Iterative Joint Data Detection and Channel Estimation for DS-CDMA Systems in the Presence of Time-Varying Channels

Erdal Panayırcı, Hakan Doğan, and Hakan A. Çırpan

***Abstract*—In this paper, we present an efficient iterative receiver structure of computationally tractable complexity for joint multiuser detection and multichannel estimation (JDE) of direct-sequence code-division multiple-access (DS-CDMA) systems operating in the presence of time-varying flat fading channel. The time-varying channel is assumed to be modeled according to a piece-wise constant channel model at the receiver. The scheme results from an application of the expectation-maximization (EM) algorithm. The resulting EM-JDE receiver updates the data bit sequences in parallel while the channel parameters are also updated in parallel. The EM algorithm provides a set of free parameters, called weight coefficients, which can be selected to optimize its performance. An optimality criterion is defined and analytical expressions for the corresponding optimized weight coefficients are given. Monte-Carlo simulations of a synchronous scenario show that the proposed JDE receiver have excellent multiuser efficiency and are robust against errors in the estimation of the channel parameters. Moreover, very short training sequences are required for the JDE schemes to converge.**

I. Introduction

MULTIUSER detection is known to drastically increase the bandwidth efficiency of code-division multiple-access (CDMA) systems compared to conventional detection using RAKE receivers [1]. However, the complexity of the optimum multiuser receiver/detection processing grows exponentially with the number of users and the number of multipaths, which prevents any possibility of implementation [2]. Thus, suboptimum feasible techniques for multiuser detection have been proposed which still approach the performance of the optimum receiver. Worth mentioning among them are linear multiuser detection [3] and iterative cancelation of multiple-access interference (MAI) in the received signal before making a data decision. An overview of suboptimum multiuser detection techniques can be found in [4] and [5]. The expectation-maximization (EM) algorithm [6], [7] is an iterative method which enables approximating the maximum-likelihood (ML) estimate when a direct calculation of this estimate is computationally prohibitive.

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Georghiades and Han proposed an EM-based receiver which performs joint data detection and estimation for the time-variant flat Rayleigh fading channel[8]. Feder and Weinstein apply the EM algorithm to the problem of estimating parameters of superimposed signals [9]. Following this approach, Borran and Nasiri-Kenari develop in [10] a computationally feasible multiuser detector for the AWGN channel. Finally, turbo EM algorithm is used in [11] for maximum likelihood sequence detection and estimation(MLSDE). Kocian and Fluery [12] considered joint data detection and channel estimation of MC-CDMA systems in the presence of flat fading channels. Panayirci at. al. extended their results to the uplink Multicarrier CDMA systems with frequency selective channels[13].

This paper is mainly an extension of the work of Kocian and Fluery to the time-varying channels. The basic assumption in their work was that the channel remains constant over whole the observation frame, which is not actually suitable for the cases requiring high mobility. We extended their results to the problem of joint multiuser data detection and channel estimation (JDE) of synchronous direct-sequence (DS)-CDMA signals in the time-varying flat Rayleigh fading channel. The time-varying channel is assumed to be modeled according to a piece-wise constant channel at the receiver. In this way, we obtain iterative methods of tractable complexity which smartly combine the two processes of data detection and channel estimation. The synchronous assumption and the flat-fading channel model provide a simple framework for studying JDE in the uplink of a DS-CDMA system. The JDE algorithms presented in this paper can also be extended to the asynchronous case and to frequency- selective channels.

The paper is organized as follows. The signal model of DS-CDMA system and the time-varying channel model is outlined in Section II, followed by a concise description of the EM technique is given and is applied to derive the so-called EM-JDE receiver in Section III. This scheme encompasses weight coefficients which can be selected to optimize its performance. An optimality criterion is defined and the corresponding optimum weight coefficients are derived. Finally, in Section sec:4, the performance of the JDE algorithms is assessed and compared to that of the minimum mean-square error (MMSE) [3] by means of MonteCarlo simulations.

Notation: Vectors (matrices) are denoted by boldface lower (upper) case letters; all vectors are column vectors; $(.)^*$, $(.)^T$ and $(.)^\dagger$ denote the conjugate, transpose and conjugate transpose, respectively; $\|.\|$ denotes the Frobenius norm; $\mathbf{I}_L$

denotes the $L \times L$ identity matrix; $diag\{.\}$ denotes a diagonal matrix; $\Re\{\cdot\}$ denotes the real part of $\{\cdot\}$.

II. Signal Model

We consider a synchronous CDMA system with K active user sharing the same propagation channel and the signal transmitted by each user experiences time-varying Rayleigh fading over the observed frame of M symbols. The complex baseband representation of the received signal, therefore, can be expressed as

$$\mathbf{z}(m) = \mathbf{R}\mathbf{B}(m)\mathbf{a}(m) + \mathbf{n}(m),\ m = 0, 1, \cdots, M-1 \quad (1)$$

where $\mathbf{z}(m) = [z_1(m), z_2(m) \cdots, z_K(m)]^T$ denote the complex vector whose components represent K received signals of the K respective users. The $K \times K$ diagonal matrix $\mathbf{B}(m)$ is given by $\mathbf{B}(m) = \text{diag}\{b_1(m), b_2(m) \cdots, b_K(m)\}$, and $b_k \in \{-1, +1\}$, denoting the binary symbols transmitted by user k during the mth signaling interval. The vector $\mathbf{a} = [a_1(0), \cdots, a_1(M-1), \cdots, a_K(0), \cdots, a_K(M-1)]^T$ represents the time-varying frequency-nonselective channel whose components are modeled as complex circularly symmetric Gaussian random variables and $\mathbf{a}(m) = [a_1(m), a_2(m) \cdots, a_K(m)]^T$. The $K \times K$ matrix $\mathbf{R}$ of the form

$$\mathbf{R} \triangleq \begin{bmatrix} 1 & \cdots & \rho_{1k} \\ \vdots & \ddots & \vdots \\ \rho_{k1} & \cdots & 1 \end{bmatrix}$$

with ρ_{jk} being the crosscorrelations between the signature waveforms of user j and k.

