Code-aided ML frame synchronization in a downlink MC-CDMA

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Keywords:
MC-CDMA, frame synchronization, channel estimation, iterative processing, EM algorithm

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***Abstract*— In this paper, a new Maximum-Likelihood frame synchronization algorithm is presented for a coded downlink MC-CDMA system. Based on [1], but using a slightly different observation model, both Data-Aided (DA) and Code-aided (CA) estimation algorithms are derived. As compared to [1], we obtain a low-complexity DA algorithm which does not suffer from timing ambiguities. Furthermore, a CA estimation algorithm is derived by applying the iterative Expectation Maximization (EM) algorithm. This new synchronization scheme accepts soft information from the turbo detector in the form of A Posteriori Probabilities (APP). The performance of the proposed algorithms are evaluated through computer simulations. At some increase in computational complexity, the CA scheme exhibits impressive performance gains as compared to the DA scheme.**

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I. Introduction

Orthogonal frequency division multiplexing (OFDM) has received intense interest from the research community during the past few decades. Its robustness to frequency selective channels has made it one of the main candidates for high data rate transmission for current and next-generation wireless and wireline applications [2].

All OFDM-based transmission requires accurate timing and frequency synchronization [3]. Additionally, the channel impulse response (CIR) must be known to coherently detect the data per subcarrier. Among the different synchronization policies, one can identify conventional techniques that are either data-aided (i.e., exploiting training symbols in the time- or frequency domain) [1], [4], [5] or blind (e.g., exploiting the presence of the cyclic prefix) [6], [7].

With the advent of powerful error-correcting codes (including turbo- and LDPC codes), these conventional techniques cannot always be applied successfully. Powerful codes lead to a combination of low BER at low SNR, thus rendering blind techniques unreliable. Similarly, data-aided algorithms require an unreasonable amount of power and bandwidth to be devoted to training. This has spurred several research groups to consider 'code-aided' or 'code-aware' estimation algorithms. These algorithms iterate between data detection and estimation, thus improving both the estimates of synchronization parameters and CIR, while simultaneously performing increasingly reliable data detection. Such techniques are often inspired by the turbo-principle [8] or the Expectation-Maximization (EM) algorithm [9], [10]. In [11], an EM-based semi-blind technique is described that performs code-aided estimation of the CIR per Multi-Carrier (MC) symbol. The same idea was applied in the frequency domain in [12] for a multi-antenna, multi-user system. The EM algorithm was again considered in [13] for estimation of the CIR for a time-varying MIMO-OFDM scenario. Finally, [14] proposes an ad-hoc code-aided channel estimator for time-varying OFDM systems. Code-aided estimation of synchronization parameters has received little attention.

In the current paper, we tackle the problem of joint channel estimation and frame synchronization for downlink MC-CDMA. Starting from the Maximum Likelihood (ML) principle, we derive an estimation algorithm based on the EM algorithm, exploiting information from the pilot symbols and coded data symbols in a systematic fashion.

II. MC-CDMA downlink system model

A. Transmitter

We consider bit-interleaved coded modulation transmission in the downlink of a MC-CDMA system with K_u active users. The Base Station transmits frames consisting of M_s MC symbols to each of the users as depicted in Fig. 1.

An information sequence intended for user k is encoded, interleaved and mapped to a signal constellation Ω, resulting in a sequence $\mathbf{d}^{(k)}$ of N_d data symbols. This sequence is broken up into M_s blocks of length $P\,(= N_d/M_s)$. Each of these blocks is spread with a length N_s spreading sequence, resulting in a sequence of $N = (N_s P)$ spread symbols. Each of these spread symbols is mapped to a unique subcarrier, resulting in a sequence $\mathbf{a}_i^{(k)} = \left[a_{i,0}^{(k)}, \ldots, a_{i,N-1}^{(k)}\right]^T$. After an Inverse Discrete Fourier Transform (IDFT) operation, a ν-point cyclic prefix is pre-appended resulting in $N+\nu$ time-domain samples per block: the samples of the i-th ($0 \le i < M_s$) block are written as $\left[s_{i,-\nu}^{(k)}, \ldots, s_{i,-1}^{(k)}, s_{i,0}^{(k)}, \ldots, s_{i,N-1}^{(k)}\right]^T$ where $s_{i,l}^{(k)} = s_{i,l+N}^{(k)}$, for $l = -\nu, \ldots, -1$ and

$$s_{i,m}^{(k)} = \sqrt{\frac{E_s}{N+\nu}} \sum_{n=0}^{N-1} a_{i,n}^{(k)} e^{j2\pi nm/N}. \qquad (1)$$

In (1) E_s denotes the energy per data symbol. We further define the MC symbol period T and the sampling period $T_s = T/N_T$.

