Blind Decision-Feedback Interference Cancellation: Framework and Implementations

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Abstract—**Interference cancellation is one of the major multiuser detection strategies for suppressing interference effects and improving system performance. In this paper, a novel blind decision-feedback interference cancellation framework and several implementations with least squares, maximum likelihood and minimum mean squared error criteria are proposed for solving the CDMA near-far problem. Compared with existing blind multiuser receivers, the proposed approaches require a minimum number of previous received signals with no subspace separation or sequence estimation. Therefore the detection complexity and delay can be lower, especially when this framework can be adaptively and/or iteratively implemented for further improving detection performance. Theoretical analysis and comparison with existing multiuser receivers as well as 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 incurred interference, like 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 strategy focuses more on interference estimation. And different interference estimation methods may lead to different interference cancellation schemes [1, 2], e.g. successive cancellation, multistage detection, decision-feedback interference cancellation (DFIC) [3, 4], etc. DFIC, including minimum mean squared error (MMSE) DFIC [3] and decorrelating DFIC [4], is the decision-driven detection scheme that combines features of successive interference cancellation and multistage detection [1]. Conventional multiuser receivers including conventional interference cancellation are known to be able to solve the near-far problem with the knowledge of the signature information of all users [1]. 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 interference cancellation as well as other multiuser detectors [5, 6, 7, 8, 9] for the practical applications where only information of desired/known user(s) is available. In existing semiblind/blind implementations, adaptive filter techniques, e.g., Wiener filtering [5], Kalman filtering [7] and subspace-based implementations [6], are among the most 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 close to linear equalization while the performance is close to maximum likelihood equalization. In multiuser DFIC, both current and previous received symbols and decision outputs are utilized for detecting desired user(s)'s data [1]. In conventional DFIC [1], 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/or adapting receiver for better interference estimation [6]. The challenge with most existing DFIC receiver design is that neither subspace separation nor receiver adapting procedure is simple and fast enough for fast-fading channels [5, 6, 7]. In some situations, there even is no enough received coherent signals for training the blind multiuser receivers.

Conventional multiuser receivers as well as the blind interference cancellation receiver with a large number of previously received symbols have been intensively investigated so far. However, the performance of blind interference cancellation receiver with limited previous knowledge is largely unknown. In order to solve the near-far problem with minimum prior knowledge as well as computation complexity and delay [8, 9], we provide an alternative blind DFIC multiuser receiver design framework, in which only a small amount of previous received symbols are required for estimating interference and detecting next symbols in addition to desired user(s)' signatures and timing. The trick is, instead of using previous received symbols for signal signature estimation or signal subspace separation, they are directly taken as 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 cancellation receivers are constructed. It is also shown that the proposed framework can be implemented in adaptive and/or iterative fashion so that the incurred complexity and detection delay can be further reduced. All these make it an attractive candidate to design blind interference cancellation receiver for high data rate systems. Theoretical analysis and comparison and computer simulations are finally presented to demonstrate the performance of these blind detectors. The proposed framework and approaches can easily be extended for asynchronous CDMA too.

II. System Model And Problem Description

The synchronous transmissions 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] and corrupted by additive white Gaussian noise (AWGN). The baseband representation of the received signal due to user k is given by

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

where α_{pk} is the pth path loss of user k's signal, $b_k[n]$ is the nth bit sent by user k. We assume that the $\{b_k[n]\}$ are independent and identically distributed random variables with $E\{b_k[i]\} = 0$ and $E\left\{|b_k[i]|^2\right\} = 1$. The parameters $c_k(t)$ denote the normalized spreading signal waveform of user k during the interval $[0,\ T]$, $0 \leq \tau_1 \leq \tau_2 \leq \ldots \leq \tau_P$, denotes P different transmission delays from the base station to user k and $A_k[n]$ is the received signal amplitude for user k at time $t = nT$, which depends on the possible channel statistics. The total baseband signal received by user k is

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

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

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

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

[2]We drop the time index n in the following discussion when it refers to the current signal.

where

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

is the intersymbol interference (ISI) to user k,

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

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

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

and $\tau_{q1} = \tau_q - \tau_1$ is the propagation delay difference between the 1st path and pth path. $\otimes$ denotes the convolutional product. $n(t)$ is AWGN with variance σ^2. Furthermore, the user k's RAKE output can be sampled at $f_s = \frac{1}{T_s}$ and straightforwardly expressed by [1]

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

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 $L = \frac{T}{T_s}$ 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 and interference cancellation is one of the receiver techniques for solving this problem [1]. However, most existing interference cancellation receivers are designed with the assumption that either the knowledge of the signature information of all user or a large number of previous received signals is available. This assumption isn't consistent with many practical situations where the receiver may only know the signatures of the expected signals not interfering signals. In following sections, a blind interference cancellation framework and several implementation of it are presented with only several previous received signals.