While the wireless channel is time-varying frequency-nonselective at the receiver, then it is assumed to be modeled according to a piece-wise constant channel. That is, the channel is assumed to be constant during L consecutive symbols. L is the parameter which may depend on the velocity or the doppler frequency. Thus, the number of channel coefficients to be estimated in an observation frame of M symbols ($M >> L$) is reduced and the quality of the channel estimation algorithm is improved. Following the piece-wise constant channel model, Eq.(1) can be replaced by

$$\mathbf{z}(m) = \mathbf{R}\mathbf{B}(m)\mathbf{a}(\lfloor \frac{m}{L} \rfloor + 1) + \mathbf{n}(m),\ m = 0, 1, \cdots, M-1 \quad (2)$$

where $\lfloor x \rfloor$ denotes the integer which is less than or equal to x. Let $q \triangleq \lfloor \frac{m}{L} \rfloor + 1$ then $\mathbf{a}(q) \triangleq [a_1(q), a_2(q), \cdots, a_K(q)]^T$, $q = 1, 2, \cdots, \Xi$. $\mathbf{a}_k \triangleq [a_k(1), a_k(2), \cdots, a_k(\Xi)]^T$ is the reduced vector of the channel coefficients and the integer Ξ is such that $L\Xi = M$. Finally, $\mathbf{n}(m)$ in (2) is a $K-$dimensional zero-mean Gaussian random vector with covariance matrix $N_0\mathbf{R}$.

In general, the time variation of the channel coefficients can be modeled using an autoregressive(AR)model of order n. For first-order case, the channel coefficients of each user can be expressed as

$$a_k(q) = \gamma_k a_k(q-1) + \epsilon_k(q),\ k = 1,2,\cdots,K;\ q = 1, 2, \cdots, \Xi \quad (3)$$

where γ_k is the time correlation coefficients and $\epsilon_k(q)$ is the additive white Gaussian noise (AWGN) with zero mean and

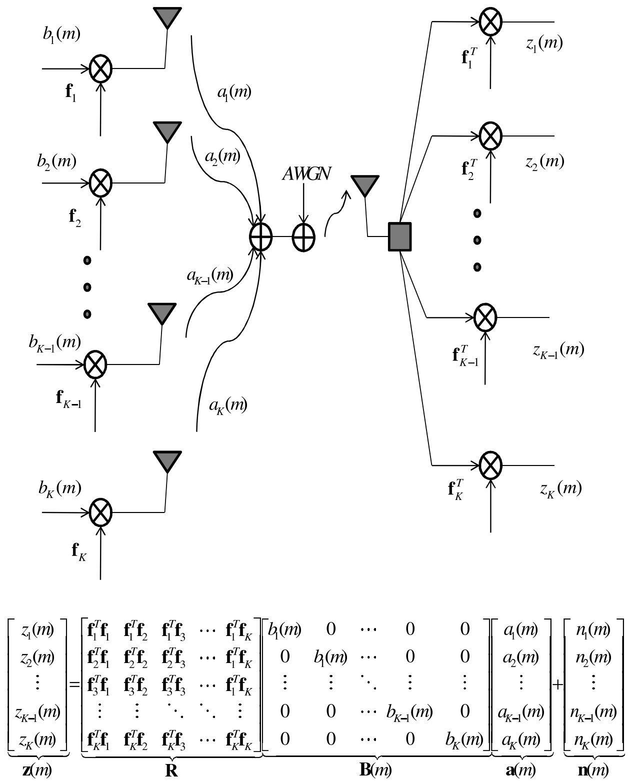

Fig. 1. System Model

variance σ_k^2. The parameter γ_k can be determined based on Jakes' model [16], [18]

$$r_k(q-q') = \sigma_k^2 J_0(2\pi f_d(q-q)), \quad for \quad q, q' = 1, 2, ..., \Xi. \quad (4)$$

where $r_k(q-q')$ is the channel time-frequency covariance function of the kth user for a Doppler power spectrum defined by the zero-order Bessel function of the first kind, $J_0(.)$, and an exponential multipath intensity profile with mean power σ_k^2. Computer simulations performed in Section 4, employ continuously time-varying channel model, and estimated based on the piece-wise constant channel model. Thus, the impact of the model mismatch will be captured.

Now let us assume that the signature waveforms are selected in such a way that the correlation function $\mathbf{R}$ is positive definite. Then $\mathbf{R}$ can be Cholesky factorization according to $\mathbf{R} = \mathbf{F}^T\mathbf{F}$, where $\mathbf{F}$ is a unique lower triangular invertible real matrix. Multiplying $\mathbf{z}(m)$ in (2) by $(\mathbf{F}^T)^{-1}$ yields

$$\begin{aligned} \mathbf{y}(m) &\triangleq (\mathbf{F}^T)^{-1}\mathbf{z}(m) \quad (5) \\ &= \mathbf{F}\mathbf{B}(m)\mathbf{a}(\lfloor \frac{m}{L} \rfloor + 1) + \mathbf{w}(m),\ m = 0, 1, \cdots, M-1. \end{aligned}$$

The complex Gaussian vector $\mathbf{w}(m) = (\mathbf{F}^T)^{-1}\mathbf{n}(m)$ is white, i.e., has covariance matrix $N_0\mathbf{I}_K$ because of Cholesky factorization. We will adopt employing this description of observation model for the subsequent analysis, since the property of the noise vector $\mathbf{w}(m)$ to be white.

The received vector (5) may be expressed in terms of the user's components as follows.

$$\mathbf{y}(m) = \sum_{k=1}^{K} \mathbf{f}_k b_k(m) a_k(\lfloor \frac{m}{L} \rfloor + 1) + \mathbf{w}(m), \quad m = 0,1,..,M-1 \tag{6}$$

where $\mathbf{f}_k$ denotes the kth column of $\mathbf{F}$ and $b_k(m)$ is data sent by the user k within the mth signaling interval. Suppose a frame of $M = L\Xi$ symbols are transmitted. We stack $\mathbf{y}(m)$ as $\mathbf{y} \triangleq [\mathbf{y}_0^T, \mathbf{y}_1^T, \cdots, \mathbf{y}_{L-1}^T]^T$, $\mathbf{y}_i \triangleq [\mathbf{y}^T(i), \mathbf{y}^T(i+L), \cdots, \mathbf{y}^T(i+(\Xi-1)L)]^T, i = 0, 1, \cdots, L-1$.

