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Communication Theory

Iterative channel estimation and data detection in frequency-selective fading MIMO channels†

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SUMMARY

Signals transmitted through multiple-input multiple-output (MIMO) wireless channels suffer from multiple-access interference (MAI), multipath propagation and additive noise. Iterative multiuser receiver algorithms mitigate these signal impairments, while offering a good tradeoff between performance and complexity. The receiver presented in this paper performs channel estimation, multiuser detection and decoding in an iterative manner. The estimation of the frequency selective, block-fading channel is initiated with the pilot symbols. In subsequent iterations, soft decisions of all the data symbols are used in an appropriate way to improve the channel estimates. This approach leads to significant improvement of the overall receiver performance, compared to other schemes. The bit-error-rate (BER) performance of the receiver is evaluated by simulations for different parameter setups. Copyright © 2004 AEI.

1. INTRODUCTION

In multiple-access communication systems several users access the transmission medium simultaneously in order to send and receive data. Thus, each user creates multiaccess interference (MAI) to all the others. Additionally, in systems where the symbol duration is smaller than the delay spread of the channel, inter-symbol interference (ISI) occurs. Interative multiuser detectors offer a solution to combat MAI and ISI successfully, while maintaining modest complexity. They were proposed by many authors in recent years, mostly for code division multiple access (CDMA) systems, but also for multiple antenna systems (see Reference [1–21] and references therein). The direct correspondence between CDMA and MIMO systems can be easily established: a CDMA system with K users is characterized by an $N \times K$ spreading matrix, whose columns are N-chips long spreading sequences of each user. A MIMO system, with K transmit antennas and N receive antennas, is characterized by an $N \times K$ channel matrix whose entries are channel impulse responses for every transmit–receive antenna pair (for a flat-fading channel entries are scalar coefficients, while in the frequency selective channel entries are vectors of channel coefficients). While the decoding and detection for the two systems are obviously very similar, channel estimation in wireless MIMO systems and in CDMA systems are considerably different tasks. In CDMA systems, the number of channel parameters to be estimated scales like the square root of the number of elements in the spreading matrix. The

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main difficulty for minimum-mean-squared-error (MMSE) channel estimation is asynchrony among users. For MIMO systems, however, the number of channel parameters scales linearly with the number of elements in the channel matrix yielding a much harder estimation problem, but antennas transmit synchronously. In this paper, we consider MIMO systems as the more challenging setup, but the presented receiver algorithm can easily be adapted for CDMA systems, as in Reference [22], or for multicarrier CDMA, cf. [23].

The basic idea of the iterative receiver algorithms presented in the aforementioned contributions [1–21] is the exchange of information between the detector and the decoder in an iterative fashion, until the performance improves no longer (or a stopping rule is satisfied). The approaches to modelling and estimating the channel, however, vary greatly. As a starting point we mention the simple AWGN channel model analyzed in References [1, 2, 15]. The iterative schemes in References [3, 6, 9, 19] are designed assuming perfect knowledge of the fading channel on the receiver side. In real systems, however, the receiver needs to estimate the channel parameters. Therefore, we are interested in channel estimation as a vital part of the receiver algorithm. The straightforward solution is estimating the channel over the training symbols, as for example, in Reference [18]. It has been shown, however, that the channel estimates can be improved if the estimation process is included in the iterative receiver chain, and the channel is reestimated in several iterations, using not only training symbols, but also information on the data symbols obtained from the decoder in the feedback loop. Such iterative estimation of the frequency-flat fading channel is considered in References [11, 16], but only for a single-user communication system. The estimation of the flat-fading channel in a synchronous CDMA system is addressed in References [5, 4]. A solution to the corresponding problem in MIMO systems is proposed in Reference [8], where the channel estimate is updated in each interation using hard decisions on the data symbols obtained from the decoder.

In realistic scenarios, the fading process in wireless channels is frequency-selective. Estimating the parameters of such a channel is a much more complicated task than estimating the flat-fading channel. The approach proposed in Reference [20] for CDMA systems is to use the soft estimates of those data symbols that are interfering with pilot symbols in order to cancel the interference on pilot positions and refine the estimates using the 'cleaned' pilots. In the iterative scheme in Reference [13], for MIMO systems in frequency-selective fading channels, hard decision feedback is used in the detector and the MMSE channel estimator to improve the estimates from the previous iteration. Hard symbol decisions, however, are unreliable in the initial iterations, and thus, can lead to erroneous estimates which propagate through the iterative process. Therefore, our approach is to use the soft decoder outputs in a feedback loop. This idea was presented in Reference [12], where soft decisions from the soft-input soft-output (SISO) decoder are fed back into the detector, which is realized as a parallel soft interference canceller, followed by an MMSE filter. The channel estimation in Reference [12] is initiated by pilot symbols, and iteratively improved using hard decisions only of those data symbols whose reliability (obtained from their soft estimates) exceeds a certain threshold. We follow the main idea of Reference [12] and use the same structure of detector and decoder. However, we introduce the novel channel estimation scheme, which achieves much better performance by exploiting soft decisions of all the symbols in a data block in a suitable way. A similar idea has recently been proposed in Reference [21], for CDMA systems in a flat-fading channel, within a different iterative detection structure. The approach described in Reference [21] is to impose an orthogonal structure on the users' pilot sequences, which allows to embed them into the data streams, and enables simple initial channel estimation. In our paper, we do not assume any particular design of pilot symbols—we consider the general case of randomly chosen symbols. It will be shown that our iterative receiver enables successful separation of several users transmitting simultaneously from different antennas, even when the number of users is larger than the number of receive antennas. Furthermore, due to the iterative gain, it allows reduction of the pilot sequence length which results in better bandwidth efficiency compared to most pilot-assisted schemes.

In our work, the multipath fading process is assumed to be block-constant. Some results on using soft symbol estimates for tracking time-varying fading channel are reported in Reference [24] for TDMA systems.