III. Blind Decision-Feedback Interference Cancellation 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 the estimation of the MAI to the first G users, we assemble M previously received and detected signal vectors into

$$\begin{aligned}\boldsymbol{\mathcal{S}} &\triangleq \begin{bmatrix}\mathbf{r}[n-1] & \mathbf{r}[n-2] & \dots & \mathbf{r}[n-M]\end{bmatrix} \\ &= \mathbf{SAB} + \mathbf{N} \\ &= \mathbf{S}_1\mathbf{A}_1\mathbf{B}_1 + \mathbf{S}_2\mathbf{A}_2\mathbf{B}_2 + \mathbf{N}\end{aligned} \tag{8}$$

where $\{\mathbf{r}[n-m] : \ 1 \leq m \leq M\}$ denotes previously received and detected M signals,

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

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, and $\mathbf{N}$ is a AWGN matrix. Obviously the minimum number of received signals a receiver requires for clearly identifying the $(K-G)$ interfering users is $M = K-G$ with $\mathrm{rank}\,(\mathbf{B}_2) = K-G$. With (8), the interference subspace can be approximated by $\bar{\mathbb{S}}_1 \triangleq \mathrm{span}\,\{\mathbf{s}_m | m = G+1, \ \dots \ K\} \approx \mathrm{span}\,\{\boldsymbol{\mathcal{S}} - \mathbf{S}_1\mathbf{A}_1\mathbf{B}_1\}$. And the MAI $\mathbf{m}$ can be rewritten by

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

where $\mathbf{f} \triangleq \mathbf{B}_2^{+}\mathbf{b}_2$ 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 $\tilde{\mathbf{n}} \triangleq -\mathbf{N}\mathbf{B}_2^{+}\mathbf{b}_2$. $[\cdot]^{+}$ denotes the general inverse.

With (10), 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 [10, 1]

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

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

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

Since

$$\mathbf{Q}_{12}^{\mathrm{H}}\mathbf{r} = \mathbf{Q}_{12}^{\mathrm{H}}\mathbf{m} + \mathbf{Q}_{12}^{\mathrm{H}}\mathbf{n} \ , \tag{13}$$

$\mathbf{f}$ can be estimated from

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

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

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

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

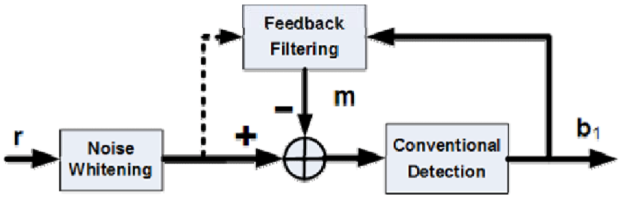

Fig. 1. A decision feedback interference cancellation block diagram

where $\mathbf{d}_1 \triangleq \mathbf{A}_1\mathbf{b}_1$, $\hat{\mathbf{D}}_1$ 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 $\mathbf{f}$.

IV. Blind Decision-Feedback Interference Cancellation Implementations

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

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

where

$$\mathbf{G} = \begin{bmatrix}\mathbf{S}_1 & (\boldsymbol{\mathcal{S}} - \mathbf{S}_1\mathbf{D}_1)\end{bmatrix} \ . \tag{17}$$

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

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

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

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

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

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

It seems that 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 seems that it is more reasonable to require

$\mathbf{S}_1$ to be unperturbed while keep $\boldsymbol{\mathcal{S}}$ estimated. Therefore it leads to a mixed least squares (MLS) interference cancellation problem expressed by

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

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

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

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 $\mathbf{Q}_{12}^{\mathrm{H}}\,[\,\mathbf{r}\quad \boldsymbol{\mathcal{S}}\,]$. The MLS-IC $\mathbf{d}_{1\mathrm{MLS}}$ can be expressed by

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

B. *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 (15), ML-IC can be written by

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

where the estimation error vector

$$\delta \;=\; \mathbf{r} - \mathbf{G}\mathbf{x}\ . \tag{25}$$

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

$$\begin{bmatrix} \mathbf{d}_{1\mathrm{ML}} \\ \mathbf{f}_{\mathrm{ML}} \end{bmatrix} \;=\; \left(\mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}\mathbf{G}\right)^{-1}\mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}^{-1}\mathbf{r}\ . \tag{26}$$

