EM Channel Estimation and Data Detection for MIMO-CDMA Systems over Slow-Fading Channels

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***Abstract*—In this paper, we present an iterative joint channel estimation and data detection technique for multiple-input multiple-output (MIMO) code-division multiple-access (CDMA) systems over Rayleigh fading channels. The proposed receiver performs the channel estimation and data detection using the expectation-maximization (EM) algorithm. We derive a closed-form expression for the optimized weight coefficients of the EM algorithm which is shown to provide a large performance improvement relative to the conventional equal-weight EM-based signal decomposition. Our results show that the receiver can achieve near-optimum performance with modest complexity using very few training symbols. Furthermore, our simulation results confirm that the proposed receiver is near-far resistant and offers fast convergence in severe near-far scenarios.**

***Index Terms*—Space-time systems, expectation-maximization, code-division multiple-access.**

I. INTRODUCTION

In MIMO CDMA systems, perfect channel knowledge is essential for efficient detection [1]. Compared with single-input single-output (SISO) CDMA systems, channel estimation in MIMO systems becomes even more challenging as the number of simultaneous transmissions and interference levels increase. While the majority of the works in MIMO systems assume perfect channel estimation, relatively few researchers have investigated the effect of channel estimation errors and the possible estimation techniques (e.g., [1], [2] and references therein). Recently, there has been an increasing interest in iterative joint channel estimation and data detection algorithms [3], [4], which take advantage of the detected data symbols in the channel estimation process. Among the iterative techniques, the expectation-maximization (EM) [5] has been considered in iterative receivers for its attractive features such as attaining the maximum likelihood (ML) solution iteratively with reduced complexity [6]. In the MIMO framework, Cozzo and Hughes [7] have proposed a joint detection and estimation (JDE) technique based on the EM algorithm in flat-fading channels with multiple antennas at both the transmitter and receiver. Chun and Ching [4] have also proposed an iterative receiver for a space-time (ST) trellis-coded system in frequency-selective fading channels, where channel estimation and data detection are performed using the EM algorithm. In this paper, we propose a JDE technique based on the EM algorithm for MIMO CDMA systems assuming synchronous transmission over flat-fading channels. We show the benefits of the iterative EM algorithm in terms of its convergence to the optimum ML with lower complexity and resistance to near-far effects. The proposed JDE receiver structure is derived, where we show that it can bring an optimum balance between the single-user matched filter detector and the parallel interference cancellation (PIC) based detector.

The rest of the paper is organized as follows. The system model is described in the following section. In Section III, the EM-based ST receiver is discussed. In Section IV, we derive a closed-form expression for the optimized weight coefficients. Simulation results and discussions are then presented in Section V. Finally, our conclusion is drawn in Section VI.

II. SYSTEM MODEL

Throughout our work, we consider a transmit diversity scheme with N=2 transmit antennas at the mobile user and M multiple receive antennas at the base station. We also consider the original STS scheme proposed in [8] for a synchronous K-user system over slow flat-fading channel. The channel coefficients are, therefore, considered fixed within a block of L codewords where each codeword has a period of $T_s = 2T_b$ and T_b denotes the bit period. The received complex low-pass equivalent signal at the m^{th} receive antenna is given by

$$r^m(t) = \sum_{l=1}^{L}\sum_{k=1}^{K} h_{1m}^k\Big[b_{k1}[l]c_{k1}(t-lT_s)+b_{k2}[l]c_{k2}(t-lT_s)\Big] + h_{2m}^k\Big[b_{k2}[l]c_{k1}(t-lT_s)-b_{k1}[l]c_{k2}(t-lT_s)\Big]+n^m(t), \quad (1)$$

where $b_{k1}[l]$ and $b_{k2}[l]$ are the odd and even data streams of the k^{th} user within the l^{th} codeword interval. The codes $c_{k1}(t)$ and $c_{k2}(t)$ represent the k^{th} user's spreading sequences with processing gain $2N_c$, where $N_c = T_b/T_c$ is the number of chips per bit, and T_c is the chip duration. Based on [8], $c_{k1}(t)$ and $c_{k2}(t)$ are assumed to be orthogonal. However, the effect of cross-correlation among different users on the overall system performance is considered. In (1), h_{im}^k, $i = 1, 2$, is