2. SIGNAL MODEL

Consider a MIMO system with K transmit antennas and N receive antennas, as depicted in Figure 1. Each transmit antenna in this multiple access system can be viewed as a user that 'sees' a single-input multiple-output (SIMO) channel. This scenario corresponds to the uplink communication between the mobile users and a multiple-antenna

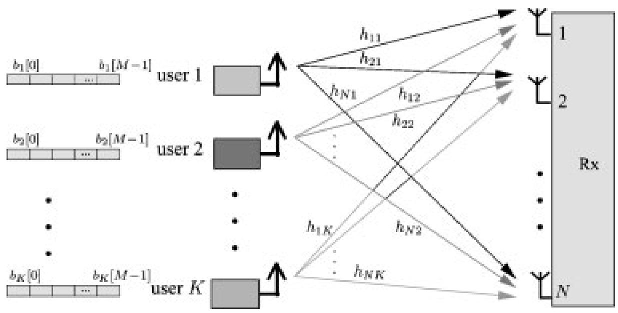

Figure 1. Multiple-input-multiple-output (MIMO) communication system.

base station. Users share the time–frequency resources and transmit in parallel blocks of M convolutionally encoded and randomly interleaved binary symbols $b_k[m] \in \{-1, +1\}$, where $k = 1, \ldots, K$ is the user index and m is the discrete symbol-time. A different random interleaver is applied for each user's data stream. The signals propagate through the frequency-selective fading channel of memory length L. The fading processes on all the receive antennas are jointly independent, which is justified by the fact that the transmitters are assumed to have different positions in a hypothetical cellular system. Since no spreading is applied, the signals from different users are identified by different channel realizations on the receive antennas. The channel impulse responses remain constant during transmission of one data block (block fading) and change randomly from block to block. This is a reasonable assumption when the block duration is not longer than the channel coherence time. Consecutive data blocks are separated by a guard interval, long enough to prevent inter-block interference (IBI). Each data block contains a preamble of P pilot symbols known to the receiver. The signal received at the nth antenna, $n = 1, \ldots, N$, in the mth symbol interval is given by

$$y_n[m] = \sum_{k=1}^{K} \sum_{l=0}^{L-1} h_{nk}[l] b_k[m-l] + v_n[m], \qquad (1)$$

where $h_{nk}[l]$ is the lth tap of the channel impulse response from the kth transmit to the nth receive antenna and $v_n[m]$ is spatially and temporally white Gaussian noise sample, with zero mean and known variance σ^2. Since there is no IBI, M-symbol long blocks transmitted from K antennas will result in $M + L - 1$ received symbols on the nth receive antenna, defined by Equation (1). Collecting them into a vector $\boldsymbol{y}_n = [y_n[0]\, y_n[1] \cdots y_n[M + L - 2]]^T$, we obtain:

$$\boldsymbol{y}_n = \underbrace{[\boldsymbol{B}_1 \boldsymbol{B}_2 \ldots \boldsymbol{B}_K]}_{\triangleq\ \boldsymbol{B}} \underbrace{\begin{bmatrix} \boldsymbol{h}_{n1} \\ \vdots \\ \boldsymbol{h}_{nK} \end{bmatrix}}_{\triangleq\ \boldsymbol{h}_n,} + \boldsymbol{v}_n = \boldsymbol{B}\boldsymbol{h}_n + \boldsymbol{v}_n,$$

where

$$\boldsymbol{B}_k = \begin{bmatrix} b_k[0] & 0 & \ldots & 0 \\ b_k[1] & b_k[0] & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ b_k[L-1] & b_k[L-2] & \ldots & b_k[0] \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & b_k[M-1] \end{bmatrix}$$

is an $(M + L - 1) \times L$ Toeplitz matrix of the kth user's data symbols, $\boldsymbol{h}_{nk} = [h_{nk}[0] h_{nk}[1] \cdots h_{nk}[L-1]]^T$ contains L channel taps and $\boldsymbol{v_n} = [v_n[0] \cdots v_n[M + L - 2]]^T$ is the noise vector on the nth antenna.

Finally, we stack these vectors for all N receive antennas into a single $N(M + L - 1) \times 1$ vector $\boldsymbol{y}$:

$$\boldsymbol{y} = (\boldsymbol{I}_N \otimes \boldsymbol{B})\, \boldsymbol{h} + \boldsymbol{v} \triangleq \mathcal{B}\boldsymbol{h} + \boldsymbol{v}, \qquad (2)$$

where $\boldsymbol{y} = [\boldsymbol{y}_1^T \boldsymbol{y}_2^T \ldots \boldsymbol{y}_N^T]^T$, $\boldsymbol{h} = [\boldsymbol{h}_1^T \boldsymbol{h}_2^T \ldots \boldsymbol{h}_N^T]^T$, $\boldsymbol{v} = [\boldsymbol{v}_1^T \boldsymbol{v}_2^T \ldots \boldsymbol{v}_N^T]^T$, $\boldsymbol{I}_N$ is the $N \times N$ identity matrix, $\otimes$ is the Kronecker product and $\mathcal{B}$ is an $N(M + L - 1) \times NKL$ block-diagonal data matrix. This signal model is suitable for channel estimation since all the NKL unknown channel parameters are collected in the vector $\boldsymbol{h}$.

3. OPTIMUM RECEIVER

The optimum multiuser receiver performs joint multiuser detection and decoding. However, this requires prohibitively large complexity (exponential in both number of users and codeword length). The widely used suboptimum approach is separation of the detection and the decoding process, as shown in Figure 2. The detector outputs are code symbol estimates, denoted by z_k. The single-user decoders compute the estimates of the information bits $\hat{\imath}_k$. In this structure, the detector does not have knowledge of the code constraints, while the decoders do not have knowledge of the signals' waveforms. The capacity loss due to this separation can be found in Reference [25].

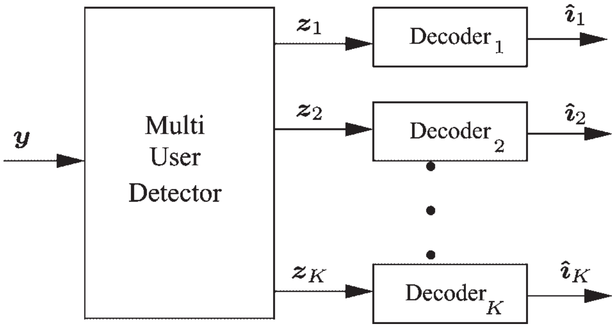

Figure 2. Separated multiuser detection and single-user decoding.