Then the received signal model can be expressed in more succinct form

$$\mathbf{y} = \mathbf{\Psi a} + \mathbf{w} \tag{7}$$

where $\mathbf{a} = [\mathbf{a}_1^T, \mathbf{a}_2^T \cdots, \mathbf{a}_K^T]^T$, $\mathbf{a}_k = [a_k(1), a_k(2) \cdots, a_k(\Xi)]^T$, $\mathbf{\Psi} = [\mathbf{\Psi}_{i,j}]$ is a $L \times K$ block-matrix whose $K\Xi \times \Xi$-dimensional block matrices are defined as

$$\mathbf{\Psi}_{i,j} = \text{diag}\{b_j(i)\mathbf{f}_j, b_j(L+i)\mathbf{f}_j, \cdots, b_j((\Xi-1)L+i)\mathbf{f}_j\}.$$

and $\mathbf{w}$ is likewise defined as vector $\mathbf{y}$.

III. Joint Data Detection and Channel Estimation with EM Algorithms (EM-JDE)

Let $\mathbf{b}$ denote a possibly vector-valued parameter to be estimated from some possibly vector-valued observation $\mathbf{y}$ with probability density $p(\mathbf{y}|\mathbf{b})$. The EM algorithm provides an iterative scheme to approach the ML estimate $\hat{\mathbf{b}} = \arg\max_{\mathbf{b}} p(\mathbf{y}|\mathbf{b})$ in cases where a direct computation of $\hat{\mathbf{b}}$ is prohibitive. The derivation of the EM algorithm relies on the concept of a hypothetical, so-called complete unobservable data $\boldsymbol{\chi}$ which, if it could be observed, would ease the estimation of $\mathbf{b}$. The observed random variable $\mathbf{y}$ which is referred to as the incomplete data within the EM framework, is related to $\boldsymbol{\chi}$ by a mapping $\boldsymbol{\chi} \mapsto \mathbf{y}(\boldsymbol{\chi})$.

The suitable approach for applying the EM algorithm for the problem at hand is to decompose the received vector in (7) into the sum [9]

$$\mathbf{y}(m) = \sum_{k=1}^{K} \mathbf{x}_k(m), \quad m = 0, 1, \cdots, M-1 \tag{8}$$

where

$$\mathbf{x}_k(m) \;\; = \;\; \mathbf{f}_k b_k(m) a_k(\lfloor \frac{m}{L} \rfloor + 1) + \mathbf{w}_k(m). \tag{9}$$

$\mathbf{x}_k(m)$ represents the received signal component transmitted by the kth user through the channel with its channel parameter $a_k(q), q \triangleq \lfloor \frac{m}{L} \rfloor + 1$. The Gaussian noise vector, $\mathbf{w}_k(m)$ in (9) represents the portion of $\mathbf{w}(m)$ in the decomposition defined by $\sum_{k=1}^{K} \mathbf{w}_k(m) = \mathbf{w}(m)$, whose variance is $N_0\beta_k$. The coefficients β_k determine the part of the noise power of $\mathbf{w}(m)$ assigned to $\mathbf{x}_k(m)$, satisfying $\sum_{k=1}^{K} \beta_k = 1$, $0 \leq \beta_k \leq 1$.

The problem now is to estimate the transmitted symbols $\mathbf{b} = \{b_k(m)\}_{k=1,m=0}^{K,M-1}$ and the complex channel responses $\mathbf{a}_k = [a_k(1), a_k(2), \cdots, a_k(\Xi)]^T$ for each user based on observed data $\mathbf{y}$. In the EM algorithm, we view the observed data $\mathbf{y}$ as the incomplete data, and define the complete data as $\boldsymbol{\chi} = \{(\mathbf{x}_1, \mathbf{a}_1), (\mathbf{x}_2, \mathbf{a}_2), ..., (\mathbf{x}_K, \mathbf{a}_K)\}$ where $\mathbf{x}_k = [x_k(0), ..., x_k(M-1)]^T$ with $M = L\Xi$ and for $k = 1, 2, \cdots, K$. Given the complete data set, the loglikelihood function of the parameter vector to be estimated $\mathbf{b}$ can be expressed as

$$\log p(\boldsymbol{\chi}|\mathbf{b}) = \sum_{k=1}^{K} (\log p(\mathbf{x}_k|\mathbf{b}_k, \mathbf{a}_k) + \log p(\mathbf{a}_k|\mathbf{b}_k)) \tag{10}$$

where, $\mathbf{x}_k = [\mathbf{x}_k^T(0), \mathbf{x}_k^T(1), \cdots, \mathbf{x}_k^T(M-1)]^T$ and $\mathbf{b}_k = [b_k(0), b_k(1), \cdots, b_k(M-1)]^T$. We neglect the $\log p(\mathbf{a}_k|\mathbf{b}_k)$ term in (10) since the data sequence $\mathbf{b}_k$ and $\mathbf{a}_k$ are independent of each other.

Expectation Step (E-Step): The first step to implement the EM algorithm, called the *Expectation Step (E-Step)*, is to compute the average log-likelihood function. The conditional expectation is taken over $\boldsymbol{\chi}$ given the observation $\mathbf{y}$ and that $\mathbf{b}$ equals its estimate calculated at ith iteration.

$$Q\left(\mathbf{b}|\mathbf{b}^{(i)}\right) = E\left\{\log p(\boldsymbol{\chi}|\mathbf{b})|\mathbf{y}, \mathbf{b}^{(i)})\right\} \tag{11}$$

Taking into account the special form of $\log p(\boldsymbol{\chi}|\mathbf{b})$ in (10), Eq. (9) can be decomposed as

$$Q\left(\mathbf{b}|\mathbf{b}^{(i)}\right) = \sum_{k=1}^{K} Q_k(\mathbf{b}_k|\mathbf{b}^{(i)}) \tag{12}$$

where

$$Q_k(\mathbf{b}_k|\mathbf{b}^{(i)}) = E\left\{\log p(\mathbf{x}_k|\mathbf{b}_k, \mathbf{a}_k)|\mathbf{y}, \mathbf{b}^{(i)}\right\}. \tag{13}$$

Note that (13) follows from (10).