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the attenuation coefficient corresponding to the k^{th} user from the i^{th} transmit antenna to the m^{th} receive antenna, where $h_{im}^k = \sqrt{\frac{E_k}{2}}\alpha_{im}^k$, α_{im}^k is the corresponding fading channel coefficient and E_k is the k^{th} user transmit energy. These attenuation coefficients are modeled as independent complex Gaussian random variables with zero mean and variance σ_k^2, where $\sigma_k^2 = \frac{E_k}{2}\sigma_h^2$, and σ_h^2=1. The noise $n^m(t)$ is Gaussian with zero mean and variance N_o. At the receiver side, the received signal is passed through a bank of matched filters where the received signal is correlated with the spreading codes assigned to the K users. Let $\mathbf{z}^m(l)$ represent the output vector of the matched filter bank at the m^{th} receive antenna during the l^{th} codeword period. Then we have

$$\mathbf{z}^m(l) = \mathbf{R}\mathbf{B}(l)\mathbf{h}^m + \mathbf{n}^m(l), \tag{2}$$

where $\mathbf{R} = \mathbf{C}^H\mathbf{C}$ is the cross-correlation matrix, $\mathbf{C}$ is an $2N_c \times 2K$ matrix which consists of the users' code sequences defined as $\mathbf{C} = [\mathbf{C}_1, \mathbf{C}_2, \ldots, \mathbf{C}_K]$, with $\mathbf{C}_k = [\mathbf{c}_{k1}, \mathbf{c}_{k2}]$, and H denotes conjugate transpose. In (2), $\mathbf{B}(l)$ represents the users data matrix within the l^{th} period, defined as $\mathbf{B}(l) = diag\{\mathbf{B}_1(l), \mathbf{B}_2(l), \ldots, \mathbf{B}_K(l)\}$, where

$$\mathbf{B}_k(l) = \begin{bmatrix} b_{k1}[l] & b_{k2}[l] \\ b_{k2}[l] & -b_{k1}[l] \end{bmatrix}, k = 1, \ldots, K; l = 1, \ldots, L,$$

and $\mathbf{h}^m$ is a $(2K \times 1)$ channel coefficients vector defined as $\mathbf{h}^m = [\mathbf{h}_1^{mT}, \mathbf{h}_2^{mT}, \ldots, \mathbf{h}_K^{mT}]^T$, where $\mathbf{h}_k^m = [h_{1m}^k, h_{2m}^k]^T$ and T denotes the transpose operation. The channel vector, $\mathbf{h}^m$, is Gaussian distributed with zero mean and covariance matrix $\mathbf{\Sigma}_{hh} = diag\{\sigma_1^2, \sigma_1^2, \sigma_2^2, \sigma_2^2, \ldots, \sigma_K^2, \sigma_K^2\}$. The noise vector, $\mathbf{n}^m(l)$, includes the noise samples at the output of the m^{th} matched filter bank during the l^{th} code period and has a Gaussian distribution with zero mean and covariance matrix $N_o\mathbf{R}$. We assume that $\{\mathbf{C}_k\}, k = 1, \ldots, K$, are selected under the condition that $\mathbf{R}$ is positive definite. Then, $\mathbf{R}$ can be factorized using the Cholesky decomposition to $\mathbf{R} = \mathbf{F}^H\mathbf{F}$, where $\mathbf{F}$ is a unique lower triangular invertible matrix [9]. Multiplying $\mathbf{z}^m(l)$ by $(\mathbf{F}^H)^{-1}$, we obtain

$$\mathbf{y}^m(l) = \mathbf{F}\mathbf{B}(l)\mathbf{h}^m + \mathbf{n}_w^m(l), \tag{3}$$

where $\mathbf{n}_w^m(l)$ is a complex Gaussian vector with zero mean and covariance matrix $N_o\mathbf{I}_{2K}$, and $\mathbf{I}_{2K}$ is an identity matrix of dimension $2K$. Note that both $\mathbf{z}^m(l)$ and $\mathbf{y}^m(l)$ have the same information about the transmitted data. Due to the whitening noise property of (3), our subsequent analysis will be based on $\mathbf{y}^m(l)$.