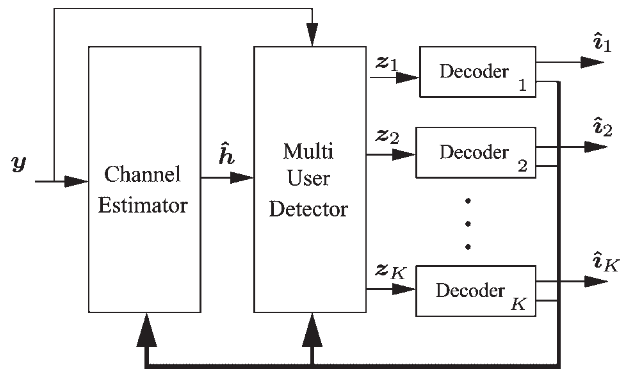

Figure 3. Iterative channel estimation, detection and decoding.

When the channel is assumed unknown to the receiver, the optimum detector should perform joint channel estimation and data detection, cf. [20]. More precisely, in our MIMO system from the Figure 1, it needs to estimate *KNL* channel coefficients $h_{nk}[l]$ (cf. signal model (2)) and *KM* data symbols $b_k[m]$, based on $N(M+L-1)$ observations collected in the received vector $\boldsymbol{y}$. The optimum solution to this estimation problem is obtained by maximizing the joint posterior probability density function (PDF) of $\boldsymbol{h}$ and $\boldsymbol{\mathcal{B}}$:

$$(\hat{\boldsymbol{h}}, \hat{\boldsymbol{\mathcal{B}}}) = \arg\max_{\boldsymbol{h},\boldsymbol{\mathcal{B}}}\{f(\boldsymbol{h}, \boldsymbol{\mathcal{B}} \,|\, \boldsymbol{y})\}.$$

Using Bayes' rule and assuming that the channel coefficients $\boldsymbol{h}$ are independent of the transmitted data $\boldsymbol{\mathcal{B}}$, we obtain:

$$f(\boldsymbol{h}, \boldsymbol{\mathcal{B}} \,|\, \boldsymbol{y}) \propto f(\boldsymbol{y} \,|\, \boldsymbol{h}, \boldsymbol{\mathcal{B}}) f(\boldsymbol{h}) \Pr(\boldsymbol{\mathcal{B}}), \tag{3}$$

where $\propto$ denotes proportionality. The conditional distribution of the received vector given the channel state and the data symbols is an $N(M+L-1)$-dimensional complex Gaussian distribution:

$$f(\boldsymbol{y} \,|\, \boldsymbol{\mathcal{B}}, \boldsymbol{h}) \propto \exp\{-\sigma^{-2}(\boldsymbol{y} - \boldsymbol{\mathcal{B}}\boldsymbol{h})^H(\boldsymbol{y} - \boldsymbol{\mathcal{B}}\boldsymbol{h})\}.$$

The PDF $f(\boldsymbol{h})$ is the prior knowledge of the channel statistics. In case of Rayleigh fading, elements of $\boldsymbol{h}$ are independent, identically distributed (i.i.d.), zero mean, complex Gaussian random variables.

The joint probability mass function of the data symbols can be factorized as

$$\Pr(\boldsymbol{\mathcal{B}}) = \prod_{m=0}^{M-1}\prod_{k=1}^{K}\Pr(b_k[m]),$$

which follows from the assumption that coded symbols are mutually independent after random interleaving.

There are 2^{KM} hypotheses on transmitted symbols for each data block. Maximization of the function (3) involves exhaustive search over all possible transmitted sequences and finding the most likely channel realization for each of them. The complexity of this approach is prohibitive for practical realization. As a suboptimum, low-complexity solution, the channel estimation and data detection are split into separate steps. Analytical study of the performance of separated channel estimation and linear multiuser detection is provided in Reference [26]. An iterative scheme is obtained by introducing a feedback loop from the decoders that supplies both the channel estimator and the detector with soft decisions on coded symbols, obtained from the code constraints. This leads to the receiver structure shown in Figure 3. The channel estimation, multiuser detection and single-user decoding are performed iteratively. In each iteration, the estimates are improved, until a saturation level is reached.

4. ITERATIVE RECEIVER ALGORITHM

In this section, the iterative receiver will be described in detail. The detailed receiver structure is shown in Figure 4.

4.1. Single-user decoding

SISO decoders for convolutionally encoded symbols perform symbol-by-symbol maximum *a-posteriori* (MAP) decoding. They are implemented using the BCJR algorithm [27,3]. The inputs to the *k*th user's decoder are soft symbol estimates $z_k[m]$ (collected in the vector $\boldsymbol{z}_k$) obtained from the detector output. Let $R = c_i/c_o$ be the rate of the convolutional code used for encoding the information sequence. Then the code symbol $b_k[m]$ belongs to the *t*th

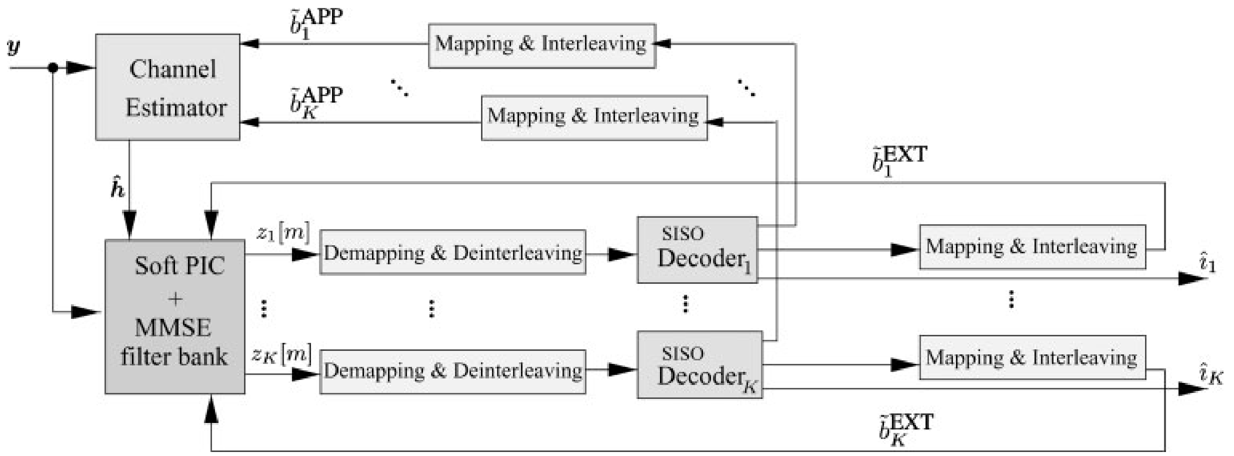

Figure 4. Iteractive receiver—the block structure.

