Blind Iterative Decision-Feedback Multiuser Detection of FEC-Coded CDMA Signals

Teng Joon Lim, Tao Zhu, and Mehul Motani

Abstract—**This letter proposes a decision-feedback multiuser detector for coded CDMA in which training symbols are not used and hence the detector may be said to be blind. The algorithm proposed builds on the concept of the adaptive decision feedback detectors described in some earlier papers.**

Index Terms—**Code-division multi-access, convolutional coding, iterative decoding, multiuser detection.**

I. Introduction

THE joint detection of a forward error control (FEC) coded multiplex of code-division multiple-access (CDMA) signals has drawn considerable interest in the research literature of late. In particular, the use of the turbo or iterative decoding concept in this context has yielded promising results [1], [5], [6]. Turbo multiuser detection treats the CDMA channel as the inner encoder in a serially concatenated coding scheme, and iteratively updates symbol probabilities using the BCJR algorithm [2] for the outer code (which is usually a convolutional code) and an appropriate multiuser detector for the CDMA "inner code".

A CDMA detector that may be used in iterative multiuser detection is the minimum mean squared error (MMSE) decision feedback detector (DFD) [4], [7]. The DFD is unique in its ability to both suppress out-of-cell interference and cancel in-cell interference using MMSE and decision feedback concepts, and may take the form of a parallel decision feedback detector (P-DFD) or a successive DFD (S-DFD). Its use of the linear MMSE filter as a feed-forward filter ensures that all multiaccess interference (MAI), whether from in-cell or out-of-cell users, is suppressed and the feedback filter cancels any residual MAI due to in-cell users.[1]

In the iterative DFD for coded CDMA systems, we model the decision statistic for the kth user's ith symbol in the mth iteration as

$$y_k^m(i) = A_k^m d_k(i) + \xi_k^m(i) \tag{1}$$

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[1]The terms "in-cell" and "out-of-cell" are used loosely. In-cell users should be understood to mean those users that the receiver is interested in detecting. It should therefore know their spreading codes and channels.

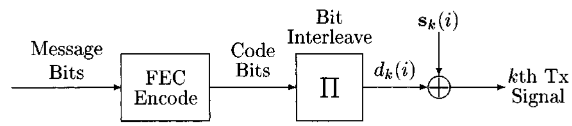

Fig. 1. Baseband block diagram of kth CDMA transmitter, showing the encoding, interleaving and spreading (multiplying with $\mathbf{s}_k(i)$) operations. All users are assumed to use the same code and interleaver and are differentiated only by their spreading sequences.

where A_k^m, the amplitude of the desired component of $y_k^m(i)$, is assumed to be constant throughout one packet transmission time, $d_k(i)$ is the ith coded symbol of the kth user and $\xi_k^m(i)$ is an interference term that is assumed to be Gaussian. The BCJR algorithm requires as an input the probabilities of $d_k(i) = \pm 1$, given the most current information available. Usually, these are assumed to be proportional to the conditional probability densities $p(y_k^m(i)|d_k(i) = \pm 1)$, which are easily computed given the Gaussian assumption on $\xi_k^m(i)$, provided that A_k^m and the variance of $\xi_k^m(i)$ are known. These two values may be estimated through time averages of $d_k^*(i)y_k^m(i)$ and $[y_k^m(i) - A_k^m d_k(i)]^2$ respectively, over the duration of a packet.

Clearly we would need training sequences known at the receiver to obtain the necessary time averages. To overcome this problem, we propose to use the blind minimum output energy (MOE) detector [3] in the first iteration to generate symbol decisions that can replace training symbols, provided the MOE detector outputs are sufficiently accurate.

II. Algorithm Description

A. Basic Idea

A block diagram of the coded CDMA transmitter and the iterative P-DFD are given in Figs. 1 and 2, respectively. In Fig. 2, $\mathbf{F}^m$ and $\mathbf{B}^m$ respectively denote the feedforward and feedback matrix filters in the mth iteration. The receiver works on a packet basis, and the integer $i \in [0, N_p - 1]$, where N_p is the packet length, represents the coded-symbol index. The received signal vector is given by

$$\mathbf{r}(i) = \mathbf{A}\mathbf{d}(i) + \mathbf{n}(i) \tag{2}$$

where $\mathbf{A}$ is the $N \times K$ channel matrix, $\mathbf{d}(i)$ is the vector of symbols contributing to $\mathbf{r}(i)$ and $\mathbf{n}(i)$ is an additive white Gaussian noise vector. In the synchronous case, N is the number of signal samples in one symbol interval, and K the number of users in total.