III. EM-Based ST Receiver

Our subsequent analysis is based on the approach proposed in [10] for the estimation problem of superimposed signals. Using this approach, the observed data is decomposed into their signal components. Then, the parameters of each signal component are estimated separately and iteratively using the EM algorithm. Accordingly, we decompose the whitening filter output, $\mathbf{y}^m(l)$, into a sum of K statistically independent components, i.e., $\mathbf{y}^m(l) = \sum_{k=1}^K \mathbf{g}_k^m(l)$, where $\mathbf{g}_k^m(l) = \mathbf{F}_k\mathbf{B}_k(l)\mathbf{h}_k^m + \mathbf{n}_{wk}^m(l)$, $\mathbf{F}_k$ is a $2K \times 2$ vector including the two columns corresponding to the k^{th} user in the matrix $\mathbf{F}$, $\mathbf{n}_{wk}^m(l)$ is a complex Gaussian vector with zero mean and covariance matrix $\beta_k^m N_o\mathbf{I}_{2K}$ and β_k^m is a non-negative value satisfying the constraint $\sum_{k=1}^K \beta_k^m = 1$. Our goal is to obtain the users' data estimates using the EM algorithm. First, we define the EM algorithm parameters:

1) *Observed data*, $\mathbf{y}$, which includes the outputs of the M whitening matched filters within a frame of L codes, which is given by $\mathbf{y} = [\mathbf{y}^{1T}, \mathbf{y}^{2T}, \ldots, \mathbf{y}^{MT}]^T$ where $\mathbf{y}^m = [\mathbf{y}^m(1)^T, \mathbf{y}^m(2)^T, \ldots, \mathbf{y}^m(L)^T]^T, m = 1, \ldots, M$.
2) *Parameters to be estimated*, $\mathbf{b}$, which includes the transmitted data bits from the K users within the frame period, $\mathbf{b} = [\mathbf{b}_1^T, \mathbf{b}_2^T, \ldots, \mathbf{b}_K^T]^T$, where $\mathbf{b}_k = [\mathbf{b}_k(1)^T, \mathbf{b}_k(2)^T, \ldots, \mathbf{b}_k(L)^T]^T, k = 1, \ldots, K$, and $\mathbf{b}_k(l) = [b_{k1}[l], b_{k2}[l]]^T, l = 1, \ldots, L$.
3) *Complete data*, $\mathbf{G}$: we employ the complete data definition in [11], where the unknown channel coefficient vectors are included as a part of the complete data as follows: $\mathbf{G} = [\mathbf{G}^{1T}, \mathbf{G}^{2T}, \ldots, \mathbf{G}^{MT}]^T$, where $\mathbf{G}^m = [(\mathbf{g}_1^m, \mathbf{h}_1^m), (\mathbf{g}_2^m, \mathbf{h}_2^m), \ldots, (\mathbf{g}_K^m, \mathbf{h}_K^m)], m = 1, \ldots, M$, and $\mathbf{g}_k^m = [\mathbf{g}_k^m(1), \mathbf{g}_k^m(2), \ldots, \mathbf{g}_k^m(L)], k = 1, \ldots, K$.

Since the components of $\mathbf{G}$ given $\mathbf{b}$ are statistically independent, the complete log-likelihood function is given by

$$\Phi(\mathbf{G}|\mathbf{b}) = \sum_{m=1}^M \sum_{k=1}^K \Phi(\mathbf{g}_k^m, \mathbf{h}_k^m|\mathbf{b}_k), \tag{4}$$

where

$$\Phi(\mathbf{g}_k^m, \mathbf{h}_k^m|\mathbf{b}_k) = \Phi(\mathbf{g}_k^m|\mathbf{h}_k^m, \mathbf{b}_k) + \Phi(\mathbf{h}_k^m|\mathbf{b}_k). \tag{5}$$