c_o-tuple of the kth user's code sequence, where $t = \lceil m/c_o \rceil$, $1 \leq t \leq M/c_o$.

In every iteration, kth user's BCJR decoder computes the *a-posteriori* probability (APP) for each symbol in a block as:

$$\text{APP}(b_k[m] = b) = \Pr(b_k[m] = b|z_k) = \\ = \sum_{(s',s)\in S_t^b} \alpha_{t-1}(s')\beta_t(s)\gamma_t(s', s),$$

where α, β, γ are forward, backward and state-transition metric in the code trellis, computed as in Reference [27], and S_t^b is a set of state pairs (s', s) such that the state transition $s' \to s$ at tth trellis stage yields the code symbol $b_k[m] = b \in \{-1, +1\}$.

The decoders also compute extrinsic probability EXT $(b_k[m] = b)$ which is information about the symbol $b_k[m]$ carried in all other code symbols $b_k[m']$, $m' \neq m, 0 \leq m' < M$. It is related to the APP as [14]:

$$\text{APP}(b_k[m] = b) \propto \text{EXT}(b_k[m] = b)p(z_k[m]|b_k[m] = b), \quad (4)$$

where $p(z_k[m]|b_k[m] = b)$ is the conditional distribution of the detector's output. It is approximated with the Gaussian PDF, as in References [3, 14, 6], and represents the *a-priori* information obtained from the detector.

In the final iteration, the decoders output hard decisions of the information bits $\hat{\imath}_k$.

To reduce the complexity of calculations at each trellis stage, we used the BCJR algorithm implemented in the logarithmic domain (Log-MAP decoder [28]). Instead of probabilities, it computes the log-likelihood ratios (LLRs) defined as:

$$\begin{aligned} \mathcal{L}^{\text{APP}}(b_k[m]) &\triangleq \log\frac{\text{APP}(b_k[m] = +1)}{\text{APP}(b_k[m] = -1)}, \\ \mathcal{L}^{\text{EXT}}(b_k[m]) &\triangleq \log\frac{\text{EXT}(b_k[m] = +1)}{\text{EXT}(b_k[m] = -1)}. \end{aligned} \quad (5)$$

A-priori LLR is given by:

$$\mathcal{L}^{\text{PRIOR}}(b_k[m]) \triangleq \log\frac{p(z_k[m] \mid b_k[m] = +1)}{p(z_k[m] \mid b_k[m] = -1)}.$$

Then, the relation between these LLRs, equivalent to Equation (4) is:

$$\mathcal{L}^{\text{APP}} = \mathcal{L}^{\text{EXT}} + \mathcal{L}^{\text{PRIOR}}.$$

Soft decision on a coded BPSK symbol is defined as a conditional mean value, given that the symbol is distributed according to probability $\Pr(b_k[m])$:

$$\tilde{b}_k[m] = \sum_{b\in\{-1,+1\}} b\,\Pr(b_k[m] = b) = 2\Pr(b_k[m] = +1) - 1. \quad (6)$$

By using APP probability in Equation (6), we obtain APP-based soft decision, denoted by $\tilde{b}_k^{\text{APP}}[m]$, and by using the EXT probability instead, we obtain the EXT-based soft decision $\tilde{b}_k^{\text{EXT}}[m]$, as:

$$\begin{aligned} \tilde{b}_k^{\text{APP}}[m] &= 2\,\text{APP}(b_k[m] = +1) - 1, \\ \tilde{b}_k^{\text{EXT}}[m] &= 2\,\text{EXT}(b_k[m] = +1) - 1. \end{aligned} \quad (7)$$

Since the Log-MAP decoder computes the LLRs, rather than probabilities, these soft decisions can easily be obtained from LLRs as:

$$\tilde{b}_k^{\text{EXT}}[m] = \tanh\left(\frac{1}{2}\mathcal{L}^{\text{EXT}}(b_k[m])\right),$$
$$\tilde{b}_k^{\text{APP}}[m] = \tanh\left(\frac{1}{2}\mathcal{L}^{\text{APP}}(b_k[m])\right), \quad (8)$$

where this relation follows directly from Equations (5) and (7).

The EXT-based soft symbol estimates are fed back from the decoders to the data detector, as shown in Figure 4. Using APP-based feedback instead degrades the performance and can affect the convergence of the iterative process, cf. [19].

The channel estimator, on the other hand, uses APP-based soft estimates. The simulation results, presented in Section 5, show that if the channel estimator would instead use the EXT-based feedback, like the detector does, the estimates would be degraded and thus the overall receiver performance.

4.2. Multi-user detection

The detector is realized as in Reference [12]: it consists of a soft parallel interference canceller (PIC) followed by K linear MMSE filters, one per user. The corresponding structure for the kth user's signal is shown in Figure 5. A detailed explanation of interference cancellation and post-filtering can be found in Reference [12]. The IC step and the MMSE filter of our detector are recomputed in each iteration for every symbol of every user. In Reference [29], this is referred to as a conditional MMSE filter.