In the training-based iterative P-DFD, training symbols are needed to estimate A_k^m and $\mathrm{var}(\xi_k^m(i))$. We propose to use

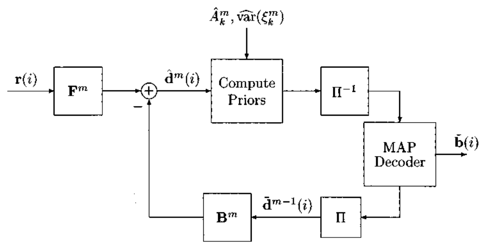

Fig. 2. Structure of the adaptive MMSE iterative P-DFD. The proposed algorithm differs from previous work in the first iteration, when the estimates of A_k^m and $\mathrm{var}(\xi_k^m)$ are obtained blindly through the adaptive MOE multiuser detector instead of using training symbols. $\tilde{\mathbf{b}}(i)$ denotes the hard decisions on the information bits.

the adaptive MOE detector to obtain the first estimates $\hat{A}_k^1$ and $\widehat{\mathrm{var}}\left(\xi_k^1(i)\right)$. The MOE detector produces the vector sequence of decision statistics

$$\hat{\mathbf{d}}^1(i) = [\mathbf{A} + \mathbf{X}(i)]^{\mathrm{H}}\mathbf{r}(i) \tag{3}$$

where $\mathbf{X}(i)$ satisfies the constraint $\mathbf{A}^{\mathrm{H}}\mathbf{X}(i) = \mathbf{0}$ and the kth column of $\mathbf{X}(i)$ is updated in time as [3]

$$\mathbf{x}_k(i+1) = \mathbf{x}_k(i) - \mu z_k^*(i)\mathbf{P}_k\mathbf{r}(i) \tag{4}$$

where $z_k(i) = (\mathbf{a}_k + \mathbf{x}_k(i))^{\mathrm{H}}\mathbf{r}(i)$ is the output of the kth filter at time i, and $\mathbf{P}_k = \mathbf{I} - \mathbf{a}_k\mathbf{a}_k^{\mathrm{H}}$ is the projection matrix for the orthogonal complement of $\mathbf{a}_k$. $\mathbf{a}_k$ is the kth column of $\mathbf{A}$.

Hard decisions based on $\hat{\mathbf{d}}(i)$ are used in estimating A_k^m and the variance of $\xi_k^m(i)$. Alternatively, instead of using (3), the mean value of $\mathbf{X}(i)$ after convergence can be used, i.e.

$$\hat{\mathbf{d}}^1(i) = \left[\mathbf{A} + \bar{\mathbf{X}}\right]^{\mathrm{H}}\mathbf{r}(i) \tag{5}$$

where $\bar{\mathbf{X}} = (1/N_{av})\sum_{i=N_p-N_{av}+1}^{N_p}\mathbf{X}(i)$, and N_{av} is selected so that the algorithm usually converges before $i = N_p - N_{av}$.

We note that (5) fits in the framework of Fig. 2 when $\mathbf{F}^1 = \left[\mathbf{A} + \bar{\mathbf{X}}\right]^{\mathrm{H}}$ and $\mathbf{B}^1 = \mathbf{0}$. In addition, the MOE detector assumes that the spreading codes and channels of all desired users are known at the receiver. If there are undesired users (perhaps from outside the cell), their contributions to $\mathbf{r}(i)$ are lumped into $\mathbf{n}(i)$. As the adaptive MOE detector does not rely on $\mathbf{n}(i)$ being white or Gaussian, this modification to the signal model does not affect the algorithm in a material way.

B. Algorithm Implementation

The iterative P-DFD can be implemented assuming that the soft decisions $\bar{\mathbf{d}}(i)$ that are fed back are equal to $\mathbf{d}(i)$, the transmitted symbols, or otherwise. When $\bar{\mathbf{d}}(i) = \mathbf{d}(i)$, the feedforward and feedback filters $\mathbf{F}$ and $\mathbf{B}$ are computed only once, at the first iteration; when $\bar{\mathbf{d}}(i) \neq \mathbf{d}(i)$, $\mathbf{F}$ and $\mathbf{B}$ in theory changes with each iteration m, as the statistics of the feedback signal $\bar{\mathbf{d}}(i)$ change.

According to [7], the algorithm assuming $\bar{\mathbf{d}}(i) \neq \mathbf{d}(i)$ works better, and therefore we will use that assumption, in which case the proposed blind iterative P-DFD algorithm can be described as follows.

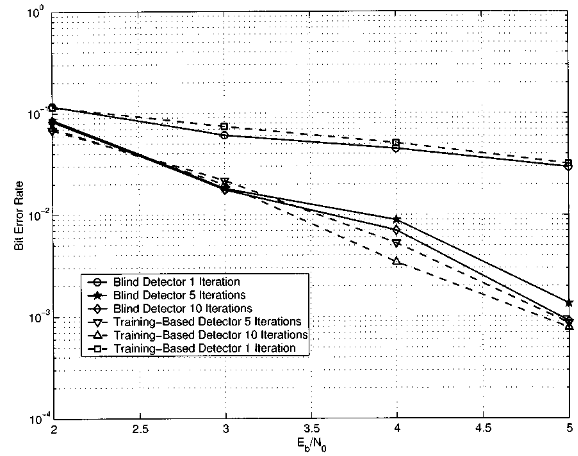

Fig. 3. BER performance comparison for blind detector and training based detector.

