Analysis of A Novel Blind Decision-Feedback Interference Cancellation Framework

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***Abstract*—Interference cancellation is one major multiuser detection strategy for suppressing interference effects and improving system performance. In this paper, a novel blind decision-feedback interference cancellation framework and its implementations with least squares, maximum likelihood and minimum mean squared error criteria are proposed and analyzed. Compared with existing blind multiuser receivers, the proposed framework and schemes require a small number of previous received signals and no subspace separation or sequence estimation. The detection complexity and delay can therefore be low. The proposed schemes can also be implemented in an adaptive fashion. Theoretical analysis as well as computer simulations is provided to demonstrate the performance of the proposed schemes.**

I. Introduction

Interference cancellation (IC) is the strategy for forming an estimate of incurred interference, like intersymbol interference (ISI), co-channel interference (CCI), adjacent channel interference (ACI), etc., and subtracting it from received signals before detection. Though it has intensively been investigated over the last decades, its commercial applications for mitigating multiuser access interference (MAI) in mobile network can only be found in the last serval years [1]. Several IC schemes, such as successive IC and subspace-based IC, have been reported to be implemented for 3G mobile network like cdma2000 and WCDMA [2]. The recent standardizing Femto cell further brought more interests and potential applications of IC techniques [3]. Compared with other detection strategies, IC focuses more on interference estimation. And different interference estimation methods may lead to different IC schemes [4], [5], e.g. successive IC, multistage detection, decision-feedback IC (DFIC) [6], [7], etc. DFIC, including minimum mean squared error (MMSE) DFIC [6] and decorrelating DFIC [7], belongs to the decision-driven schemes that combines features of successive IC and multistage detection [4]. Conventional IC receivers are known to be able to solve the near-far problem with the knowledge of the signature information of all users [4]. However this assumption isn't consistent with many practical situations where the receiver may only know the signatures of the expected signals not interfering signals. Recent research has been devoted to semiblind/blind implementation of IC for the practical applications in which adaptive filter techniques, e.g., Wiener filtering [8], Kalman filtering [9] and subspace-based implementations [10], are among the popular choices.

Decision-feedback techniques, including decision-feedback channel equalization and signal detection, have intensively been discussed since 1960s. In single-user decision-feedback equalization (DFE), previous decision outputs are feeded back for estimating ISI and detecting the next symbol. DFE is known to have the complexity similar to linear equalization while the performance is close to maximum likelihood equalization. In multiuser DFIC, both current and previously received symbols and decision outputs are utilized for detecting desired user(s)'s data [4]. In conventional DFIC [4], other users' current decision outputs as well as their signal signatures are usually used for estimating interference and detecting desired information. In blind DFIC, only received signals and detection outputs of the desired user(s) are available for separating signal subspaces and adapting receiver for better interference estimation [10]. The challenge with existing DFIC receiver design is that neither subspace separation nor receiver adapting procedure is simple and fast enough, especially for fast-fading channels [8], [10], [9].

Conventional multiuser receivers as well as the blind IC receiver with a large number of previously received symbols have been intensively investigated. However, the performance of blind interference cancellation receiver with limited previous knowledge is largely unknown. In order to solve the near-far problem with less prior knowledge, computation complexity and delay [11], [12], we provide an alternative blind DFIC multiuser receiver design framework, in which only a small amount of previous symbols are necessary for estimating interference and detecting next symbols in addition to desired user(s)' signatures and timing. The trick is, instead of signal signature estimation or signal subspace separation, previous symbols are directly taken as the signal space bases, termed *blind signal signatures*, for separating interference from received signals. Thereafter, with different signal estimation criteria including least squares (LS), maximum likelihood (ML) and MMSE, several blind interference cancellers are constructed. It is shown that the proposed framework can be implemented in a adaptive and iterative fashion so that the incurred complexity and detection delay can be further reduced. These make it an attractive framework candidate to design blind interference cancellation receivers for high data rate applications. Theoretical analysis and computer simulations are also presented to demonstrate the performance of these blind detectors. The proposed framework and schemes can easily be extended for asynchronous CDMA too when a truncated-window model is applied [4].