In larger systems (e.g. in CDMA systems with large number of users K) updating the filter for each symbol

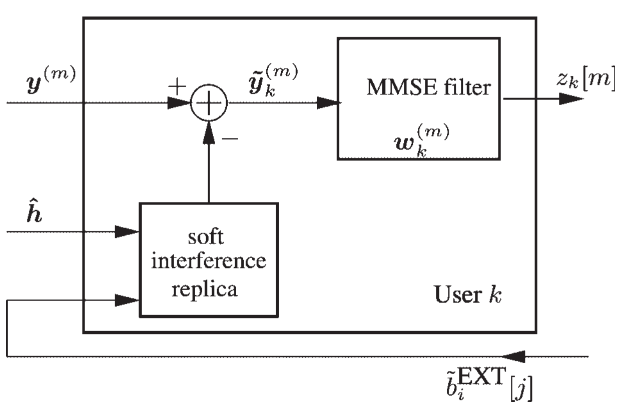

Figure 5. Interference cancellation and MMSE filtering.

can be computationally costly. In such cases, at the expense of a slight performance loss, the complexity can be reduced by applying the unconditional MMSE filter instead of the conditional one. The unconditional filter is calculated only once per data block, for each user, in each iteration.

In the mth symbol interval, the inputs to the soft IC stage for the kth user are the received symbols affected by the transmitted symbol $b_k[m] : \boldsymbol{y}^{(m)} = [y[m]\ y[m+1] \cdots y[m+L-1]]^T$, the channel estimate $\hat{\boldsymbol{h}}$ and the EXT-based soft estimates of symbols that influence $\boldsymbol{y}^{(m)}$, i.e., $\tilde{b}_i^{\text{EXT}}[j]$, $i = 1, \ldots, K, m-L+1 \leq j \leq m+L-1$. Replicas of MAI and ISI components for each user are calculated as in Reference [12] and subtracted from the received signal. The resulting signal, $\tilde{\boldsymbol{y}}_k^{(m)}$, contains the symbol of interest, $b_k[m]$, and the residual interference due to non-perfect channel and data estimation. Therefore, the signal is further processed by a linear MMSE filter $\boldsymbol{w}_k^{(m)}$, which is obtained from

$$\boldsymbol{w}_k^{(m)} = \arg\min_{\boldsymbol{w}} \mathsf{E}\{\|b_k[m] - \boldsymbol{w}^H \tilde{\boldsymbol{y}}_k^{(m)}\|^2\}$$

The filter output is a soft value $z_k[m] = \boldsymbol{w}_k^{(m)H}\tilde{\boldsymbol{y}}_k^{(m)}$, closest to the true symbol value $b_k[m]$ in the mean squared-error sense and it is delivered as *a-priori* information to the kth SISO decoder.

4.3. Channel estimation

4.3.1. Linear MMSE channel estimation

Minimization of the mean squared estimation error (MSE) is a widely used optimization criterion in parameter estimation. We adopt this approach for estimating the channel coefficients in $\boldsymbol{h}$. The received data vector $\boldsymbol{y}$ is a linear function of channel parameters. In general, for any linear data model, if the observed data and the unknown parameters are jointly Gaussian distributed, the resulting MMSE parameter estimator is a linear function of the data [30]. In our model (2), we assume that channel coefficients in the vector $\boldsymbol{h}$ are independent, complex Gaussian distributed random variables, with zero mean and unit variance, while symbols in the matrix $\boldsymbol{B}$ have discrete binary distribution determined by the probabilities $\Pr(b_k[m] = +1)$. Consequently, the resulting distribution of the observed vector $\boldsymbol{y}$ is not Gaussian, thus the MMSE channel estimator is not linear. Due to the shape of the PDF $f(\boldsymbol{y})$, the derivation of the exact MMSE estimator is a complicated task. Therefore, we constrain the channel estimator to be a linear function of $\boldsymbol{y}$:

$$\hat{\boldsymbol{h}}_{\text{LMMSE}} = \boldsymbol{A}\boldsymbol{y}.$$

Then, matrix $\boldsymbol{A}$ satisfies the Wiener–Hopf equation [30]:

$$\boldsymbol{C}_{\boldsymbol{yy}}\boldsymbol{A}^H = \boldsymbol{C}_{\boldsymbol{yh}},$$

where $\boldsymbol{C}_{\boldsymbol{yy}}$ and $\boldsymbol{C}_{\boldsymbol{yh}}$ are the covariance matrices. Taking into account that $\boldsymbol{y}$, $\boldsymbol{h}$ and $\boldsymbol{v}$ have zero mean, and that the elements of $\boldsymbol{h}$ are i.i.d., we obtain:

$$\begin{aligned}\boldsymbol{C}_{\boldsymbol{yy}} &= \underset{\mathcal{B}}{\mathsf{E}}\,\underset{h}{\mathsf{E}}\,\underset{v}{\mathsf{E}}\{\boldsymbol{yy}^H\} = \underset{\mathcal{B}}{\mathsf{E}}\{\mathcal{B}\mathcal{B}^H\} + \sigma^2\boldsymbol{I},\\ \boldsymbol{C}_{\boldsymbol{yh}} &= \underset{\mathcal{B}}{\mathsf{E}}\,\underset{h}{\mathsf{E}}\,\underset{v}{\mathsf{E}}\{\boldsymbol{yh}^H\} = \underset{\mathcal{B}}{\mathsf{E}}\{\mathcal{B}\} \triangleq \tilde{\mathcal{B}},\end{aligned} \tag{9}$$

where the index under the expectation operator denotes the random variable with respect to which the expectation is taken. The entries of matrix $\tilde{\mathcal{B}}$ are exact (hard) values for known pilot symbols, and soft APP-based estimates of data symbols (cf. (6)). Unless stated otherwise, all expectations in the subsequent expressions are taken with respect to $\boldsymbol{B}$ (using APPs), therefore, we omit the index to simplify the notation. The linear MMSE (LMMSE) estimator is then:

$$\begin{aligned}\hat{\boldsymbol{h}}_{\text{LMMSE}} &= C_{\boldsymbol{yh}}^H C_{\boldsymbol{yy}}^{-1}\boldsymbol{y} =\\ &= \tilde{\mathcal{B}}^H\left(\mathsf{E}\{\mathcal{B}\mathcal{B}^H\} + \sigma^2\boldsymbol{I}_{N(M+L-1)}\right)^{-1}\boldsymbol{y}.\end{aligned}$$