The second summand in (5) is neglected as it is independent of $\mathbf{b}$. Therefore, (5) is reduced to

$$\Phi(\mathbf{g}_k^m, \mathbf{h}_k^m|\mathbf{b}_k) \propto \sum_{l=1}^L (\mathbf{g}_k^m(l) - \mathbf{F}_k\mathbf{B}_k(l)\mathbf{h}_k^m)^H \times (\mathbf{g}_k^m(l) - \mathbf{F}_k\mathbf{B}_k(l)\mathbf{h}_k^m). \tag{6}$$

By neglecting the terms in (6) which are independent of $\mathbf{b}$, the conditional likelihood in (6) can be simplified to

$$\Phi(\mathbf{g}_k^m, \mathbf{h}_k^m|\mathbf{b}_k) \propto \sum_{l=1}^L Re\{\mathbf{h}_k^{m^H}\mathbf{B}_k(l)\mathbf{F}_k^H\mathbf{g}_k^m(l)\}, \tag{7}$$

where $Re\{\cdot\}$ denotes the real part of the argument. Notice that, due to the orthogonality assumption between the two codes assigned to each user [8], $\mathbf{F}_k^H\mathbf{F}_k$ is reduced to an identity matrix of dimension two, $\mathbf{I}_2$, and consequently $\mathbf{B}_k(l)^H\mathbf{F}_k^H\mathbf{F}_k\mathbf{B}_k(l) = 2\mathbf{I}_2$. At the i^{th} iteration, the E-step of the EM algorithm is implemented by taking the expectation of the complete log-likelihood function defined in (4) with respect to the observed data vector, $\mathbf{y}$, and the current EM data estimates, $\mathbf{b}^i$, i.e.,

$$\mathcal{Q}(\mathbf{b}|\mathbf{b}^i) = \sum_{k=1}^{K} \mathcal{Q}_k(\mathbf{b}_k|\mathbf{b}^i), \tag{8}$$

where $\mathcal{Q}_k(\mathbf{b}_k|\mathbf{b}^i) = \sum_{m=1}^{M} E\left[\Phi(\mathbf{g}_k^m, \mathbf{h}_k^m|\mathbf{b}_k)|\mathbf{y}, \mathbf{b}^i\right]$, and E represents expectation. From (7), the expectation of the individual log-likelihood function is reduced to

$$\mathcal{Q}_k(\mathbf{b}_k|\mathbf{b}^i) = \sum_{m=1}^{M}\sum_{l=1}^{L} Re\left\{E\left[\mathbf{h}_k^{m^H}\mathbf{B}_k(l)\mathbf{F}_k^H\mathbf{g}_k^m(l)|\mathbf{y}, \mathbf{b}^i\right]\right\}. \tag{9}$$

To find the joint conditional expectation in (9), we evaluate $E\left[\mathbf{g}_k^m(l)|\mathbf{y}, \mathbf{b}^i, \mathbf{h}\right]$ where $\mathbf{h} = [\mathbf{h}^1, \mathbf{h}^2, \ldots, \mathbf{h}^M]$. Then the subsequent expression is used to find $E\left[f(\mathbf{h}_k^m)|\mathbf{y}, \mathbf{b}^i\right]$, where $f(\mathbf{h}_k^m)$ denotes the resultant function in $\mathbf{h}_k^m$. By noting that the conditional probability density function, $P\left(\mathbf{g}_k^m(l)|\mathbf{y}, \mathbf{b}^i, \mathbf{h}\right)$, is Gaussian with mean [10]

$$E\left[\mathbf{g}_k^m(l)|\mathbf{y}, \mathbf{b}^i, \mathbf{h}\right] = \mathbf{F}_k\mathbf{B}_k(l)^i\mathbf{h}_k^m + \beta_k^m \times \left(\mathbf{y}^m(l) - \sum_{j=1}^{K}\mathbf{F}_j\mathbf{B}_j(l)^i\mathbf{h}_j^m\right), \tag{10}$$

the conditional expectation of the likelihood function in (9), after some algebraic manipulations, can be expressed as