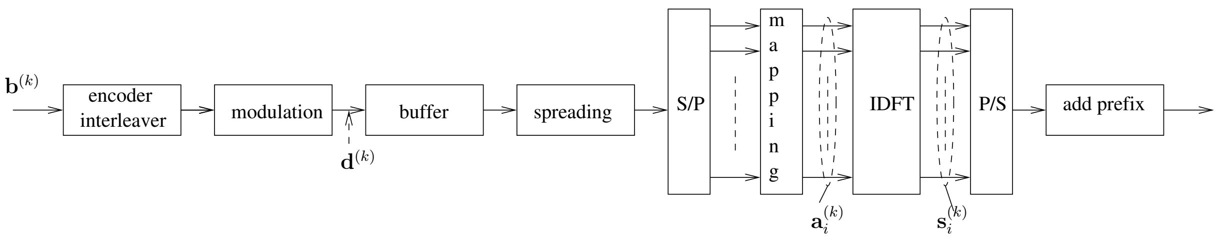

Fig. 1. Frame construction for the k-th user.

Finally, the signals of the K_u different users are added, shaped with a normalized transmit filter and transmitted over the channel to the mobile stations. A Common Control Physical Channel (CCPCH) is assumed whereby a sequence of M_p MC symbols is time-multiplexed at the header of the composite Dedicated Physical Channels (DPCH). These symbols do not undergo spreading (i.e, $N_s = 1$ in the CCPCH). A fraction (say, $f \in [0,1]$) of the subcarriers of the MC symbols in the CCPCH is devoted to training symbols, which serve to synchronize the mobile receivers. The remainder of the carriers (i.e., the fraction $1-f$) is taken up with administrative data. For convenience, we will refer to these M_p MC symbols as 'pilot MC symbols'. The pilot MC symbols may have a repetitive structure in the time-domain, to accommodate specific synchronization algorithms [4].

B. Receiver

Each user has to process a total of $M = M_s + M_p$ MC symbols. From this point on, we focus on a specific mobile station, say the k'-th. The signal from the base station propagates to the k'-th mobile station through a channel with overall Channel Impulse Response (CIR) $h_{ch}(t)$. This CIR incorporates the transmit filter, physical propagation channel and receive filter (e.g., matched filter). We assume a quasi-static block-fading channel that remains constant during each frame but can vary independently from frame to frame. The CIR is assumed to have a delay spread no greater than LT_s: $h_{ch}(t) = 0$ for $t < 0$ and for $t > LT_s$. Additionally, the signal arrives at the mobile station with a certain delay $\tau \in [0, \tau_{max}]$[1] and is corrupted by thermal noise. Hence, we may write the received signal $r(t)$ as

$$r(t) = \sum_{i=0}^{M_p-1} \sum_{m=-\nu}^{N-1} s_{i,m} h_{ch}(t - mT_s - iT - \tau) \quad (2)$$
$$+ \sum_{i=0}^{M_s-1} \sum_{m=-\nu}^{N-1} \sum_{k=1}^{K_u} s_{i,m}^{(k)} h_{ch}(t - mT_s - (i + M_p)T - \tau)$$
$$+ w(t)$$

where the first term corresponds to the control channel, the second term to the K_u dedicated channels and $w(t)$ is the baseband representation of the Additive White Gaussian Noise (AWGN) with power spectral density $N_0/2$ per real dimension.

[1] τ_{max} is assumed to be known to the receiver.