The estimators for each antenna $n = 1, \ldots, N$ are decoupled:

$$\hat{\boldsymbol{h}}_{n\,\text{LMMSE}} = \tilde{\boldsymbol{B}}^H\left(\mathsf{E}\{\boldsymbol{BB}^H\} + \sigma^2\boldsymbol{I}_{M+L-1}\right)^{-1}\boldsymbol{y}_n. \tag{10}$$

For evaluation of this estimator it is necessary to invert an $(M+L-1)$-dimensional matrix, which is computationally too expensive. Therefore, we will reformulate expression (10) in order to reduce the dimensionality. To this end, we first note that, due to the independency of the users and of the data symbols within one block, for BPSK symbols it holds:

$$\begin{aligned}&\forall i,j \in \{1,\ldots,K\},\ \forall m,n \in \{0,1,\ldots,M-1\}\\ &\mathsf{E}\{b_i[m]b_j[n]\} = \begin{cases}\tilde{b}_i[m]\tilde{b}_j[n], & i \neq j, m \neq n\\ 1, & i = j, m = n.\end{cases}\end{aligned}$$

Consequently, all the main-diagonal elements of the data covariance matrix $\mathsf{E}\{\boldsymbol{BB}^H\}$ have the form of $\sum \mathsf{E}\{b_k^2[m]\} = \sum 1$, while all the other elements are of the type $\sum \tilde{b}_i[m]\tilde{b}_j[n]$, where sums run over variable number of terms (depending on the actual element in the matrix). Now, let us observe another matrix, constructed as $\mathsf{E}\{\boldsymbol{B}\}\mathsf{E}\{\boldsymbol{B}^H\} \equiv \tilde{\boldsymbol{B}}\tilde{\boldsymbol{B}}^H$. Its main-diagonal elements are of the type $\sum \tilde{b}_k^2[m]$, while all the off-diagonal elements are equal to the corresponding elements of the matrix $\mathsf{E}\{\boldsymbol{BB}^H\}$. In other words, the following relation holds:

$$\mathsf{E}\{\boldsymbol{BB}^H\} = \tilde{\boldsymbol{B}}\tilde{\boldsymbol{B}}^H + \boldsymbol{\Lambda}, \tag{11}$$

with the diagonal matrix $\boldsymbol{\Lambda}$ defined as:

$$\begin{aligned}\boldsymbol{\Lambda} &= \sum_{k=1}^{K}\boldsymbol{\Lambda}_k\\ \boldsymbol{\Lambda}_k &= \begin{bmatrix}\boldsymbol{\Lambda}_{k1} & & \\ & \boldsymbol{\Lambda}_{k2} & \\ & & \boldsymbol{\Lambda}_{k3}\end{bmatrix},\end{aligned} \tag{12}$$

$$\boldsymbol{\Lambda}_{k1} = \mathsf{diag}\left\{\mathsf{var}\{b_k[0]\}, \sum_{m=0}^{1}\mathsf{var}\{b_k[m]\}, \ldots, \sum_{m=0}^{L-2}\mathsf{var}\{b_k[m]\}\right\},$$

$$\boldsymbol{\Lambda}_{k2} = \mathsf{diag}\left\{\sum_{m=0}^{L-1}\mathsf{var}\{b_k[m]\}, \sum_{m=1}^{L}\mathsf{var}\{b_k[m]\}, \ldots, \sum_{m=M-L}^{M-1}\mathsf{var}\{b_k[m]\right\},$$

$$\boldsymbol{\Lambda}_{k3} = \mathsf{diag}\left\{\sum_{m=M-(L-1)}^{M-1}\mathsf{var}\{b_k[m]\}, \ldots, \sum_{m=M-2}^{M-1}\mathsf{var}\{b_k[m]\}, \mathsf{var}\{b_k[M-1]\}\right\},$$

where the symbol variance is

$$\mathsf{var}\{b_k[m]\} = \mathsf{E}\left\{|b_k[m] - \mathsf{E}\{b_k[m]\}|^2\right\} = 1 - \tilde{b}_k^2[m].$$

Inserting Equation (11) into Equation (10) we obtain:

$$\hat{\boldsymbol{h}}_{n\,\text{LMMSE}} = \tilde{\boldsymbol{B}}^H\left(\tilde{\boldsymbol{B}}\tilde{\boldsymbol{B}}^H + \underbrace{\boldsymbol{\Lambda} + \sigma^2\boldsymbol{I}}_{\triangleq\boldsymbol{\Delta}}\right)^{-1}\boldsymbol{y}_n. \tag{13}$$

After applying the matrix inversion lemma to Equation (13), the final expression yields:

$$\hat{\boldsymbol{h}}_{n\,\text{LMMSE}} = (\tilde{\boldsymbol{B}}^H\boldsymbol{\Delta}^{-1}\tilde{\boldsymbol{B}} + \boldsymbol{I})^{-1}\tilde{\boldsymbol{B}}^H\boldsymbol{\Delta}^{-1}\boldsymbol{y}_n. \tag{14}$$

The matrix to be inverted in Equation (14) is KL-dimensional, which is much smaller compared to Equation (10). The elements of the diagonal matrix $\boldsymbol{\Delta}$ perform scaling of the rows of matrix $\boldsymbol{B}$, taking into account the variances of the noise and of the soft symbol estimates. For example, for $0 \leqslant l \leqslant (L-1)$, the llth element of $\boldsymbol{\Delta}$ is:

$$(\boldsymbol{\Delta})_{ll} = \sum_{k=1}^{K}\sum_{m=0}^{l}\mathsf{var}\{b_k[m]\} + \sigma^2.$$

If the transmitted data symbols in $\boldsymbol{B}$ were known to the receiver, i.e. if $\tilde{b}_k[m] = b_k[m]$, then it holds: $\boldsymbol{\Lambda} = \boldsymbol{0}$, $\boldsymbol{\Delta} = \sigma^2\boldsymbol{I}$. In this case, the estimator (14) is the exact MMSE estimator for a given $\boldsymbol{B}$ (recall that conditioned on the given matrix $\boldsymbol{B}$, random vectors $\boldsymbol{h}$ and $\boldsymbol{y}$ are jointly Gaussian, thus the linear MMSE is the true MMSE estimator):

$$\hat{\boldsymbol{h}}_{n\,\mathrm{MMSE}|\boldsymbol{B}} = (\boldsymbol{B}^H\boldsymbol{B} + \sigma^2\boldsymbol{I})^{-1}\boldsymbol{B}^H\boldsymbol{y}_n. \qquad (15)$$

Thus, for the training part of the data burst (first P symbols), the estimator (14) is the exact MMSE for given pilot symbols (whose variance is zero), while for the data part the variances of the estimates of unknown data symbols are taken into account through the matrix $\boldsymbol{\Delta}$.