II. System Model And Problem Description

The synchronous transmission in a single-cell DS/CDMA system with K active users is discussed here. The channel is a multiplath channel with P strong paths [1] 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 $E\{|b_k[i]|^2\} = 1$. 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

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

The received signal $\tilde{r}(t)$ is passed through the corresponding chip matched filter (CMF), $\phi(t)$, and RAKE combiner. The combined output $r(t)$ is [2]

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

where

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

is the ISI to user k,

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

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

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

and $\tau_{q1} = \tau_q - \tau_1$ is the propagation delay difference between the 1st path and pth path. $\otimes$ denotes the convolutional product. $n(t) \in \boldsymbol{\mathcal{N}}\left(0,\ \sigma^2\right)$. Furthermore, the user k's RAKE output can be sampled at $f_s = \frac{1}{T_s}$ and expressed by [4]

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

[1]Strong paths are those to be explicitly combined by a RAKE receiver.
[2]We drop the time index n when it refers to the current signal.

where $\mathbf{S} = [\mathbf{s}_1\ \mathbf{s}_2\ \ldots\ \mathbf{s}_K]$ is the actual spreading sequence matrix containing both ISI and MAI and $L = \frac{T}{T_s} \le L_c$ is the number of samples per symbol. Because of the existing of $m_{\text{MAI}}(t)$, conventional matched filter receiver suffers from the so-called near-far problem and IC is one of the receiver techniques for solving this problem [4]. However, most existing IC receivers are designed with the assumption that either the knowledge of the signature information of all user or a large number of previously received signals is available. In following sections, a novel blind IC framework and its implementations are presented.

III. Blind DFIC Framework

Without loss of the generality, the signals for the first G desired users will be detected with the assumption $\mathbf{S}_1 = [\,\mathbf{s}_1 \quad \mathbf{s}_2 \quad \ldots \quad \mathbf{s}_G\,]$ is known beforehand. With (7) and $\mathbf{b} = \left[\mathbf{b}_1^{\mathrm{H}}\ \mathbf{b}_2^{\mathrm{H}}\right]^{\mathrm{T}}$, $\mathbf{b}_1 = [b_1\ \cdots\ b_G]^{\mathrm{H}}$ is the data vector we want to detect and $\mathbf{b}_2 = [b_{G+1}\ \cdots\ b_K]^{\mathrm{T}}$ is the data vector embedded in interference. For estimating the MAI to the first G users, we assemble M previously detected signal symbols $\{\mathbf{r}[n-m]:\ 1 \le m \le M\}$ into

$$\begin{aligned} \boldsymbol{\mathcal{S}} \quad &= \quad \left[\, \mathbf{r}[n-1] \quad \mathbf{r}[n-2] \quad \ldots \quad \mathbf{r}[n-M] \,\right] \\ &= \quad \mathbf{S}_1 \mathbf{A}_1 \mathbf{B}_1 + \mathbf{S}_2 \mathbf{A}_2 \mathbf{B}_2 + \mathbf{N} \\ &= \quad \mathbf{SAB} + \mathbf{N} \end{aligned} \tag{8}$$

where $\mathbf{B}$ is the data matrix for $\boldsymbol{\mathcal{S}}$

$$\mathbf{B} \quad = \quad \begin{bmatrix} \mathbf{B}_1 \\ \mathbf{B}_2 \end{bmatrix}, \tag{9}$$

with $\mathbf{A}_1$, $\mathbf{A}_2$, $\mathbf{B}_1$ and $\mathbf{B}_2$ the amplitude matrices and data matrices for desired users and interfering users, respectively, $\mathbf{S}_2$ is the original interfering signals' signatures, and $\mathbf{N}$ is a Guassian matrix. Obviously the minimum number of received signals a receiver requires for unambiguously identifying the $(K - G)$ interfering users is $M \ge \operatorname{rank}(\mathbf{B}_2) = K - G$. With (8), the interference subspace can be approximated by $\bar{\mathbb{S}}_1 = \operatorname{span}\{\mathbf{s}_m | m = G+1,\ \ldots\ K\} \approx \operatorname{span}\{\boldsymbol{\mathcal{S}} - \mathbf{S}_1 \mathbf{A}_1 \mathbf{B}_1\}$. The MAI can be denoted by