$$\mathcal{Q}_k(\mathbf{b}_k|\mathbf{b}^i) = \sum_{l=1}^{L} \mathcal{Q}_k(\mathbf{b}_k(l)|\mathbf{b}^i), \tag{11}$$

where

$$\begin{aligned}\mathcal{Q}_k(\mathbf{b}_k(l)|\mathbf{b}^i) = \sum_{m=1}^{M} Re\Big\{&(1-\beta_k^m)\left(a_{11}(l)^i|(h_{1m}^k)^i|^2\right.\\ &+a_{12}(l)^i\left(h_{1m}^k\right)^{i^*}(h_{2m}^k)^i + a_{21}(l)^i\left(h_{2m}^k\right)^{i^*}\left(h_{1m}^k\right)^i\\ &\left.+a_{22}(l)^i|(h_{2m}^k)^i|^2\right) + \beta_k^m\left(\mathbf{h}_k^m\right)^{i^H}\mathbf{B}_k(l)\\ &\times\left(\mathbf{z}_k^m(l) - \sum_{j=1,j\neq k}^{K}\mathbf{R}_{kj}\mathbf{B}_j(l)^i\left(\mathbf{h}_j^m\right)^i\right)\Big\},\end{aligned} \tag{12}$$

$a_{qv}(l)^i, q, v \in \{1, 2\}$, are defined in terms of the current and next data estimates, and $\mathbf{R}_{kj}$ is the 2×2 cross-correlation matrix corresponding to the two spreading codes assigned to user k and j. In (12), the conditional expectation of the attenuation coefficients given $\mathbf{y}$ and $\mathbf{b}^i$ is given by $(h_{qm}^k)^i = E\left[\mathbf{h}^m|\mathbf{y}, \mathbf{b}^i\right]_{2(k-1)+q} = \left[(\mathbf{h}^m)^i\right]_{2(k-1)+q}$, and $(h_{qm}^{k*}h_{vm}^j)^i = (h_{qm}^k)^{i^*}(h_{vm}^j)^i + (\mathbf{\Omega}_{hh}^i)_{2(j-1)+v, 2(k-1)+q}$, where $q, v \in \{1, 2\}$, $k, j \in \{1, \ldots, K\}$ and $\mathbf{\Omega}_{hh}^i = E\left[(\mathbf{h}^m - (\mathbf{h}^m)^i)(\mathbf{h}^m - (\mathbf{h}^m)^i)^H|\mathbf{y}, \mathbf{b}^i\right]$. Similar to [11], we prove that the conditional distribution of the channel vector, $\mathbf{h}^m$, given $\mathbf{y}$ and $\mathbf{b}^i$ is Gaussian with mean $(\mathbf{h}^m)^i = \left(\sum_{l=1}^{L}\mathbf{B}(l)^i\mathbf{R}\mathbf{B}(l)^i + N_o\mathbf{\Sigma}_{hh}^{-1}\right)^{-1}\sum_{l=1}^{L}\mathbf{B}(l)^i\mathbf{z}^m(l)$, and covariance $\mathbf{\Omega}_{hh}^i = \left(N_o^{-1}\sum_{l=1}^{L}\mathbf{B}(l)^i\mathbf{R}\mathbf{B}(l)^i + \mathbf{\Sigma}_{hh}^{-1}\right)^{-1}$. From (8), the M-step of the EM algorithm is performed by maximizing the individual likelihood functions $\mathcal{Q}_k(\mathbf{b}_k|\mathbf{b}^i)$, $k = 1, \ldots, K$, as

$$\mathbf{b}_k^{i+1} = \arg\max_{\mathbf{b}_k}\mathcal{Q}_k(\mathbf{b}_k|\mathbf{b}^i). \tag{13}$$

Furthermore, as the codewords of each user are statistically independent, each component of $\mathbf{b}_k^{i+1}$ can be obtained separately by maximizing the corresponding summand in (11) i.e.,

$$\mathbf{b}_k^{i+1}(l) = \arg\max_{\{b_{k1}(l), b_{k2}(l)\}}\mathcal{Q}_k(\mathbf{b}_k(l)|\mathbf{b}^i). \tag{14}$$

From the likelihood function in (12), we notice that the EM-based ST receiver can be interpreted as follows: the channel coefficients of the K users are estimated based on the observed data, $\mathbf{y}$, and the previous data estimates $\mathbf{b}^i$. The data bits of each user are then detected from (12) based on the balancing weight, β_k^m, between the ST parallel interference cancelation receiver and the ST single-user coherent detector.