The receiver is fully digital and samples the received signal $r(t)$ at a rate $1/T_s$ resulting in a sequence of samples $\{r(lT_s)\}$. Following [1], we break up τ as $\tau = \Delta T_s + \delta T_s$with $\Delta \in \{0, 1, \ldots, \Delta_{max} \doteq \lfloor \tau_{max}/T_s \rfloor\}$ and $\delta \in [0,1[$. Defining $h(t) = h_{ch}(t - \delta T_s)$, the channel is fully characterized by the vector $\mathbf{h} = [h(0), h(T_s), \ldots, h((L-1)T_s)]^T$ and Δ. We sample the signal at times $-\nu T_s, \ldots, ((M_s + M_p)T + (\Delta_{max} + L - \nu - 1)T_s)$, yielding an observation $\mathbf{r}$. We select ν such that $\nu T_s > LT_s$ so that the MC system does not suffer from inter-symbol-interference (ISI).

When the receiver has available an estimate of $\mathbf{h}$ (say $\hat{\mathbf{h}}$) and of Δ (say, $\hat{\Delta}$), data detection is a well-known task. Since we focus on channel estimation and synchronization, we will not give a full description of the detector. From our point of view, data detection is a process that computes, in an iterative manner, a posteriori probabilities of the spread data symbols $p\left(a_{i,n}^{(k')} \middle| \mathbf{r}, \hat{\mathbf{h}}, \hat{\Delta}\right)$, $0 \le i < M_s$, $0 \le n < N$. For additional details, the reader is referred to [15] and to [16].

III. Channel Estimation

It is clear that the detector from the previous section requires the estimates of both the delay shift Δ and the channel taps $\mathbf{h}$. In this section we describe how these quantities may be estimated by the k'-th user. We start from the Maximum Likelihood (ML) criterion and derive a Data-Aided (DA) estimator. Then, capitalizing on the Expectation-Maximization (EM) algorithm, a code-aided (CA) estimator is constructed that exploits information from both the pilot MC symbols *and* the data MC symbols.

A. ML estimation

We first write our observation into a more convenient form. We start again from our observation-vector $\mathbf{r}$. Note that the length of this vector is independent of Δ.

We now introduce row-vectors of length N_T: $\mathbf{s}_C^i = [s_{i,-\nu}, \ldots, s_{i,N-1}]$ consists of the $N_T = N + \nu$ time-domain samples of the i-th pilot MC symbol ($i = 0, \ldots, M_p - 1$). Similarly, $\mathbf{s}_D^i = \left[s_{i,-\nu}^{(k')}, \ldots, s_{i,N-1}^{(k')}\right]$ consists of the $N_T = N + \nu$ time-domain samples of the i-th data MC symbol ($i = 0, \ldots, M_s - 1$) of the k'-th user. Then a vector $\mathbf{s}$ of length $(N_T(M_s + M_p) + 2L - 2)$ is constructed by concatenating all these time-domain samples, padded with $L-1$ zeros at the beginning and end of the vector, leading to

$$\mathbf{s} \doteq \left[\mathbf{0}_{1\times(L-1)}\, \mathbf{s}_C^0 \ldots \mathbf{s}_C^{M_p-1}\, \mathbf{s}_D^0 \ldots \mathbf{s}_D^{M_s-1}\, \mathbf{0}_{1\times(L-1)}\right] \quad (3)$$

where $\mathbf{0}_{X\times Y}$ is an $X \times Y$ matrix consisting of all zeros.

Now we define an $(N_T(M_s+M_p)+L-1)\times L$ Toeplitz matrix $\mathbf{S}$ as follows: the n-th row of $\mathbf{S}$ is obtained by time-reversing the n-th until the $(n+L-1)$-th sample of $\mathbf{s}$. For instance, the first row is given by $\left[s_{0,-\nu}, \mathbf{0}_{1\times(L-1)}\right]$, the second row by $\left[s_{0,-\nu+1}, s_{0,-\nu}, \mathbf{0}_{1\times(L-2)}\right]$ and so forth. Note that we can write $\mathbf{S}$ as the sum of two Toeplitz matrices of size $(N_T(M_s+M_p)+L-1)\times L$: $\mathbf{S}=\mathbf{S}_P+\mathbf{S}_D$, where $\mathbf{S}_P$ contains only the pilot MC symbols and $\mathbf{S}_D$ contains only the data MC symbols.

