathcal{S}}$ and $\mathbf{D}_1$ are known beforehand, we first define the parameter vector $\phi = \left[\bar{\sigma}^2\ \mathbf{d}_1^{\mathrm{H}}\ \mathbf{f}^{\mathrm{H}}\right]^{\mathrm{H}}$, where $\bar{\sigma}^2 = (1+\frac{M}{M+G-K})\sigma^2$, for computing the FIM

$$\mathbf{I}(\phi) = \mathrm{E}\left\{\left(\frac{\partial \ln \mathcal{L}}{\partial \phi}\right)\left(\frac{\partial \ln \mathcal{L}}{\partial \phi}\right)^{\mathrm{H}}\right\} \qquad (31)$$

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

$$\ln \mathcal{L} = C - L \ln \bar{\sigma}^2 - \frac{1}{2\bar{\sigma}^2} \parallel \mathbf{e} \parallel_2^2 , \qquad (32)$$

C is a constant and $\mathbf{e} = \mathbf{r} - \mathbf{S}_1\mathbf{d}_1 + (\boldsymbol{\mathcal{S}} - \mathbf{S}_1\mathbf{D}_1)\mathbf{f}$. Providing $\boldsymbol{\mathcal{S}}$ and $\mathbf{D}_1$ are known, the closed-form CRLB expression of $\mathbf{d}_1$ is then given by

$$\mathrm{CRLB}\left(\mathbf{x} \mid \boldsymbol{\mathcal{S}},\ \mathbf{D}_1\right) = (1+\frac{M}{M+G-K})\sigma^2\left(\mathbf{G}^{\mathrm{H}}\mathbf{G}\right)^{+} . \qquad (33)$$

where $\mathbf{x} = [\,\mathbf{d}_1^{\mathrm{H}} \quad \mathbf{f}^{\mathrm{H}}\,]^{\mathrm{H}}$.

VI. 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 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.

VII. Conclusions

In this paper, we proposed a blind interference cancellation framework as well as several implementations. They are simple and direct and require a minimum amount of previous detected symbols.

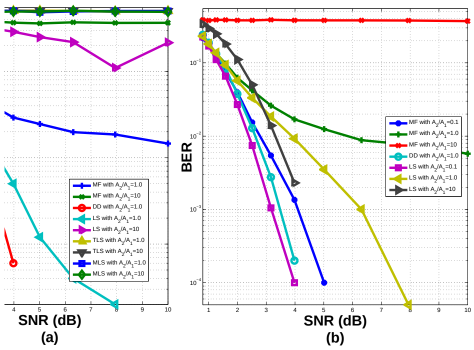

Fig. 2. (a) The performance of the proposed blind DF-ICs against SNR, $M = 12$. (b) The performance of the proposed blind LS detector, $M = 63$.

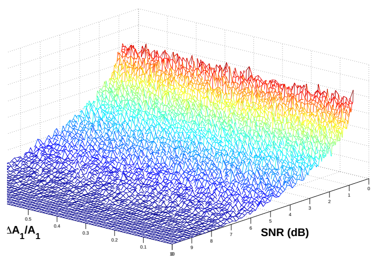

Fig. 3. The performance of the LS DF-IC against amplitude estimation error $\Delta A_1/A_1$ and SNR, $M = 63$.

References

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

[2] S. Wang and J. Caffery. On interference cancellation for synchronous cdma. In *International Symposium on Wireless Communications (ISWC) 2002*, September 2002.

[3] R. Kohno. Pseudo-noise sequences and interference cancellation techniques for spread spectrum systems-spread spectrum theory and techniques in japan. *IEICE Trans.*, E(74):1083–1092, May 1991.

[4] M. Varanasi and B. Aazhang. Near-optimum demodulation for coherent communications in asynchronous gaussian cdma channels. *Proc. 22nd Conf. on Information Sciences and Systems*, (129):15–26, March 1988.

[5] M. Kaveh and J. Salz. Cross-polarization cancellation and equalization in digital transmission over dually polarized multipath fading channels. *AT&T Technical Journal*, 64:2211–2245, December 1985.

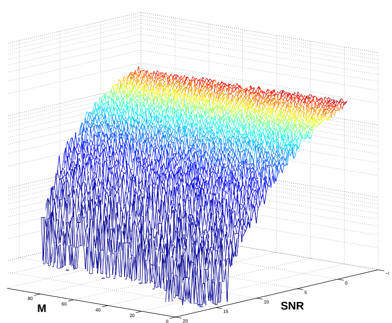

Fig. 4. The performance of the LS DF-IC against M and SNR.

[6] A. Duel-Hallen. Decorrelating decision-feedback detector for asynchronous code-division multiple-access channels. *IEEE Trans. On Communications*, 43:421–434, February 1995.

[7] U. Madhow and M. Honig. Mmse interference suppression for direct-squence spread spectrum cdma. *IEEE Trans. on Communication*, 42:3178–3188, December 1994.

[8] U. Madhow. Blind adaptive interference suppression for direct-sequence cdma. *Proceedings of the IEEE*, 86(10):2049–2069, October 1998.

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

[10] X. Zhang and W. Wei. Blind adaptive multiuser detection based on kalman filtering. *IEEE Transactions on Signal Processing*.

[11] S. Wang, J. Caffery, Jr. and H. Shen. Semi-blind decorrelating detection for synchronous cdma. *IEEE Wireless Communications and Networking Conference (WCNC) 2003*, 4:379–384, March 2003.

[12] S. Wang, S. G. Kim, et al. Semi-blind adaptive multiuser detection for asynchronous cdma. In *2005 IEEE International Conference On Electro Information Technology (eit2005)*, Lincoln, Nebraska, May 2005.

[13] S. Wang, S. G. Kim, et al. Blind adaptive multiuser detection. In *IEEE GlobeCom 2005*, St. Louis, Missouri, November 2005.

[14] S. V. Huffel and J. Vandewalle. *The total least squares problem: computational aspects and analysis*, volume 9. Society for Industrial and Applied Mathematics, 1991.

[15] S. Haykin. *Adaptive Filter Theory*. Prentice Hall, 3 edition, 1996.

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