IV. Optimized Weights (β_k^m)

From (12), we notice that $Q_k(\mathbf{b}_k(l)|\mathbf{b}^i)$ is a sum of M statistically independent terms given $\mathbf{b}$ and its EM estimate $\mathbf{b}^i$, which are related to the M receive antennas. Since the spatial channels corresponding to the links between the transmit and receive antennas are considered independent, β_k^m can be separately optimized. In this case, we choose the weight coefficients to minimize the linear mean-square error between the true signal vector, $\mathbf{d}_k^m(l) = \mathbf{F}_k\mathbf{B}_k(l)\mathbf{h}_k^m$, and its estimate $(\mathbf{d}_k^m(l))^i = E\left[\mathbf{g}_k^m(l)|\mathbf{y}, \mathbf{b}^i\right]$ as

$$\beta_k^m = \arg\min_{\beta_k^m} E\left[\|\left(\mathbf{d}_k^m(l)\right)^i - \mathbf{d}_k^m(l)\|^2\right], \tag{15}$$

where $\|\cdot\|$ denotes the vector norm. Taking the expectation of (10) with respect to $\mathbf{h}^m$, we have $(\mathbf{d}_k^m(l))^i = \mathbf{F}_k\mathbf{B}_k(l)^i\left(\mathbf{h}_k^m\right)^i + \beta_k^m\left(\mathbf{y}^m(l) - \sum_{j=1}^{K}\mathbf{F}_j\mathbf{B}_j(l)^i\left(\mathbf{h}_j\right)^i\right)$. In order to simplify our analysis, we assume that $\mathbf{n}_w = 0$ and $L \to \infty$. Similar to [11], according to these asymptotic assumptions, the estimate $(\mathbf{h}^m)^i$ is consistent, and it can be considered known at the receiver. It follows that $(\mathbf{d}_k^m(l))^i = \mathbf{F}_k\mathbf{B}_k(l)^i\mathbf{h}_k^m + \beta_k^m\left(\sum_{j=1}^{K}\mathbf{F}_j\left(\mathbf{B}_j(l) - \mathbf{B}_j(l)^i\right)\mathbf{h}_j^m\right)$. Substituting both $\mathbf{d}_k^m(l)$ and $(\mathbf{d}_k^m(l))^i$ in (15) and by removing the terms independent of β_k^m, we have

$$\beta_k^m = \arg \min_{\beta_k^m} \Bigg\{ -2\beta_k^m Re\Bigg\{E\Bigg[\mathbf{h}_k^{m^H}\left(\mathbf{B}_k(l)-\mathbf{B}_k(l)^i\right) \times \sum_{j=1}^{K}\mathbf{R}_{kj}\left(\mathbf{B}_j(l)-\mathbf{B}_j(l)^i\right)\mathbf{h}_j^m\Bigg]\Bigg\} + (\beta_k^m)^2 \times E\Bigg[\Bigg|\Bigg|\sum_{j=1}^{K}\mathbf{F}_j\left(\mathbf{B}_j(l)-\mathbf{B}_j(l)^i\right)\mathbf{h}_j^m\Bigg|\Bigg|^2\Bigg]\Bigg\}. \quad (16)$$