Neglecting the terms independent of $\mathbf{b}_k$, from (10), $\log p(\mathbf{x}_k|b_k, \mathbf{a}_k)$ can be calculated as

$$\log p(\mathbf{x}_k|\mathbf{b}_k, \mathbf{a}_k) \sim \sum_{m=0}^{M-1} \Re\{\mathbf{f}_k^T b_k(m) a_k^*(\lfloor \frac{m}{L} \rfloor + 1)\mathbf{x}_k(m)\}. \tag{14}$$

Inserting (14) in (13), we have for $Q_k(\mathbf{b}_k|\mathbf{b}^{(i)})$

$$Q_k(\mathbf{b}_k|\mathbf{b}^{(i)}) = \sum_{m=0}^{M-1} \Re\{\mathbf{f}_k^T b_k(m)(a_k^*(\lfloor \frac{m}{L} \rfloor + 1)\mathbf{x}_k(m))^{(i)}\} \tag{15}$$

where, adopting the notation used in [12],

$$\left(a_k^*(\lfloor \frac{m}{L} \rfloor + 1)\mathbf{x}_k(m)\right)^{(i)} \triangleq E\left\{a_k^*(\lfloor \frac{m}{L} \rfloor + 1)\mathbf{x}_k(m)|\mathbf{y}, \mathbf{b}^{(i)}\right\}. \tag{16}$$

The above expectation can be calculated by applying the conditional expectation rule as

$$\left(a_k^*(\lfloor \frac{m}{L} \rfloor + 1)\mathbf{x}_k(m)\right)^{(i)} = E\{a_k^*(\lfloor \frac{m}{L} \rfloor + 1) E(\mathbf{x}_k(m)|\mathbf{y}, \mathbf{b}^{(i)}, \mathbf{a})|\mathbf{y}, \mathbf{b}^{(i)}\}$$

From (9) it follows that the conditional distribution of $\mathbf{x}_k(m)$ given $\mathbf{y}$, $\mathbf{a}$ and $\mathbf{b} = \mathbf{b}^{(i)}$ is Gaussian with mean

$$E(\mathbf{x}_k(m)|\mathbf{y}, \mathbf{b}^{(i)}, \mathbf{a}) = \mathbf{f}_k b_k^{(i)}(m) a_k(\lfloor \frac{m}{L} \rfloor + 1) \tag{17}$$

$$+\beta_k \left(\mathbf{y}(m) - \sum_{j=1}^{K} \mathbf{f}_j b_j^{(i)}(m) a_j(\lfloor \frac{m}{L} \rfloor + 1)\right)$$

where $b_k^{(i)}(m) \triangleq E(b_k(m)|\mathbf{y}, \mathbf{b}^{(i)}, \mathbf{a})$. Inserting (17) in (17), rewrite (13) can be written as

$$\begin{aligned}(a_k^*(\lfloor\frac{m}{L}\rfloor+1)\mathbf{x}_k(m))^{(i)} = \\ \mathbf{f}_k b_k^{(i)}(m) E\{|a_k(\lfloor\frac{m}{L}\rfloor+1)|^2|\mathbf{y},\mathbf{b}^{(i)}\} \quad (18)\\ +\beta_k\Bigg[E\{a_k^*(\lfloor\frac{m}{L}\rfloor+1)|\mathbf{y},\mathbf{b}^{(i)}\}\mathbf{y}(m) \\ -\sum_{j=1}^{K}\mathbf{f}_j b_j^{(i)}(m)E\{a_j(\lfloor\frac{m}{L}\rfloor+1)a_k^*(\lfloor\frac{m}{L}\rfloor+1)|\mathbf{y},\mathbf{b}^{(i)}\}\Bigg].\end{aligned}$$

The prior pdf of $\mathbf{a} = [\mathbf{a}_1^T, \mathbf{a}_2^T, \cdots, \mathbf{a}_K^T]^T$ is Gaussian and can be expressed as

$$p(\mathbf{a}) \sim \exp\left[-(\mathbf{a}-\mathbf{m})^\dagger\mathbf{C}^{-1}(\mathbf{a}-\mathbf{m})\right] \quad (19)$$

where mean and covariance are $\mathbf{m}\triangleq[\mathbf{m}_1^T, \mathbf{m}_2^T, \cdots, \mathbf{m}_K^T]^T$ and $\mathbf{C}^{-1} = \text{diag}\{\mathbf{C}_1^{-1}, \mathbf{C}_2^{-1}, \cdots \mathbf{C}_K^{-1}\}$ respectively.

Furthermore, since $\mathbf{w} \sim N(0, N_0\mathbf{I})$ form (7) the conditional pdf of $\mathbf{a}$ given $\mathbf{y}$ and $\mathbf{b}^{(i)}$ can be written as follows

$$\begin{aligned}p(\mathbf{a}|\mathbf{y},\mathbf{b}^{(i)}) &\sim p(\mathbf{y}|\mathbf{a},\mathbf{b}^{(i)})p(\mathbf{a}) \\ &\sim \exp\Bigg[-\frac{1}{N_0}(\mathbf{y}-\mathbf{\Psi}^{(i)}\mathbf{a})^\dagger(\mathbf{y}-\mathbf{\Psi}^{(i)}\mathbf{a}) - \\ &\qquad (\mathbf{a}-\mathbf{m})^\dagger\mathbf{C}^{-1}(\mathbf{a}-\mathbf{m})\Bigg].\end{aligned}$$