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

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

$$\mathbf{e}_{\mathrm{BMSE}} \;=\; \mathrm{E}\left\| \begin{bmatrix} \hat{\mathbf{d}}_1 \\ \hat{\mathbf{f}} \end{bmatrix} - \begin{bmatrix} \mathbf{d}_1 \\ \mathbf{f} \end{bmatrix} \right\|_2^2 . \tag{27}$$

The MMSE estimation can then be written by

$$\begin{bmatrix} \mathbf{d}_{1\mathrm{MMSE}} \\ \mathbf{f}_{\mathrm{MMSE}} \end{bmatrix} = \arg\min_{\mathbf{x}} \mathrm{E}\left\|\mathbf{r} - \mathbf{G}\mathbf{x}\right\|_2 \tag{28}$$

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

$$\begin{bmatrix} \mathbf{d}_{1\mathrm{MMSE}} \\ \mathbf{f}_{\mathrm{MMSE}} \end{bmatrix} \;=\; \left(\mathbf{R}_{\mathbf{x}} + \mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}\mathbf{G}\right)^{-1}\mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}^{-1}\mathbf{r} \tag{29}$$

where

$$\mathbf{R}_{\mathbf{x}} \;=\; \mathrm{E}\left\{ \begin{bmatrix} \mathbf{d}_1\mathbf{d}_1^{\mathrm{H}} & \mathbf{d}_1\mathbf{f}^{\mathrm{H}} \\ \mathbf{f}\mathbf{d}_1^{\mathrm{H}} & \mathbf{f}\mathbf{f}^{\mathrm{H}} \end{bmatrix} \right\} . \tag{30}$$

V. Implementation Considerations

A. *Adaptive Detection*

When transmitted signals experience channel condition changes, it is better for the receiver to response fast enough to follow this change with minimum adaptive lag. With (8) and (15), it shows that the proposed DFIC framework M previously received symbols for the next detection so that it may be able to track channel fast. Since its implementations typically involve the inverse of $\mathbf{G}^{\mathrm{H}}\mathbf{G}$ in (18), $\mathbf{G}^{\mathrm{H}}\mathbf{R}_{\bar{\mathbf{n}}}\mathbf{G}$ in (26), etc., one of the possible approaches is to follow the well-known Sherman-Morrison-Woodbury matrix inverse lemma [11]. For example, if we define

$$\boldsymbol{\Phi}[n] \;=\; \mathbf{G}^{\mathrm{H}}[n]\mathbf{G}[n]\ , \tag{31}$$

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

$$\boldsymbol{\Phi}[n+1] \;=\; \boldsymbol{\Phi}[n] + \mathbf{u}[n]\mathbf{u}^{\mathrm{H}}[n]\ . \tag{32}$$

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

$$\boldsymbol{\Phi}^{-1}[n+1] = \boldsymbol{\Phi}^{-1}[n] - \frac{\boldsymbol{\Phi}^{-1}[n]\mathbf{u}[n]\mathbf{u}^{\mathrm{H}}[n]\boldsymbol{\Phi}^{-1}[n]}{1+\mathbf{u}^{\mathrm{H}}[n]\boldsymbol{\Phi}^{-1}[n]\mathbf{u}[n]}\ . \tag{33}$$

B. *Iterative Detection*

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

$$\hat{\mathbf{d}}_1 \;=\; \min f\left(\mathbf{r};\ \boldsymbol{\mathcal{S}}, \hat{\mathbf{D}}_1\right)\ , \tag{34}$$

which subject to some possible constraints, where the $f(\cdot)$ is the objective function. Iterative detection is one the approaches for solving this optimization problem. For this, (34) may be extended to

$$\hat{\mathbf{d}}_1 \;=\; \min f\left(\mathbf{r};\ [\boldsymbol{\mathcal{S}}\ \mathbf{r}]\,,\left[\hat{\mathbf{D}}_1\ \hat{\mathbf{d}}_1\right]\right)\ . \tag{35}$$

And one iterative framework for solving (35) can be expressed by

$$\hat{\mathbf{d}}_1[n+1] \;=\; \min f\left(\mathbf{r};\ [\boldsymbol{\mathcal{S}}\ \mathbf{r}]\,,\left[\hat{\mathbf{D}}_1\ \hat{\mathbf{d}}_1[n]\right]\right)\ . \tag{36}$$

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. This can be shown in Fig. V-C.

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.