Finally, we define an $(N_T(M_s+M_p)+\Delta_{max}+L-1)\times L$ matrix $\mathbf{S}_\Delta$ as

$$\mathbf{S}_\Delta = \begin{bmatrix} \mathbf{0}_{\Delta\times L} \\ \mathbf{S} \\ \mathbf{0}_{(\Delta_{max}-\Delta)\times L} \end{bmatrix}. \quad (4)$$

These transformations enable us to write the following simple relationship between $\mathbf{r}$, $\mathbf{S}_\Delta$ and $\mathbf{h}$:

$$\mathbf{r} = \mathbf{S}_\Delta \mathbf{h} + \mathbf{w} \quad (5)$$

where $\mathbf{w}$ embeds the thermal noise and the Multiple Access Interference (MAI) and is modeled as a zero-mean complex Gaussian random variable with variance σ^2 per real dimension. Note that by substituting $\mathbf{S}=\mathbf{S}_P+\mathbf{S}_D$ into (4), we can break up $\mathbf{S}_\Delta = \mathbf{S}_{\Delta,P}+\mathbf{S}_{\Delta,D}$.

The ML estimate of the delay shift and channel taps is obtained by maximizing the log-likelihood function

$$\left[\hat{\Delta}, \hat{\mathbf{h}}\right] = \arg\max_{\Delta,\mathbf{h}} \left\{\log p\left(\mathbf{r}\,|\Delta,\mathbf{h}\right)\right\} \quad (6)$$

where

$$p\left(\mathbf{r}\,|\Delta,\mathbf{h}\right) \propto \sum_{\mathbf{s}} p\left(\mathbf{r}\,|\Delta,\mathbf{h},\mathbf{s}\right) p\left(\mathbf{s}\right) \quad (7)$$

and

$$p\left(\mathbf{r}\,|\Delta,\mathbf{h},\mathbf{s}\right) \propto \exp\left(-\frac{1}{2\sigma^2}\left\|\mathbf{r}-\mathbf{S}_\Delta\mathbf{h}\right\|^2\right) \quad (8)$$

Unfortunately, the summation in (7) is intractable in practice, as it requires the evaluation of (8) over all possible codewords.

B. Data-Aided estimation

The summation in (7) can be avoided by only taking into account the pilot MC symbols, leading a

$$\left[\hat{\Delta}, \hat{\mathbf{h}}\right] = \arg\max_{\Delta,\mathbf{h}} \left\{\log p\left(\mathbf{r}\,|\Delta,\mathbf{h},\mathbf{S}_P,\mathbf{S}_D=\mathbf{0}\right)\right\}$$

which can easily be solved as

$$\hat{\Delta} = \arg\max_{\Delta} \left\{\Re\left(\mathbf{r}^H \mathbf{S}_{\Delta,P}\left(\mathbf{S}_P^H\mathbf{S}_P\right)^{-1}\mathbf{S}_{\Delta,P}^H\mathbf{r}\right)\right\} \quad (9)$$

and

$$\hat{\mathbf{h}} = \left(\mathbf{S}_P^H\mathbf{S}_P\right)^{-1}\mathbf{S}_{\hat{\Delta},P}^H\mathbf{r}. \quad (10)$$

Note that, contrary to the DA estimator from [1], the matrix to be inverted in (10) is independent of Δ, thus reducing the computational load at the receiver.

One of the main drawbacks of many frame synchronization algorithms for MC systems is the presence of ambiguities . For instance, the ML DA estimator from [1] is not able to estimate values of Δ beyond N_T: when $\Delta_{max} > N_T$ ambiguities occur. For the estimator we propose, which is based on a slightly different observation model, no ambiguity is present. To illustrate this point, we plot a typical realization of the cost-function (9) for a single-user system in Fig. 2.