After some algebra it can be shown that

$$p(\mathbf{a}|\mathbf{y},\mathbf{b}^{(i)}) \sim N(\boldsymbol{\mu}^{(i)}, \mathbf{\Sigma}^{(i)}) \quad (20)$$

where

$$\begin{aligned}\boldsymbol{\mu}^{(i)} &= \mathbf{\Sigma}^{(i)}\left[\mathbf{C}^{-1}\mathbf{m}+\frac{1}{N_0}\mathbf{\Psi}^{(i)\dagger}\mathbf{y}\right] \\ \mathbf{\Sigma}^{(i)} &= \left[\mathbf{C}^{-1}+\frac{1}{N_0}(\mathbf{\Psi}^{(i)})^\dagger\mathbf{\Psi}^{(i)}\right]^{-1} \quad (21)\end{aligned}$$

and the matrix $\mathbf{\Psi}^{(i)}$ is defined in (7). Assuming the channel variations follow an AR model of order 1, elements of (22) can be calculated as given Appendix 1.

Note that $K\Xi \times 1$ vector $\boldsymbol{\mu}^{(i)}$ and $K\Xi \times K\Xi$ matrix $\mathbf{\Sigma}^{(i)}$ in (21) may be expressed as in terms of subblock vectors and matrices corresponding to each user as

$$\boldsymbol{\mu}^{(i)} = \left[\left(\boldsymbol{\mu}_1^{(i)}\right)^T, \left(\boldsymbol{\mu}_2^{(i)}\right)^T, \cdots, \left(\boldsymbol{\mu}_K^{(i)}\right)^T\right], \ \mathbf{\Sigma}^{(i)} = \left[\mathbf{\Sigma}_{k,l}^{(i)}\right]_{k,l=1}^{K} \quad (22)$$

where $\boldsymbol{\mu}_k^{(i)} = \boldsymbol{\mu}_k^{(i)}[q], \ q = 1, 2, \cdots, \Xi$, and $\mathbf{\Sigma}_{k,l}^{(i)} = \mathbf{\Sigma}_{k,l}^{(i)}[p,q], \ p, q = 1, 2, \cdots, \Xi$.

Now let us compute the expectations on the right hand side of Eq. (18). For notational simplicity define $q \triangleq (\lfloor\frac{m}{L}\rfloor+1)$, $m = 1, 2, \cdots, M = L\Xi$.

$$\begin{aligned}a_k^{(i)}(q) &\triangleq E(a_k(q)|\mathbf{y},\mathbf{b}^{(i)}) = \boldsymbol{\mu}_k^{(i)}[q] \\ (|\ a_k(q)\ |^2)^{(i)} &\triangleq E(a_k(q)a_k^*(q)|\mathbf{y},\mathbf{b}^{(i)}) \\ &= \mathbf{\Sigma}_{k,k}^{(i)}[q,q]+\boldsymbol{\mu}_k^{(i)}[q](\boldsymbol{\mu}_k^{(i)}[q])^* \\ (a_k^*(q)a_j(q))^{(i)} &= E\{(a_k^*(q)a_j(q)|\mathbf{y},\mathbf{b}^{(i)}\} \\ &= \mathbf{\Sigma}_{k,j}^{(i)}[q,q]+\boldsymbol{\mu}_j^{(i)}[q](\boldsymbol{\mu}_k^{(i)}[q])^*. \quad (23)\end{aligned}$$

Maximization-Step(M-Step): From (11) and (12), the second step to implement the EM algorithm is the *M-Step* where the parameter $\mathbf{b}$ is updated at the $(i+1)$th iteration according to

$$\mathbf{b}^{(i+1)} = \arg\max_{\mathbf{b}} Q(\mathbf{b}|\mathbf{b}_i) = \sum_{k=1}^{K} Q_k(\mathbf{b}_k|\mathbf{b}^{(i)}). \quad (24)$$

M-Step can be performed by maximizing the terms $Q_k(\mathbf{b}_k|\mathbf{b}^{(i)})$ individually in (24), as follows

$$\mathbf{b}_k^{(i+1)} = \arg\max_{\mathbf{b}_k} Q_k(\mathbf{b}_k|\mathbf{b}^{(i)}) \quad (25)$$

where from (15)

$$Q_k(\mathbf{b}_k|\mathbf{b}^i) = \sum_{m=0}^{M-1} b_k(m)\Re\{\mathbf{f}_k^T((a_k^*(\lfloor\frac{m}{L}\rfloor+1)\mathbf{x}_k(m))^{(i)}\}. \quad (26)$$

Moreover, when no coding is used, since $b_k(m)$ are independent of each other, it follows from (25) that each component of $\mathbf{b}_k^{(i+1)}$ can be separately obtained by maximizing the corresponding summation in the right-hand expression, as follows

$$b_k^{(i+1)}(m) = \text{sgn}\left[\Re\{\mathbf{f}_k^T(a_k^*(\lfloor\frac{m}{L}\rfloor+1)\mathbf{x}_k(m))^{(i)}\}\right] \quad (27)$$

where the term $((a_k^*(\lfloor\frac{m}{L}\rfloor+1)\mathbf{x}_k(m))^{(i)}$ has been previously obtained in (18) and sgn(.) denotes the signum function. Note that it was shown in [12] that for large observations frame M, the first term in (23) is negligible compared to the second one. By using this property and substituting (18) into (27), along with (23) we obtain

$$\begin{aligned}b_k^{i+1}(m) = \text{sgn}\Bigg[\Re\Bigg\{&b_k^{(i)}(m)|a_k(\lfloor\frac{m}{L}\rfloor+1)|^2)^{(i)}(1-\beta_k) \\ &+\beta_k\left(a_k^*(\lfloor\frac{m}{L}\rfloor+1)\right)^{(i)} \\ &\left[z_k(m)-\sum_{j=1,j\neq k}^{K}\rho_{kj}b_j^{(i)}(m)\left(a_j(\lfloor\frac{m}{L}\rfloor+1)\right)^{(i)}\right]\Bigg\}\Bigg]. \quad (28)\end{aligned}$$

where $z_k(m) = \mathbf{f}_k^T\mathbf{y}(m)$ and $a_k(\lfloor\frac{m}{L}\rfloor+1)^{(i)}$ shows estimate of the time varying channel. Estimate of channel is obtained by (22) after initialization which is explained in the next section.