$$\begin{aligned} \mathbf{m} \quad &= \quad \mathbf{S}_2 \mathbf{A}_2 \mathbf{b}_2 \\ &= \quad \big(\boldsymbol{\mathcal{S}} - \mathbf{S}_1 \mathbf{A}_1 \mathbf{B}_1 - \mathbf{N}\big) \mathbf{B}_2^{+} \mathbf{b}_2 \\ &= \quad \boldsymbol{\mathcal{S}} \mathbf{f} - \mathbf{S}_1 \mathbf{D}_1 \mathbf{f} + \tilde{\mathbf{n}} \end{aligned} \tag{10}$$

with $\mathbf{f} = \mathbf{B}_2^{+} \mathbf{b}_2$ the projection of $\mathbf{m}$ onto the interfering subspace of $\mathbf{S}_2 \mathbf{A}_2 \mathbf{B}_2$, $\mathbf{D}_1 = \mathbf{A}_1 \mathbf{B}_1$, $\tilde{\mathbf{n}} = -\mathbf{N} \mathbf{B}_2^{+} \mathbf{b}_2$, and $[\cdot]^{+}$ the general inverse.

With (10), the MAI $\mathbf{m}$ can be estimated providing $\mathbf{f}$ is known. For this, we perform QR-decomposition on $\mathbf{S}_1$ so that [13], [4]

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

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 (10) to get

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

Combining (7), (8) and (12) into

$$\mathbf{Q}_{12}^{\mathrm{H}} \mathbf{r} \quad = \quad \mathbf{Q}_{12}^{\mathrm{H}} \mathbf{S}_1 \mathbf{A}_1 \mathbf{B}_1 + \mathbf{Q}_{12}^{\mathrm{H}} \mathbf{m} + \mathbf{Q}_{12}^{\mathrm{H}} \mathbf{n}\ , \tag{13}$$

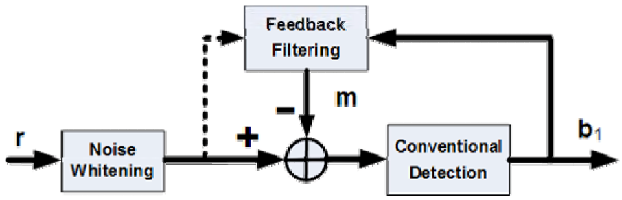

Fig. 1. A decision feedback interference cancellation block diagram

$\mathbf{f}$ can be estimated from

$$\mathbf{Q}_{12}^{\mathrm{H}}\mathbf{r} \quad = \quad \mathbf{Q}_{12}^{\mathrm{H}}\boldsymbol{\mathcal{S}}\mathbf{f}+\mathbf{Q}_{12}^{\mathrm{H}}\bar{\mathbf{n}} \ , \tag{14}$$

where $\bar{\mathbf{n}}=\tilde{\mathbf{n}}+\mathbf{n}$. After $\mathbf{f}$ is estimated, $\mathbf{m}$ can be estimated using (10) 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

$$\mathbf{S}_1\mathbf{d}_1 \quad \approx \quad \mathbf{r}-\left(\boldsymbol{\mathcal{S}}-\mathbf{S}_1\hat{\mathbf{D}}_1\right)\hat{\mathbf{f}} \ , \tag{15}$$

where $\mathbf{d}_1=\mathbf{A}_1\mathbf{b}_1$, $\mathbf{A}_1$ can be simply taken as a scaling vector, $\hat{\mathbf{D}}_1$ denotes previous detection outputs, which can be done using either Viterbi algorithm or other sub-optimal detection schemes, and $\hat{\mathbf{f}}$ denotes an estimate of $\mathbf{f}$. 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 DFIC and shown in Fig. 1.

IV. Blind DFIC Schemes

A. Least Squares Interference Cancellation

In traditional least squares estimations, the observation matrix is assumed to be error-free and all estimation errors are supposed to come from $\mathbf{r}$. This can be formulated by

$$\begin{bmatrix}\mathbf{d}_{1\text{LS}}\\ \mathbf{f}_{\text{LS}}\end{bmatrix} \quad = \quad \arg\min_{\mathbf{x}}\|\mathbf{r}-\mathbf{G}\mathbf{x}\|_2 \tag{16}$$

where

$$\mathbf{G} \quad = \quad [\mathbf{S}_1 \quad (\boldsymbol{\mathcal{S}}-\mathbf{S}_1\mathbf{D}_1)] \ . \tag{17}$$