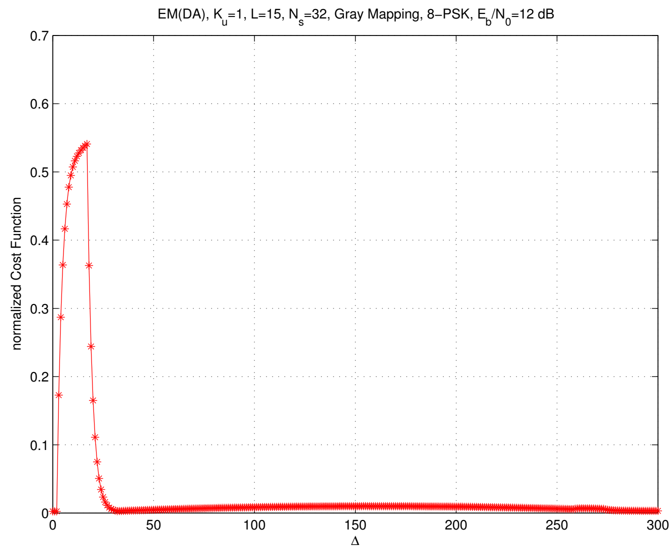

Fig. 2. DA frame synchronization: trial value of Δ vs. cost function. Δ equals 17.

While DA estimation algorithms perform well for uncoded systems, this is no longer true when error-correcting codes are concerned. Since such codes operate in low SNR regimes, many pilot symbols may be required to acquire reliable estimates. As this results in a significant loss in terms of power and bandwidth, there is great interest in developing algorithms that are also able to exploit the data MC symbols. In the following section, we describe a possible approach: the EM algorithm. It turns out that there are some very nice connections between the resulting code-aided algorithm and the conventional DA algorithm.

C. EM estimation

1) Principle: The Expectation-Maximization (EM) algorithm is a method that iteratively solves the ML problem (6) [9]. It requires us to define the so-called *complete data* $\mathbf{z}$. The complete data is related to the observation $\mathbf{r}$ through some, possibly random, mapping $\mathbf{r}=g(\mathbf{z})$. Let us denote the parameter to be estimated θ (e.g., in our case, θ is a notational shorthand for the vector $\left[\Delta, \mathbf{h}^T\right]$).

The EM algorithm starts from an initial estimate of θ (say, $\hat{\theta}(0)$) and iteratively computes new estimates. At iteration ξ, the EM algorithm consists of two steps: given the current estimate $\hat{\theta}(\xi)$, we first take the expectation of the log-likelihood function of the complete data, given the observation $\mathbf{r}$ and the current estimate of θ:

$$Q\left(\theta|\,\hat{\theta}(\xi)\right) = E_{\mathbf{z}}\left[\log\, p\left(\mathbf{z}|\,\theta\right)\Big|\mathbf{r};\hat{\theta}(\xi)\right]. \quad (11)$$

In the second step, we maximize $Q\left(\theta|\,\hat{\theta}\,(\xi)\right)$ with respect to θ to find a new estimate:

$$\hat{\theta}\,(\xi+1) = \arg\max_{\theta}\left\{Q\left(\theta|\,\hat{\theta}\,(\xi)\right)\right\}. \qquad (12)$$

Convergence of the EM algorithm is guaranteed in a sense that the likelihoods of the estimates are non-decreasing:

$$p\left(\mathbf{r}|\,\hat{\theta}\,(\xi+1)\right) \geq p\left(\mathbf{r}|\,\hat{\theta}\,(\xi)\right) \qquad (13)$$

for $\xi = 0, \ldots, +\infty$. Any value $\hat{\theta}$ for which $\hat{\theta} = \arg\max_{\theta} Q\left(\theta|\,\hat{\theta}\right)$ is called a *solution* of the EM algorithm. One of these solutions is the ML estimate. In order to achieve convergence to the ML estimate, a good initial estimate of θ is required.

2) Code-aided estimation: We take as as complete data $\mathbf{z} = [\mathbf{r}, \mathbf{s}]$. Let us define $\widetilde{\mathbf{S}}_{\Delta} = E_{\mathbf{s}}\left[\mathbf{S}_{\Delta}|\,\mathbf{r}, \hat{\theta}\,(\xi)\right]$. Note that $\widetilde{\mathbf{S}}_{\Delta}$ can be obtained from the knowledge of the APPs $p\left(a_{i,n}^{(k')}\,\middle|\,\mathbf{r}, \hat{\mathbf{h}}, \hat{\Delta}\right)$, computed by the detector. Also, define $\widetilde{\mathbf{S}^H\mathbf{S}} = E_{\mathbf{s}}\left[\mathbf{S}^H\mathbf{S}|\,\mathbf{r}, \hat{\theta}\,(\xi)\right]$. We can then show that the EM algorithm leads to the following updated estimates of the delay shift and the channel taps:

$$\hat{\Delta}\,(\xi+1) = \arg\max_{\Delta}\left\{\Re\left(\mathbf{r}^H\widetilde{\mathbf{S}}_{\Delta}\left(\widetilde{\mathbf{S}^H\mathbf{S}}\right)^{-1}\widetilde{\mathbf{S}}_{\Delta}^H\mathbf{r}\right)\right\}. \quad (14)$$

and

$$\hat{\mathbf{h}}\,(\xi+1) = \left(\widetilde{\mathbf{S}^H\mathbf{S}}\right)^{-1}\widetilde{\mathbf{S}}_{\hat{\Delta}(\xi+1)}^H\mathbf{r}. \qquad (15)$$

When we approximate $\widetilde{\mathbf{S}^H\mathbf{S}} \approx \widetilde{\mathbf{S}}^H\widetilde{\mathbf{S}}$, the code-aided EM-based algorithm is formally obtained by replacing in the corresponding DA algorithms, pilot symbols with a posteriori symbol expectations. For additional details, the reader is again referred to [15].

Computational complexity: The computational complexity of the proposed EM estimator is quite large. To reduce the computational load, we can *embed* the EM estimation iterations within the detection iterations: we perform a single decoding iteration per EM iteration, and maintain state information within the detector from one iteration to the next.

IV. Numerical Results

To validate the proposed algorithms, we have carried out Monte Carlo simulations. We consider a system with $K_u = 5$ users, using a convolutional code with constraint length 5, rate $R = 1/2$ and polynomial generators $(23)_8$ and $(35)_8$. A block length of $N_b = 240$ information bits was chosen, leading to $N_c = 480$ coded bits. Coded bits are Gray-mapped onto an 8-PSK constellation, resulting in $N_d = 160$ data symbols. This sequence of N_d 8-PSK symbols is broken up into $M_s = 20$ blocks of $P = 8$ symbols. Spreading sequences are real Walsh-Hadamard sequences, with chips belonging to $\left\{-\frac{1}{\sqrt{N_s}}, +\frac{1}{\sqrt{N_s}}\right\}$ and have a length $N_s = 32$, leading to $N = PN_s = 256$ required subcarriers. To initialize the EM algorithm, the $M_s = 20$ data MC symbols are preceded by $M_p = 1$ pilot MC symbols. Within the pilot

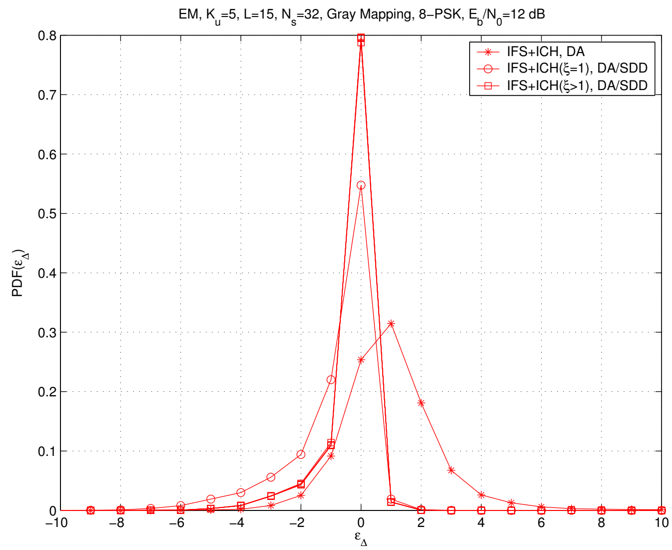

Fig. 3. Frame synchronization: pmf of estimation error at 12 dB

MC symbols, only a fraction $f = 0.25$ of the subcarriers are devoted to training. The remaining 75% of the carriers is reserved for administrative data, and cannot be used during the synchronization/estimation process. The channel has length $L = 15$ and was modeled with independent components, each being a zero-mean complex Gaussian random variable with an exponential power delay profile [1] $E\left[|h\,(l)|^2\right] = \sigma_h^2 \exp\left(-l/5\right),\, l = 0, \ldots, L-1$, where σ_h^2 is chosen such that the average energy per subcarrier is normalized to unity. Hence, the energy of the channel is concentrated mainly in the first few channel taps. To avoid ISI, a cyclic prefix of length $\nu = 16$ is employed. The estimation stages will be embedded in the detection stages. We will denote joint frame synchronization and channel estimation by IFS+ICH (for Imperfect Frame Synchronization with Imperfect Channel knowledge).