Since

$$E\left[h_{qm}^{k^*}h_{vm}^{j}\right] = \begin{cases} \sigma_k^2, & j=k, q=v \\ 0, & \text{otherwise} \end{cases}$$

where $j,k \in \{1,\ldots,K\}$, and $q,v \in \{1,2\}$, the optimized weight in (16) reduces to

$$\beta_k^m = \arg \min_{\beta_k^m} \Bigg\{ -4\beta_k^m\sigma_k^2 E\Bigg[\bigg(\left(b_{k1}(l)-b_{k1}(l)^i\right)^2 + \left(b_{k2}(l)-b_{k2}(l)^i\right)^2\bigg)\Bigg] + 2\left(\beta_k^m\right)^2 \times\sum_{j=1}^{K}\sigma_j^2 E\left[\left(\left(b_{j1}(l)-b_{j1}(l)^i\right)^2 + \left(b_{j2}(l)-b_{j2}(l)^i\right)^2\right)\right]\Bigg\}. \quad (17)$$

We notice that $E\left[\left(b_{jq}(l)-b_{jq}(l)^i\right)^2\right] = 4P_{e_j}^{m,i}, j = 1,\ldots,k, q=1,2,$ where the probability of error, $P_{e_j}^{m,i} = P\left(b_{j1}(l)\neq b_{j1}(l)^i\right) = P\left(b_{j2}(l)\neq b_{j2}(l)^i\right)$. Consequently, (17) can be expressed as

$$\beta_k^m = \arg\min_{\beta_k^m}\Bigg\{16\left((\beta_k^m)^2-2\beta_k^m\right)\sigma_k^2P_{e_k}^{m,i} + 16(\beta_k^m)^2\sum_{j=1,j\neq k}^{K}\sigma_j^2P_{e_j}^{m,i}\Bigg\}. \quad (18)$$

By differentiating (18) with respect to β_k^m, we obtain the minimum mean-square error (MMSE) optimum balancing weight at the i^{th} EM iteration as

$$(\beta_k^m)^i = \frac{\sigma_k^2P_{e_k}^{m,i}}{\sum_{j=1}^{K}\sigma_j^2P_{e_j}^{m,i}}. \quad (19)$$

Suppose that the performance of the EM-based ST receiver with M=1 receive antenna will converge to the single-user (SU) bound with known channel, given by $P_{e,SU} = Q\left(\sqrt{\frac{2\left(|h_{1m}^k|^2+|h_{2m}^k|^2\right)}{N_o}}\right)$, where $Q(x) = 1/\sqrt{2\pi}\int_x^\infty e^{-x^2/2}dx$. Substituting with the EM channel estimates in the single-user bound, $P_{e,SU}$, we obtain an approximation for $P_{e_k}^{m,i}$, i.e., $P_{e_k}^{m,i} \approx Q\left(\sqrt{\frac{2\left(|(h_{1m}^k)^i|^2+|(h_{2m}^k)^i|^2\right)}{N_o}}\right)$.

The importance of the optimized weight coefficients arises from the fact that it determines the best balance between the single-user matched filter detector and the ST PIC based detector. In the literature, the partial PIC has proven to be near-far resistant where it achieves a performance close to the ML detector [12].

V. Simulation Results

In this section, we examine the bit error rate (BER) performance of the proposed EM-JDE receiver in MIMO CDMA systems. In all cases, we consider a system with two transmit and $M=1,2$ receive antennas. We also consider an uplink synchronous transmission of a data block of 20 codewords (L=20) over a flat-fading channel. Without loss of generality, we consider a 5-user system with the first user as the desired one. A training codeword of two training bits is used for the initialization of the EM receiver. We design the cross-correlation matrix to satisfy the standard form of STS systems [8][13]. Therefore, $\mathbf{R}$ is represented by

$$\mathbf{R} = \begin{bmatrix} \mathbf{R}_{11} & \ldots & \mathbf{R}_{1K} \\ \vdots & \ldots & \vdots \\ \mathbf{R}_{K1} & \ldots & \mathbf{R}_{KK} \end{bmatrix},$$

where

$$\mathbf{R}_{kj} = \begin{bmatrix} \rho^{kj} & 0 \\ 0 & \rho^{kj} \end{bmatrix}, k,j=1,\ldots,K,$$

and

$$\rho^{kj} = \begin{cases} 1 & j=k \\ \rho=0.3 & j\neq k. \end{cases}$$

Without loss of generality, throughout all our simulation results, we consider the average BER of the first user, BER_1. As reference, we include the BER performance of the ST MMSE separate detection and estimation (ST MMSE-SDE) receiver (i.e., where both channel estimation and data detection are implemented separately using the MMSE concept [14]) assuming perfect channel estimation. Fig. 1 presents the BER performance of the proposed ST EM-JDE using 2×1 and 2×2 antenna configuration. As a reference, the results are compared with the BER performance of the SU system assuming unknown channel. The results show that the proposed ST EM-JDE receiver attains the full system diversity.