$\mathbf{d}_1$ as well as $\mathbf{f}$ can therefore be estimated by

$$\begin{bmatrix}\mathbf{d}_{1\text{LS}}\\ \mathbf{f}_{\text{LS}}\end{bmatrix} \quad = \quad \mathbf{G}^{+}\mathbf{r}. \tag{18}$$

Besides the traditional LS assumption, another one is to assume both $\mathbf{G}$ and $\mathbf{r}$ are noise-polluted so that (16) becomes the total least squares (TLS) problem

$$\begin{bmatrix}\mathbf{G}_{\text{TLS}}\\ \begin{bmatrix}\mathbf{d}_{1\text{TLS}}\\ \mathbf{f}_{\text{TLS}}\end{bmatrix}\end{bmatrix} \quad = \quad \arg\min_{\mathbf{Y},\ \mathbf{x}}\left\|\begin{bmatrix}\mathbf{G}\\ \mathbf{r}\end{bmatrix}-\begin{bmatrix}\mathbf{Y}\\ \mathbf{Y}\mathbf{x}\end{bmatrix}\right\|_2 \ . \tag{19}$$

Let $\mathbf{G}=\mathbf{U}^{'}\mathbf{\Sigma}^{'}\mathbf{V}^{'\mathrm{T}}$ and $[\mathbf{G}\ \mathbf{r}]=\mathbf{U}\mathbf{\Sigma}\mathbf{V}^{\mathrm{T}}$ be the SVD of $\mathbf{G}$ and $[\mathbf{G}\ \mathbf{r}]$, respectively. If $\sigma_K^{'}>\sigma_{K+1}$, the TLS estimation of $\mathbf{d}_1$ and $\mathbf{f}$ is

$$\begin{bmatrix}\mathbf{d}_{1\text{TLS}}\\ \mathbf{f}_{\text{TLS}}\end{bmatrix} \quad = \quad \left(\mathbf{G}^{\mathrm{T}}\mathbf{G}-\sigma_{K+1}^2\mathbf{I}\right)^{-1}\mathbf{G}^{\mathrm{T}}\mathbf{r} \ . \tag{20}$$

In reality, either (16) or (19) is not accurate since $\mathbf{S}_1$ is known to be noise-free and $\boldsymbol{\mathcal{S}}$ is noise-corrupted. It is more reasonable to require $\mathbf{S}_1$ to be unperturbed while keep $\boldsymbol{\mathcal{S}}$ estimated. This leads to a mixed least squares (MLS) interference cancellation problem

$$\begin{bmatrix}\boldsymbol{\mathcal{S}}_{\text{MLS}}\\ \begin{bmatrix}\mathbf{d}_1+\hat{\mathbf{D}}_1\mathbf{f}\\ \mathbf{f}\end{bmatrix}\end{bmatrix} = \arg\min_{\mathbf{Z},\ \mathbf{y}}\left\|\begin{bmatrix}\boldsymbol{\mathcal{S}}\\ \mathbf{r}\end{bmatrix}-\begin{bmatrix}\mathbf{Z}\\ [\mathbf{S}_1\ \ \mathbf{Z}]\,\mathbf{y}\end{bmatrix}\right\|_2 \ . \tag{21}$$

If $\sigma_{K-G}^{\prime}>\sigma_{K-G+1}$, the MLS estimation of $\mathbf{f}$ is

$$\mathbf{f}_{\text{MLS}}=\left(\boldsymbol{\mathcal{S}}^{\mathrm{H}}\mathbf{Q}_{12}\mathbf{Q}_{12}^{\mathrm{H}}\boldsymbol{\mathcal{S}}-\sigma_{K-G+1}^2\mathbf{I}\right)^{-1}\boldsymbol{\mathcal{S}}^{\mathrm{H}}\mathbf{Q}_{12}\mathbf{Q}_{12}^{\mathrm{H}}\mathbf{r} \tag{22}$$

where $\sigma_{K-G}^{\prime}$ 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 $\mathbf{d}_{1\text{MLS}}$ can be expressed by

$$\mathbf{d}_{1\text{MLS}} \quad = \quad \mathbf{S}_1^{+}\mathbf{r}-\mathbf{S}_1^{+}\left(\boldsymbol{\mathcal{S}}-\mathbf{S}_1\mathbf{D}_1\right)\mathbf{f}_{\text{MLS}} \tag{23}$$