In Fig. 3, we show, for a SNR of 12 dB, the simulated probability mass function (pmf) of the estimation error $\varepsilon_{\Delta} = \hat{\Delta} - \Delta$ (see Fig. 3). The DA estimator has a fairly broad pmf, with a maximum $\varepsilon_{\Delta} = 1$. The pmf of ε_{Δ} for the code-aided EM estimator is much more narrow, with a distinct maximum at $\varepsilon_{\Delta} = 0$. After $\xi = 2$ iterations, the pmf does not change noticeably. It should be noted that although only 80% of the frames result in a correct estimate of Δ, this does not mean that the Frame Error Rate equals 20%: when $\varepsilon_{\Delta} > 0$ (resp. $\varepsilon_{\Delta} < 0$), inter-symbol-interference occurs between the current and the next (resp. previous) MC symbol. Since the first few channel taps carry most of the energy, the situation $\varepsilon_{\Delta} < 0$ is not very critical. On the other hand, $\varepsilon_{\Delta} > 0$ should be avoided, as the estimate of $\mathbf{h}$ will not capture the dominant components. From Fig. 3 it is clear that the latter situation occurs only rarely for the EM-based estimator.

Finally, Fig. 4 shows the BER for joint frame synchronization and channel estimation. As expected, the DA estimator gives rise to large degradations. On the other hand, the EM estimator results in a BER degradation of around 0.2 dB as

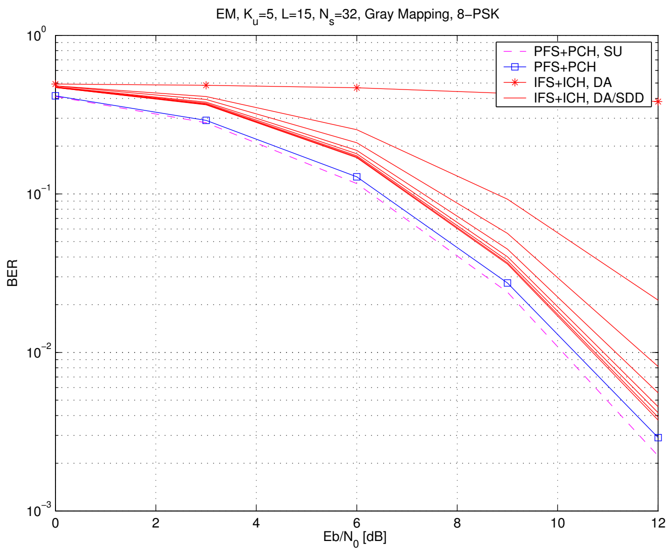

Fig. 4. Joint frame synchronization and channel estimation: BER performance

compared to the case of perfect frame synchronization and perfect channel knowledge after roughly $\xi = 4$ EM iterations.

V. Conclusions

We have presented a novel code-aided estimation algorithm for joint frame synchronization and channel impulse response estimation for downlink MC-CDMA. Based on the EM algorithm, the receiver iterates between data detection and estimation, with the exchange of soft information in the form of a posteriori probabilities. Compared to the data-aided algorithm, the code-aided algorithm results in impressive gains in terms of mean squared estimation error and BER performance. Although the complexity of this estimator is fairly large, we have described how the computational load may be reduced, resulting in a practical algorithm.

The proposed algorithm can easily be extended to take into account other parameters (frequency offsets, for instance) and other observation models (such as frequency-domain channel estimation).

Acknowledgement

This work has been supported by the Interuniversity Attraction Poles Program P5/11- Belgian Science Policy.

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