As a conclusion, Equation (28) can be interpreted as joint channel estimation and data detection with partial interference cancelation. At each iteration step during data detection, the interference reduced signal is fed into a single user receiver consisting of a conventional coherent detector. As a result, a K-user optimization problem has been decomposed into K independent optimization problems which can be resolved in a computationally feasible way. Finally we remark that this paper is an extension of the work [12] to the problem of joint channel estimation and data detection for the uplink multicarrier DS-CDMA systems operating in the presence of the time -varying channels. In [12] the same problem is investigated for DS-CDMA systems in the presence of flat fading channels.

A. Initialization

The initial under sampled MMSE channel estimation has been evaluated based on pilot symbols. The corresponding pilot symbols positions, $p_1, ..., p_p$ are regularly distributed over frame length M starting with $p_1 = 1$ and ending with $p_p = M$. The remaining channel coefficients are obtained using linear interpolation. Initial MMSE estimate of $\mathbf{B}(m)$ data bits is computed from the observation of $\mathbf{z}(m)$ while assuming the channel coefficients have already been estimated. We refer to this method for obtaining $\mathbf{a}(m)$ and $\mathbf{B}(m)$ as MMSE separate detection and estimation (MMSE-SDE) scheme.

B. Optimal Selection of $\beta_k' s$

In usual parameter estimation problems in the presence of superimposed signals it has been shown that the optimal values of the coefficients β_k's are chosen as equal weights that is $\beta_k = 1/K$ [9]. However, the equally selected weights will not be optimal when the received SNR's of each of the K users are not equal to each other and if there is some correlations between the super imposed signals, as the case we consider in our work. The optimal β values can be determined in this case so as to minimize the bit-error probability as the number of iterations i goes to infinity. Since this is a mathematically intractable nonlinear optimization problem we will adopt a more manageable yet a suboptimal approach presented by Kocian and Fluery [12] and extend their method for the case when each user is affected by a different flat-fading, time-varying channel. As pointed out in [12], a tractable way to determine the optimal coefficients of all the users $\boldsymbol{\beta} = [\beta_1, \beta_2, \cdots, \beta_K]^T$ is to minimize the total linear mean-squared error between the true signal components $\mathbf{s}_k(m) = \mathbf{f}_k b_k(m) a_k(\lfloor \frac{m}{L} \rfloor + 1)$ and their estimated values at the ith iteration $\mathbf{s}_k^{(i)}(m) \triangleq E\left\{\mathbf{x}_k(m)|\mathbf{y}, \mathbf{b}^{(i)}\right\}$ for $k = 1, 2, \cdots, K$, after projected on $\mathbf{f}_k$. That is

$$\boldsymbol{\beta}_{k,opt}^{(i)} \triangleq \arg\min_{\beta_k} E\left\{\| \ \mathbf{f}_k^T \left(\mathbf{s}_k^{(i)}(m) - \mathbf{s}_k(m)\right) \|^2\right\}. \quad (29)$$

From (17) it follows that

$$\mathbf{s}_k^{(i)}(m) = \mathbf{f}_k b_k^{(i)}(m) a_k^{(i)}(\lfloor \frac{m}{L} \rfloor) + \beta_k \left(\mathbf{y}(m) - \sum_{j=1}^{K} \mathbf{f}_j b_j^{(i)}(m) a_j^{(i)}(\lfloor \frac{m}{L} \rfloor)\right). \quad (30)$$

Substituting (9) in (30), assuming $\mathbf{w}(m) \approx 0$ [17], and taking into account the fact that the channel is asymptotically known, that is $a_k^{(i)}(\lfloor \frac{m}{L} \rfloor) \rightarrow a_k(\lfloor \frac{m}{L} \rfloor)$ as $i \rightarrow +\infty$, the terms on the left hand side of (30) can be expressed as

$$\mathbf{f}_k^T \mathbf{s}_k^{(i)}(m) = b_k^{(i)}(m) a_k(\lfloor \frac{m}{L} \rfloor) \beta_k \sum_{j=1}^{K} \rho_{kj} a_j(\lfloor \frac{m}{L} \rfloor) \left(b_j(m) - b_k^{(j)}(m)\right) \quad (31)$$

where $\rho_{kj} \triangleq \mathbf{f}_k^T \mathbf{f}_j$. Substituting (30) and (31) in (29) and after some algebra yields

$$\boldsymbol{\beta}_{k,opt}^{(i)} = (-2\beta_k + \beta_k^2) E\left\{|a_k(\lfloor \frac{m}{L} \rfloor)|^2 \mid b_k(m) - b_k^{(i)}(m) \mid^2\right\} + \beta_k^2 \sum_{j \neq k} \rho_{kj} E\left\{|a_j(\lfloor \frac{m}{L} \rfloor)|^2 \mid b_j(m) - b_j^{(i)}(m) \mid^2\right\} \quad (32)$$

The expectations above can be evaluated as follows.

$$E\left\{|a_k(\lfloor \frac{m}{L} \rfloor)|^2 \mid b_k(m) - b_k^{(i)}(m) \mid^2\right\} = \sigma_k^2(q)\left[1 - \Re\{b_k(m) b_k^{(i)}(m)\}\right] = \sigma_k^2(q) P_{b,j}^{(i)}(q) \quad (33)$$

where $P_{b,j}^{(i)}(q) \triangleq$ Prob $\left[b_j^{(i)}(m) \neq b_j(m)\right]$ and from (ref29), $\sigma_k^2(q) \triangleq \mathbf{\Sigma}_{k,k}^{(i)}[q,q] + \boldsymbol{\mu}_k^{(i)}[q](\boldsymbol{\mu}_k^{(i)}[q])^*$. Differentiating (33) with respect to $\beta_k, k = 1, 2, \cdots, K$, equating the resulting equations to zero and solving for β_k's we have

$$\beta_{k,opt}^{(i)} = \frac{\sigma_k^2(q) P_{b,k}^{(i)}(q)}{\sum_{j=1}^{K} \rho_{kj}^2 \sigma_j^2(q) P_{b,j}^{(i)}(q)}, \quad 0 \leq \beta_{k,opt}^{(i)} \leq 1. \quad (34)$$