B. Maximum Likelihood Interference Cancellation

For the linear Gaussian signal model in (15), ML-IC can be written by

$$\begin{bmatrix}\mathbf{d}_{1\text{ML}}\\ \mathbf{f}_{\text{ML}}\end{bmatrix} \quad = \quad \arg\min_{\mathbf{x}}\left\{\delta^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}\delta\right\} \tag{24}$$

where $\delta=\mathbf{r}-\mathbf{G}\mathbf{x}$ is the estimation error vector and $\mathbf{R}_{\bar{\mathbf{n}}}$ is the correlation matrix of $\bar{\mathbf{n}}$ calculated with (34). Therefore the ML estimation of $\mathbf{d}_1$ can be given by

$$\begin{bmatrix}\mathbf{d}_{1\text{ML}}\\ \mathbf{f}_{\text{ML}}\end{bmatrix} \quad = \quad \left(\mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}\mathbf{G}\right)^{-1}\mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}^{-1}\mathbf{r} \ . \tag{25}$$

C. Mini. Mean-Square Error Interference Cancellation

With MMSE criterion, $\mathbf{d}_1$ is estimated with minimizing the Bayesian mean squared error (BMSE) and the MMSE estimation can then be written by

$$\begin{bmatrix}\mathbf{d}_{1\text{MMSE}}\\ \mathbf{f}_{\text{MMSE}}\end{bmatrix} \quad = \quad \arg\min_{\mathbf{x}}\mathrm{E}\,\|\mathbf{r}-\mathbf{G}\mathbf{x}\|_2^2 \tag{26}$$

If $\mathbf{r}$, $\mathbf{d}_1$ and $\mathbf{f}$ are jointly Gaussian, (26) can be solved by

$$\begin{bmatrix}\mathbf{d}_{1\text{MMSE}}\\ \mathbf{f}_{\text{MMSE}}\end{bmatrix} \quad = \quad \left(\mathbf{R}_{\mathbf{x}}+\mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}\mathbf{G}\right)^{-1}\mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}^{-1}\mathbf{r} \tag{27}$$

where

$$\mathbf{R}_{\mathbf{x}} \quad = \quad \mathrm{E}\left\{\begin{bmatrix}\mathbf{d}_1\mathbf{d}_1^{\mathrm{H}} & \mathbf{d}_1\mathbf{f}^{\mathrm{H}}\\ \mathbf{f}\mathbf{d}_1^{\mathrm{H}} & \mathbf{f}\mathbf{f}^{\mathrm{H}}\end{bmatrix}\right\} \ . \tag{28}$$

V. Implementation Considerations

A. Adaptive Detection

When the channel experiences fading, it may be a good idea for the receiver to response fast enough to track this fluctuation. With (8) and (15), it shows that the proposed DFIC framework only requires M previous symbols before the next detection. However, it involves the inverse of $\mathbf{G}^{\mathrm{H}}\mathbf{G}$ in (18), $\mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}\mathbf{G}$ in (25). One of the possible approaches is to follow the well-known Sherman-Morrison-Woodbury matrix inverse lemma [14]. For example, if we define

$$\mathbf{\Phi}[n] \quad = \quad \mathbf{G}^{\mathrm{H}}[n]\mathbf{G}[n] \ , \tag{29}$$

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

$$\mathbf{\Phi}[n+1] \quad = \quad \mathbf{\Phi}[n]+\mathbf{u}[n]\mathbf{u}^{\mathrm{H}}[n] \ . \tag{30}$$

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

$$\mathbf{\Phi}^{-1}[n+1] \quad = \quad \mathbf{\Phi}^{-1}[n] - \frac{\mathbf{\Phi}^{-1}[n]\mathbf{u}[n]\mathbf{u}^{\mathrm{H}}[n]\mathbf{\Phi}^{-1}[n]}{1+\mathbf{u}^{\mathrm{H}}[n]\mathbf{\Phi}^{-1}[n]\mathbf{u}[n]} \ . \quad (31)$$

B. Iterative Detection

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

$$\hat{\mathbf{d}}_1 \quad = \quad \min f\left(\mathbf{r};\ \boldsymbol{\mathcal{S}}, \hat{\mathbf{D}}_1\right) \ , \quad (32)$$

subject to possible constraints, where the $f(\cdot)$ is the objective function. Iterative detection is one the approaches for solving this optimization problem with extending (32) into

$$\hat{\mathbf{d}}_1[n+1] \quad = \quad \min f\left(\mathbf{r};\ [\boldsymbol{\mathcal{S}}\ \mathbf{r}], \left[\hat{\mathbf{D}}_1\ \hat{\mathbf{d}}_1[n]\right]\right) \ . \quad (33)$$

C. Coded Blind Interference Cancellation

In reality, an IC detector will cancel the interfering signal exactly provided that the decision was correct and channel information is known. Otherwise, it may increase the contribution of the interferers. This means that the previous detection results of $\mathbf{D}_1$ play a critical role here. For better interference estimation performance, channel coding/decoding schemes may be applied with detecting $\mathbf{D}_1$ before the next interference estimation and signal detection.