4.3.2. Approximate estimators

In the previous work [31], we proposed to replace the unknown data matrix $\boldsymbol{B}$ in the MMSE estimator formula (15) by its soft estimate $\tilde{\boldsymbol{B}}$. Thus we obtain the estimator:

$$\hat{\boldsymbol{h}}_n = (\tilde{\boldsymbol{B}}^H\tilde{\boldsymbol{B}} + \sigma^2\boldsymbol{I})^{-1}\tilde{\boldsymbol{B}}^H\boldsymbol{y}_n. \qquad (16)$$

This corresponds to putting the scaling matrix $\boldsymbol{\Delta} = \sigma^2\boldsymbol{I}$ in Equation (14), as if the variances of the symbol estimates were zero. The simulations show that in the small MIMO system (with two to four transmit antennas and two receive antennas) this approximation has almost negligible influence on the receive performance. In larger systems, however, and in different multiple-access schemes (e.g. multicarrier CDMA, as in Reference [23]), this approximation significantly degrades the channel estimates and thus reduces receiver's performance.

The estimators given by Equations (14) and (16) assume independent, complex Gaussian channel coefficients and require the knowledge of the noise power at the receiver. If we do not take into account any prior statistical knowledge of the channel and the noise, the least-squares (LS) estimation approach can be applied. For known matrix $\boldsymbol{B}$ it yields the following result:

$$\hat{\boldsymbol{h}}_{n\,\mathrm{LS}|\boldsymbol{B}} = (\boldsymbol{B}^H\boldsymbol{B})^{-1}\boldsymbol{B}^H\boldsymbol{y}_n. \qquad (17)$$

When the data symbols are not known, the approximate LS-like estimator can be obtained by replacing the unknown symbols in Equation (17) with their soft estimates as in Reference [31]:

$$\hat{\boldsymbol{h}}_n = (\tilde{\boldsymbol{B}}^H\tilde{\boldsymbol{B}})^{-1}\tilde{\boldsymbol{B}}^H\boldsymbol{y}_n. \qquad (18)$$

The APP-based soft symbol estimates in $\tilde{\boldsymbol{B}}$ are recomputed in each iteration and the channel estimate given by Equations (14), (16) or (18) is updated. The comparison of the iterative LS and MMSE channel estimation is presented in the following section.

5. SIMULATION RESULTS

We simulated the iterative receiver for the uplink in a MIMO system with $N = 2$ receive and $K \in \{2, 3, 4\}$ transmit antennas. Thus, the *system load* β, defined as $\beta = K/N$, is larger than or equal to 1. The transmitted data blocks were encoded with a convolutional code of rate $R = 1/2$, memory 2, with generator polynomials (7,5) in octal notation. The data blocks contained either 300 ('short blocks') or 900 ('long blocks') coded data symbols. A preamble of each block consisted of a short ($P = 15$ symbols) or long ($P = 50$ symbols) pilot sequence. Thus, the effective code rate is

$$R_{\mathrm{eff}} = R\frac{M-P}{M},$$

where M is the total block length (including the pilots and the data). The system's *spectral efficiency* ρ, is given by $\rho = \beta R_{\mathrm{eff}}$. All users were transmitting with the same average power. The number of iterations in the receiver was limited to 4 or 5.

As a performance measure for channel estimation, we use the average relative estimation error defined as $\delta = \mathsf{E}_h\{||\boldsymbol{h} - \hat{\boldsymbol{h}}||^2/||\boldsymbol{h}||^2\}$. Figure 6 shows the decrease of δ during iterations for different noise levels, in a 2×2 MIMO system with the simplest, LS-like channel estimator (18). In the first iteration, the channel is estimated over pilot symbols only (soft estimates of data symbols in $\tilde{\boldsymbol{B}}$ are equal to zero). In each subsequent iteration, the soft symbol estimates are recomputed, the channel estimate error is recalculated and significantly improved (e.g. from 6%

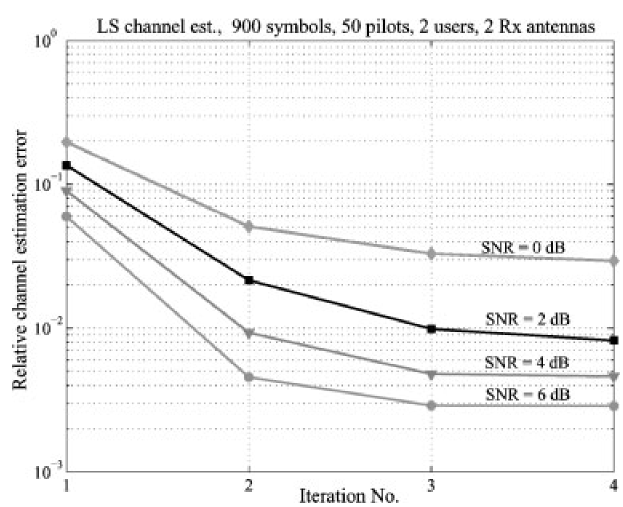

Figure 6. Reduction of the relative channel estimation error by iterative estimation, for least-squares (LS)-like approach (18).