It can be seen from (34) that $\beta_{k,opt}^{(i)}$ is depend on the the time index $q = (\lfloor \frac{m}{L} \rfloor + 1), m = 1, 2, \cdots, M = \Xi L$, since channel coefficients are time-varying over the entire observation frame length M. In the case of $\rho_{kj} = 0$, the interferences caused by other users can be fully eliminated and the best performance corresponding to a single user detector performance can be achieved. The bit-error probability $P_{b,j}^{(i)}(q)$ can be evaluated by assuming the performance of the multiuser detector is close to a single user detector performance.

In this case $P_{b,j}^{(i)}(q) \approx Q(\sqrt{2|a_j^{(i)}(q)|^2/\sigma^2})$ where $Q(.)$ is the error function defined by $Q(x) = 1/\sqrt{2\pi} \int_x^\infty e^{-t^2/2} dt$.

It follows from (34) that the coefficients $\{\beta_{k,opt}^{(i)}\}_{k=1}^K$ are not equal to each other as will be seen in the computer simulations, the BER performance of each user is better than the case if these coefficients were selected to be equal to each other.

IV. Simulations

In this section, performance of an uplink DS-CDMA system based on the proposed receiver operating over time-varying channels is investigated by Monte Carlo simulations. The system parameters are chosen as follows: Number of users $K = 8$, number of pilot symbols $p = 4$, frame length $M = 40$, $T_s = 136 \times 10^{-6}$,and equal cross-correlation coefficients $\rho_{k,k'} = 0.4, k, k' = 1, ..., 8, k \neq k'$.

We investigate here two different pilot insertion scenarios to asses performance. The EM-JDE algorithm was proposed for static channels by [12] for DS-CDMA systems. Therefore, the first scenario are comparable to those used in [12] and pilot symbols are inserted at the head of the frame. In Fig.2, to demonstrate the performance degradation of the EM-JDE algorithm employing static channel model in case of using time-varying channels, three iterations have been carried out. Bit error rate (BER) performances as function of bit energy to noise power density ratio (E_b/N_0) were obtained for f_d=0Hz, f_d=25Hz and f_d=50Hz Doppler shifts. It was observed that proposed EM-JDE in [12] outperforms MSE-SDE for f_d=0Hz

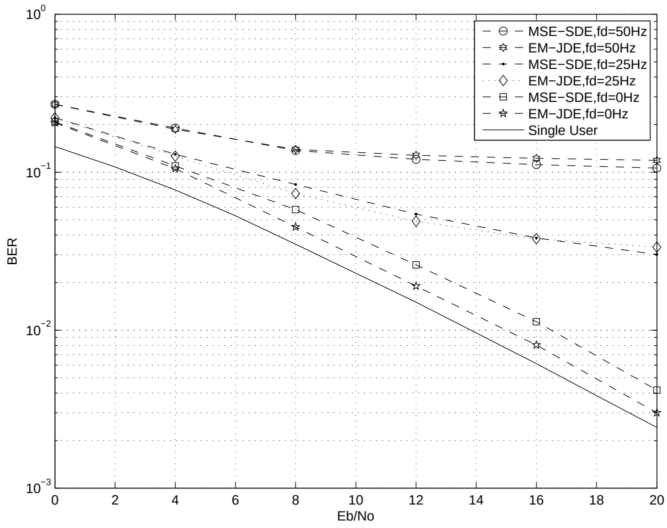

Fig. 2. BER performances of the EM-JDE employing static channel model for time varying channels

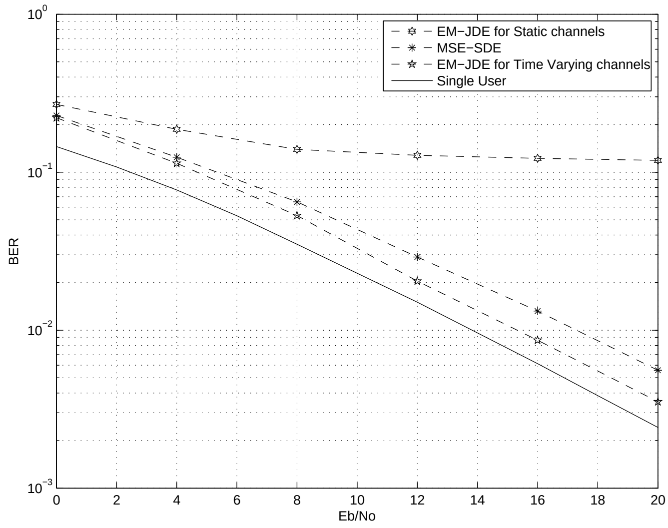

Fig. 3. Comparision of EM-JDE algorithms (fd=50Hz,L=1)

(static channels). In particular, it is seen that the EM-JDE algorithm proposed in [12] exhibits a gain of about 1.5 dB over MSE-SDE detection for BPSK modulation at $SER = 10^{-2}$. However, it was shown that the algorithm of [12] yields the error floors for time-varying channels.

In the second scenario, the p pilot bits are regularly spread within the frame to track the channel. In this case, the normalized time spacing between two adjacent known bit positions is equal to $p_{j+1} - p_j = 13$. According to Shannons Sampling Theorem we can expect, that the EM-JDE scheme provides accurate estimates of the channel coefficients as long as the normalized Doppler frequency does not exceed $f_d T_s = 0.5/(p_{j+1} - p_j)$=0.038. Therefore, the cut-off Doppler frequency for a given sampling time is $280Hz$. In Fig.3, the proposed EM-JDE algorithm for time varying channels is compared to the EM-JDE algorithm employing static channel model for three iteration. It was shown that MSE-SDE performance is improved according to first scenario because of the usage of combtype pilot pattern. It was also demonstrated that the proposed EM-JDE algorithm is able to perform better than the EM-JDE employing static channel model. Moreover, it was demonstrated that smart combination of data detection and channel estimation in JDE outperforms the separate detection and estimation scheme. In particular, it is observed that a savings of about 2 dB is obtained at $SER = 10^{-2}$, as compared with the MSE-SDE detection.