VI. Performance Analysis

A. 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 $L \geq M \geq (K-G)$, previously 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 [8], [10], [9].

B. Noise Enhancement

It is known that there is a noise enhancement issue in LS-based decorrelating detection. With conventional decorrelating detection, the output signal-to-noise ratio (SNR) for user k is decreased by $[\mathbf{R}_{\mathbf{s}}^{+}]_{kk}$. Due to the noise item $\mathbf{N}$ in $\boldsymbol{\mathcal{S}}$, there is an additional noise enhancement in the proposed LS-DFIC. Following Girko's Law, providing $\alpha = \frac{K-G}{M}$ 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, $M \to \infty$ [15]. Therefore the covariance matrix of $\bar{\mathbf{n}}$ can be expressed by

$$\mathbf{R}_{\bar{\mathbf{n}}} \quad = \quad \frac{2M+K-G}{M}\sigma^2\mathbf{I} \ . \quad (34)$$

Since $\frac{2M+K-G}{M}\sigma^2 > \sigma^2$, the receiver output noise is enhanced. This noise enhancement ratio $\beta = \frac{2M+K-G}{M}$ is illustrated in Fig. 2.

C. AME and Near-Far Resistance

A commonly used performance measure for a multiuser detector is asymptotic multiuser efficiency (AME) and NFR [4]. The AME of the proposed schemes is

$$\bar{\eta}_k \quad = \quad \frac{M}{2M+G-K}\left[\mathbf{R}_{\mathbf{s}}^{+}\right]_{kk}^{-1} \ . \quad (35)$$

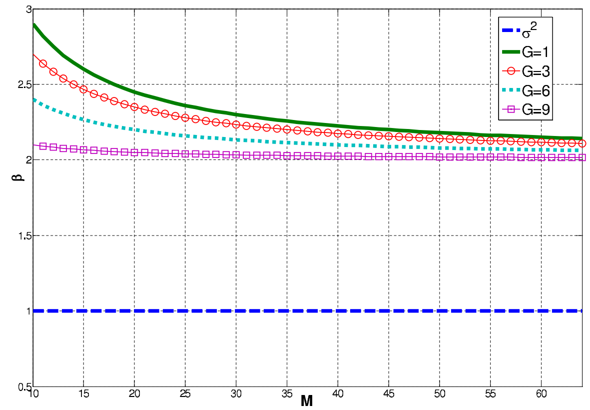

Fig. 2. The noise enhancement, $K = 10$ and $L = 64$.

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 $\phi = \left[\bar{\sigma}^2\ \mathbf{d}_1^{\mathrm{T}}\ \mathbf{f}^{\mathrm{T}}\right]^{\mathrm{T}}$, where $\bar{\sigma}^2 = (1+\frac{M}{M+G-K})\sigma^2$, for computing the FIM

$$\mathbf{I}(\phi) \quad = \quad \mathrm{E}\left\{\left(\frac{\partial \ln \mathcal{L}}{\partial \phi}\right)\left(\frac{\partial \ln \mathcal{L}}{\partial \phi}\right)^{\mathrm{T}}\right\} \quad (36)$$

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

$$\ln \mathcal{L} \quad = \quad C - L\ln\bar{\sigma}^2 - \frac{1}{2\bar{\sigma}^2}\parallel \mathbf{e} \parallel_2^2 \ , \quad (37)$$

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

$$\mathrm{CRLB}\left(\mathbf{x} \mid \boldsymbol{\mathcal{S}},\ \mathbf{D}_1\right) = (1+\frac{M}{M+G-K})\sigma^2\left(\mathbf{G}^{\mathrm{H}}\mathbf{G}\right)^{+} \ . \quad (38)$$