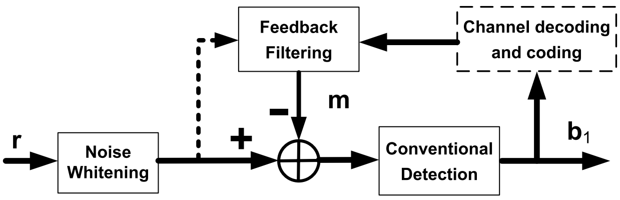

Fig. 2. A coded blind decision feedback interference cancellation

VI. 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 [5, 6, 7].

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 $K, M \rightarrow \infty$ [12]. Therefore the covariance matrix of $\bar{\mathbf{n}}$ can be expressed by

$$\mathbf{R}_{\bar{\mathbf{n}}} = \frac{2M+K-G}{M}\sigma^2\mathbf{I} \ . \tag{37}$$

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. 1.

C. *AME and Near-Far Resistance*

A commonly used performance measure for a multiuser detector is asymptotic multiuser efficiency (AME) and NFR [1]. The AME of the proposed schemes is

$$\bar{\eta}_k = \frac{M}{2M+G-K}\left[\mathbf{R}_{\mathbf{s}}^{+}\right]_{kk}^{-1} \ . \tag{38}$$

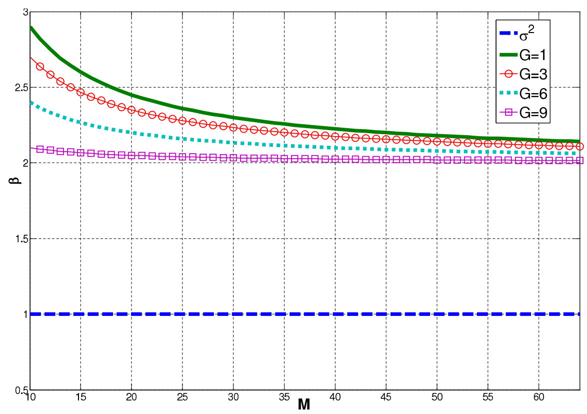

Fig. 3. The noise enhancement, $K = 10$ and $L = 64$.

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

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

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

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

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

$$\mathrm{CRLB}\left(\mathbf{x} \mid \boldsymbol{\mathcal{S}}, \mathbf{D}_1\right) = (1+\frac{M}{M+G-K})\sigma^2\left(\mathbf{G}^{\mathrm{H}}\mathbf{G}\right)^{+} \ . \tag{41}$$

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

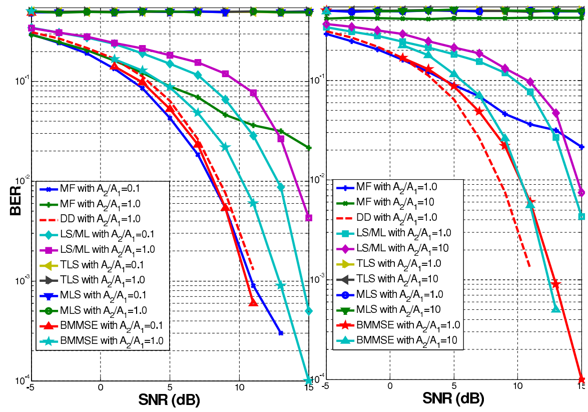

Fig. 4. The performance of the proposed blind DF-ICs against SNR, $G = 3$, $K = 10$ and $M = 40$.

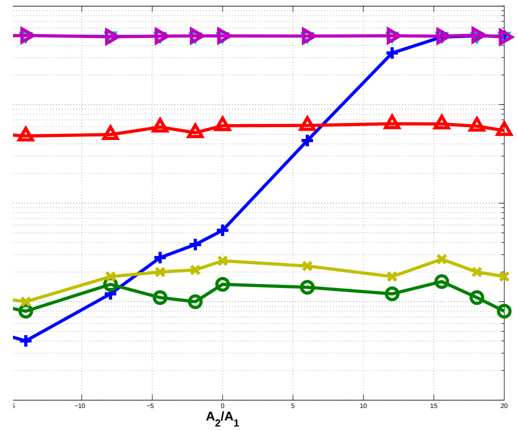

Fig. 5. The near-far resistance performance of the proposed DF-IC, $M = 40$, $K = 2$, $G = 1$ and SNR $= 10$dB.

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.

VIII. Conclusions

In this paper, a blind interference cancellation framework and several implementations of it are presented. They are simple and direct and require a minimum amount of previous received and detected symbols. Therefore, their implementation complexity and detection delay can be much lower, especially when it is implemented in adaptive and iterative fashion. Besides the implementation considerations, we also discussed their performance in terms of BER, AME, CRLB, etc. and compare it with other existing multiuser receiver designs. Some tradeoffs between complexity and performance gain for multiuser receiver design are revealed. Computer simulation results are provided to support our conclusions.

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