In the First Iteration,

1) Run the adaptive MOE algorithm and compute $\bar{\mathbf{X}}$;
2) Form soft decisions $\hat{\mathbf{d}}(i) = [\mathbf{A} + \bar{\mathbf{X}}]^{\mathrm{H}}\mathbf{r}(i)$, and derive hard decisions $\tilde{\mathbf{d}}(i) = \mathrm{dec}[\hat{\mathbf{d}}(i)]$, where $\mathrm{dec}(\cdot)$ denotes the hard decision operation;
3) Using $\tilde{\mathbf{d}}(i)$, $i \in [0, N_p - 1]$, obtain estimates of A_k^1 and $\mathrm{var}\left(\xi_k^1(i)\right)$;
4) Compute priors using Gaussian assumption on $\xi_k^1(i)$, de-interleave the priors and input them to the BCJR algorithm (MAP decoder).

In Subsequent Iterations,

1) Interleave *a posteriori* probabilities (APP's) of coded bits (one of the outputs of the MAP decoder), form soft estimates $\bar{\mathbf{d}}(i)$ from the APP's, and use $\bar{\mathbf{d}}(i)$ to compute necessary time-averaged correlation matrices (see [7]);
2) Compute $\mathbf{F}^m$ and $\mathbf{B}^m$ using correlation matrices just found in step 1 above;
3) Form soft estimates of coded symbols $\hat{\mathbf{d}}(i) = \mathbf{F}\mathbf{r}(i) - \mathbf{B}\bar{\mathbf{d}}(i)$, and hard decisions $\tilde{\mathbf{d}}(i) = \mathrm{dec}\left[\hat{\mathbf{d}}(i)\right]$.
4) Obtain $\hat{A}_k^m$ and $\widehat{\mathrm{var}}\left(\xi_k^m(i)\right)$ from $\tilde{\mathbf{d}}(i)$, compute priors, de-interleave, and input to MAP decoder.

III. Simulations and Conclusions

Simulations were done to compare the performance of the training-based and proposed blind iterative detectors. In the simulations, a total of six users are assumed to be active in an isolated cell. For each user, a $(2, 1, 2)$ convolutional encoder and a random interleaver are used in the transmitter. Random

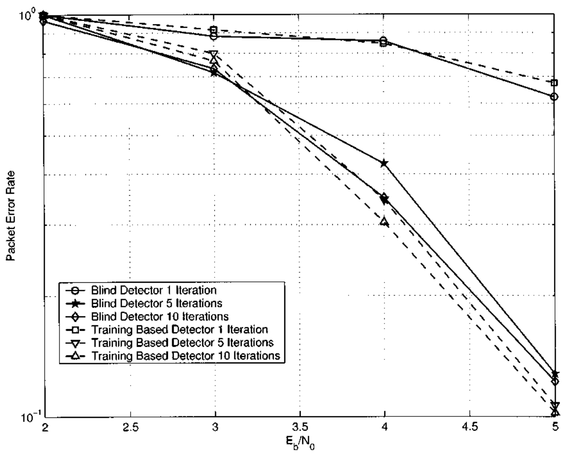

Fig. 4. PER performance comparison for blind detector and training based detector.

Gaussian spreading codes[2] with length 8 are used for all six users. Each uncoded data packet contains 300 symbols. For simulations of the training-based detector, a training sequence containing 200 training bits is inserted into every coded data packet. For the blind detector, $N_{av} = 200$. Simulation results for bit error rate (BER) and packet error rate (PER) performance are shown in Figs. 3 and 4, respectively. (Note: An error packet is defined as a packet containing at least one bit error.)

From the simulation results, we can see that the BER and PER curves for the blind detector are very close to those of the training-based detector. The variations are not more than 0.5 dB for E_b/N_0 in the range of 2–5 dB.

[2]The chip values were taken from an $\mathcal{N}(0,1)$ distribution.

We are uncertain at this point as to the effect of using a more powerful code on BER and PER. Intuitively of course, it should improve performance; however, if total bandwidth expansion is kept constant, using a lower-rate code means lowering the processing gain, which adversely affects the performance of the MOE detector. Whether this reduction in the reliability of thestatistics in the first iteration will offset the gains provided by a lower-rate code is therefore an interesting open question.

In this letter, we have integrated the blind MOE detector into the training-based iterative parallel decision-feedback detector, to create a blind iterative detector for coded CDMA. Simulations show that the blind detector does not suffer any significant performance penalty compared to the training-based one but removes the need to transmit training symbols.

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