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

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 M amplitude estimates are averaged for the next detection without additional amplitude filtering. From Fig. 3, it shows that the performance of the MMSE interference cancellor is comparable to single-user matched filter (SU-MF) and the decorrelating detector when interfering signal power is small. When the interfering signal power becomes larger, the SU-MF suffers from the near-far issue and BER performance become very bad since its near-far resistance is small. However, the MMSE interference cancellor as well as the LS interference cancellor still works very well with strong near-far resistance. In Fig. 4, the near-far resistance of the proposed interference cancellors is checked with changing interfering signal power. We can see that the both the LS-based and MMSE-based interference cancellors have good resistance to interferences. But compared with the conventional decorrelating detection, these decision-feedback interference cancellors have a higher noise floor. This is also confirmed in the previous analysis.

Table 1. The comparison between 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 approaches, they typically require much more than L signals before their first detection.

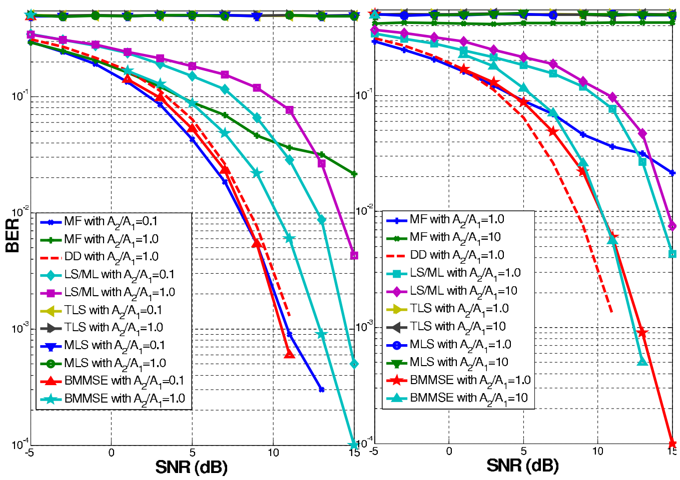

Fig. 3. The performance of the proposed blind DF-ICs against SNR, $G = 3$, $K = 10$ and $M = 40$.

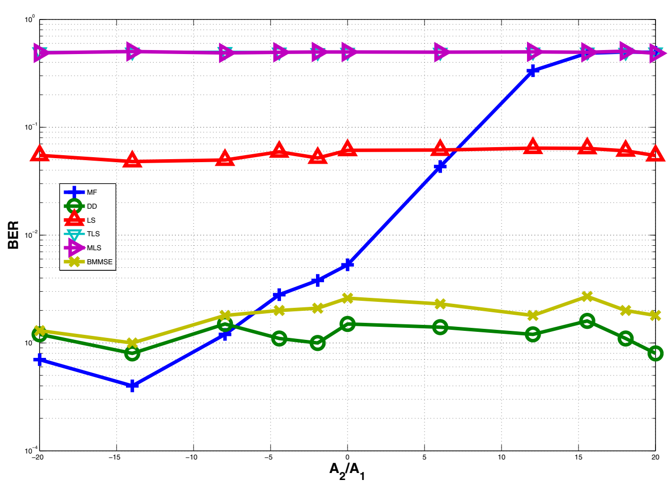

Fig. 4. The near-far resistance performance of the proposed DF-IC, $M = 40$, $K = 2$, $G = 1$ and SNR $= 10$dB.

VIII. Conclusions

In this paper, a blind IC framework and several implementations are presented. They are simple and direct, which require a small amount of previous symbols. Therefore, their implementation complexity and detection delay can be much lower. In addition, its performance in terms of BER, AME, CRLB, etc. is analyzed and compared with existing receiver designs. Some tradeoffs between complexity and performance gain can therefore be revealed.

References

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

[2] S. Wang, et al. Toward forward link interference cancellation. In *CDG Technology Forum*, Burlingame, CA, April 2006.

[3] Airvana. Enhancd cdma2000 support for femto/pico devices. In *3GPP2 TSG-C WG3 C30-20070514-022*, San Diego, California, May 2007.

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

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

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

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

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

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

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

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

[12] S. Wang, et al. Semi-blind adaptive multiuser detection for asynchronous cdma. In *2005 IEEE International Conf. On Electro Info. Tech. (eit2005)*, Lincoln, Nebraska, May 2005.

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

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

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