In Figs. 2 we examine the near-far effect property of the proposed receiver for $M=2$ receive antennas. We fix the received SNR of the first user γ_1 at 8 dB, while the interfering users have equal SNR ratios relative to γ_1, varying from -10 to 60 dB. We also compare the performance of the ST EM-JDE receiver considering optimum β_k^m values (19) and equal β_k^m values ($\beta_k^m = 1/K$). The results show that the EM receiver with optimum β_k^m is near-far resistant. Also when the interference level is high, a reliable estimate of the multiple-access interference (MAI) is obtained and consequently the MAI removal is performed efficiently. On the other hand, the performance of the MMSE-SDE receiver degrades due to noise enhancement. We can notice the effect of β_k^m on the performance of the ST EM-JDE receiver. That is, compared with the case of equal β_k^m, the optimum weights, β_k^m, achieve the best balance between the ST single-user coherent detector and the ST parallel interference cancelation receiver (12).

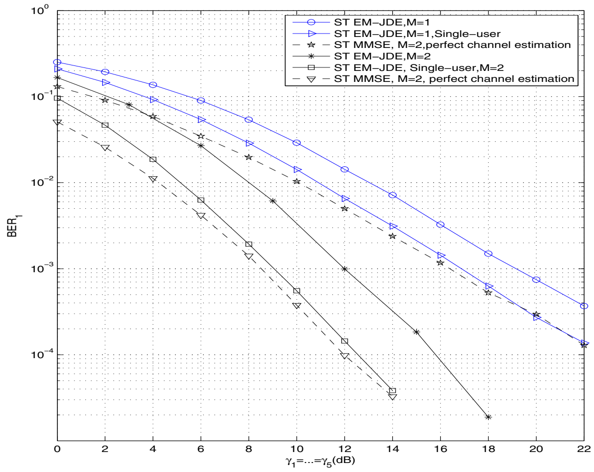

Fig. 1. BER performance for ST EM-JDE receiver with M=1,2 receive antennas, $L = 20, p = 1, \rho = 0.3$, 3 iterations.

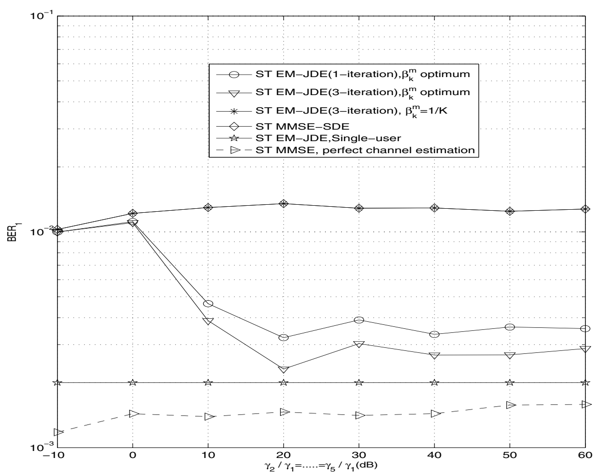

Fig. 2. BER as a function of the MAI level for M=2 receive antennas, $L = 20, p = 1, \rho = 0.3, \gamma_1$=8dB.

VI. Conclusion

We have developed an iterative joint detection and estimation receiver based on the EM algorithm for MIMO CDMA systems. Using Monte-Carlo simulations, we examined the performance of our proposed receiver in flat-fading channels. It was shown that with few training bits, the receiver can attain performance close to the single-user bound in few iterations. We have also shown that the proposed receiver attains the full system diversity through accurate channel estimates.

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