In Fig.4 we also investigate the selection of sub-frame length (L) for f_d=50Hz and f_d=100Hz. In the case of L=4, it was shown that $BER = 10^{-2}$ performance of the EM-JDE is degrading after 1 dB and 2 dB for f_d=50Hz and f_d=100 Hz respectively. Therefore, it was concluded that EM-JDE must calculate all channel variations ($L = 1$) for higher SNR and Doppler frequencies.

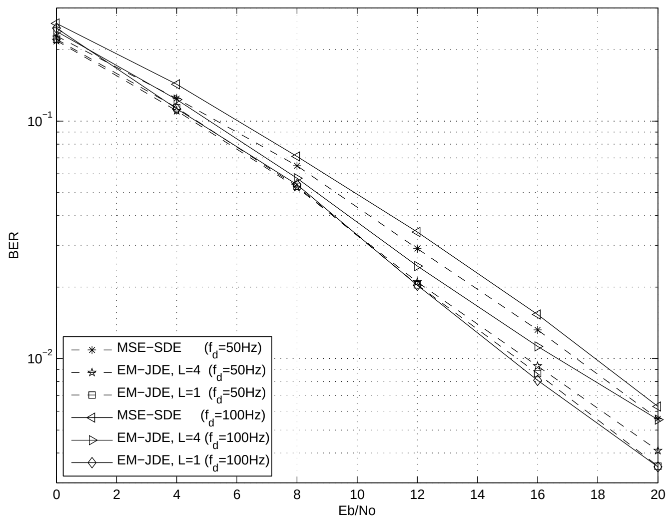

Fig. 4. BER performance of EM-JDE algorithms for different L values (f_d=50Hz)

V. Conclusions

We presented an efficient iterative receiver structures of tractable complexity for joint multiuser detection and multichannel estimation (JDE) of direct-sequence code-division multiple-access signals in the presence of time-varying flat fading channels. The schemes result from an application of EM algorithms. The EM-JDE receiver updates both the channel parameters and the data bit sequences in parallel. A closed form expression was derived for the data detection which incorporates the channel estimation as well as the partial interference cancelation steps in the algorithm. It was concluded that few pilot symbols were sufficient to initiated the EM algorithm very effectively. A comparison with other previously known receiver structures was also made. In static channel, we observed that all schemes perform almost similarly. However, computer simulations demonstrated the effectiveness of the proposed algorithms in terms of BER performances when the channel is fast fading. We conclude that the robustness of the EM-JDE which smartly combine the data detection and channel estimation in multiuser systems, unlike architectures where both process are implemented separately.

APPENDIX A
AR MODEL CALCULATIONS

We restrict ourselves to a first-order AR model, although all the derivations presented in this work are applicable to higher order models. Assuming the channel variations follow an AR model of order 1, the true channel coefficients are related to each other by

$$a_k(q) = \gamma_k a_k(q-1) + \epsilon_k(q),\ q = 1,2,\cdots,\Xi;\ k = 1,2,\cdots,K \quad (35)$$

where γ_k is the time correlation coefficient between observation blocks of each user. The initial values $a_k(0), k = 1,2,\cdots,K$ are assumed to be known. Using matrix notations, (35) can be expressed as

$$\mathbf{M}_k \mathbf{a}_k = \boldsymbol{\xi}_k + \boldsymbol{\epsilon}_k \quad (36)$$

where

$$\mathbf{M}_k \triangleq \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ -\gamma_k & 1 & 0 & \cdots & 0 & 0 \\ 0 & -\gamma_k & 1 & \cdots & 0 & 0 \\ \ddots & \ddots & \ddots & \ddots & \ddots & \ddots \\ 0 & 0 & 0 & \cdots & -\gamma_k & 1 \end{bmatrix};$$

$$\boldsymbol{\xi}_k \triangleq \left[\ \gamma_k a_k(0), 0, \ldots, 0,\ \right]^T;$$

$$\boldsymbol{\epsilon}_k \triangleq \left[\ \epsilon_k(1), \epsilon_k(2), \ldots, \epsilon_k(\Xi),\ \right]^T,$$

and $\mathbf{a}_k = [a_k(1), a_k(2), \cdots, a_k(\Xi)]^T$. Since $\boldsymbol{\epsilon}_k \sim N(0, \sigma_k^2 \mathbf{I}_\Xi)$, it follows from (36) that

$$\begin{aligned} \mathbf{m}_k &\triangleq E(\mathbf{a}_k) = \mathbf{M}_k^{-1}\boldsymbol{\xi}_k \\ &= a_k(0)[\gamma_k, \gamma_k^2, \cdots, \gamma_k^Q]^T, \\ \mathbf{C}_k &\triangleq E\left\{(\mathbf{a}_k - \mathbf{m}_k)(\mathbf{a}_k - \mathbf{m}_k)^\dagger\right\} \\ &= \sigma_k^2 \mathbf{M}_k^{-1}(\mathbf{M}_k^{-1})^T. \end{aligned} \quad (37)$$

After some algebra the (i,j)th component of $\mathbf{C}_k$ for $j = 1,2,\cdots,\Xi$ can be found as

$$\mathbf{C}_k(i,j) = \begin{cases} \sigma_k^2 \gamma_k^{j-1} & \text{if } i = 1 \\ \sigma_k^2(\gamma_k^{i+j-2} + \gamma_k^{i+j-4} + \cdots \gamma_k) & \text{if } i < j. \end{cases}$$

It can be shown that $\mathbf{C}_k^{-1} = \mathbf{M}_k^T \mathbf{M}_k / \sigma_k^2$ for $k = 1,2,\cdots,\Xi$.

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