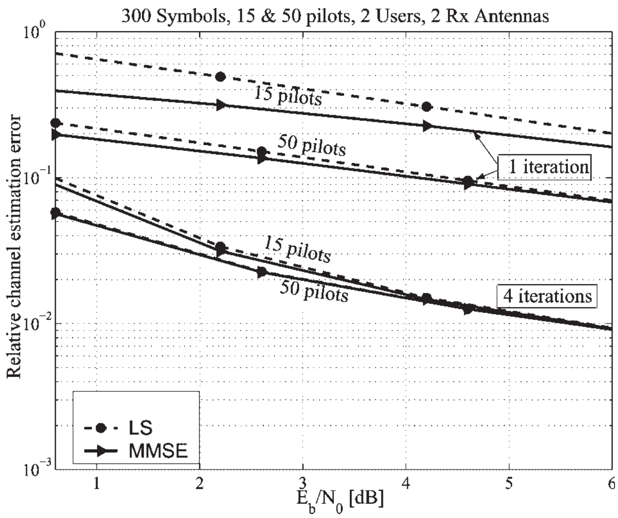

Figure 7. Average relative channel estimation error δ for LS and MMSE estimators.

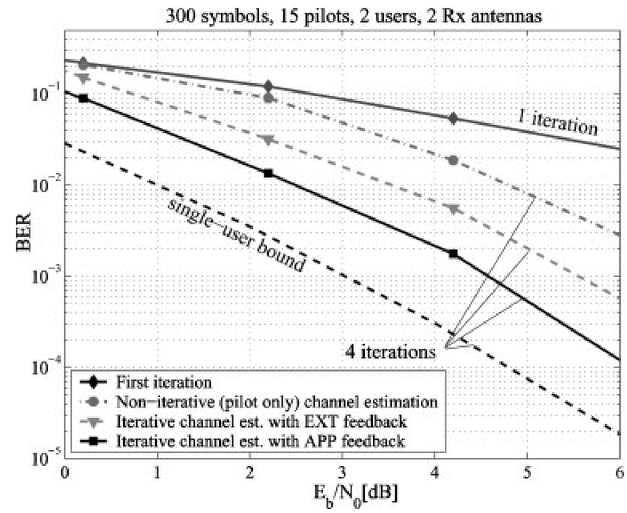

Figure 8. Bit error rate (BER) for different channel estimation approaches.

error in the first iteration to 0.3% in the last iteration, for $E_b/N_0 = 6\,\text{dB}$).

We compared the performance of the LMMSE estimator (14) with the approximate MMSE-like estimator (16) in a 2×2 and 3×2 system. Simulations show that using the approximate estimator in our setup negligibly degrades the performance (less than 0.1 dB). Therefore, we omit the corresponding plot. However, we observed significant degradation of the performance in other system setups, i.e. in CDMA and multicarrier CDMA system [23].

In Figure 7, we compare MMSE-like versus LS-like channel estimation ((16) and (18), respectively) for a 2×2 MIMO system with short data blocks and different number of pilots. For short pilot sequences, MMSE benefits from additional knowledge of the noise variance and yields better estimates in the first iteration (pilot-only estimation). After four iterations, however, the initial loss of LS-like estimation is compensated for by the iteration gain and both estimators converge to the same residual error. Thus, we conclude that for iterative estimation it is sufficient to use the simpler LS-like approach. Note also that for higher SNR reduced pilot sequence length (4.76% of the total block length) allows sufficiently good channel estimates.

Figure 8 shows in full lines the bit-error rate (BER) after first and fourth iteration for the receiver with LS-like channel estimator that uses APPs to update $\tilde{\boldsymbol{B}}$. The iteration gain is large. For comparison, dashed lines show the performance of the receiver that performs pilot-only LS-like estimation (no update during iterations), and of the receiver that uses EXT-based soft symbol estimates to update LS-like channel estimate. APP-based iterative channel estimation over the whole data block by far outperforms both the non-iterative (pilot-only) estimation as well as the EXT-based iterative estimation. This result justifies the iterative structure in Figure 4. The single-user bound in Figure 8 represents the receiver's performance when there is only one user in the system (no MAI), and the channel is perfectly known at the receiver. The performance gap with respect to this bound is about 1.4 dB. This result is obtained using short data blocks, which are disadvantageous in our setup: since fading is assumed block-constant, longer data blocks allow better channel estimation, which yields lower BER for longer blocks. This can be observed by comparing Figure 8 with Figure 9, which shows the BER for long blocks, with 15 and 50 pilot symbols. Longer training sequences allow better initial channel estimation which leads to a BER that is closer to the single-user bound, and approaches the BER with perfectly known channel. The reduction of pilot sequence length to 15 symbols causes a loss of less than 0.5 dB for $E_b/N_0 \geq 4\,\text{dB}$.

Figure 10 depicts the receiver's performance when the number of users in the system is increased, while keeping the number of receive antennas constant ($N = 2$). The transmitted data blocks contain 900 data and 50 pilot symbols. For this case, the load of $\beta = 1$ corresponds to a spectral efficiency of $\rho = 0.474$ and the load of $\beta = 3/2$ corresponds to $\rho = 0.71$. The iterative receiver can successfully separate three users, with a BER that is very close

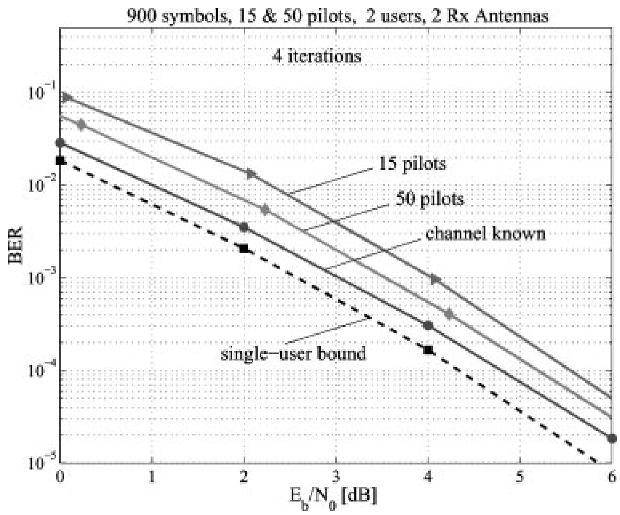

Figure 9. BER for estimated and perfectly known channel.

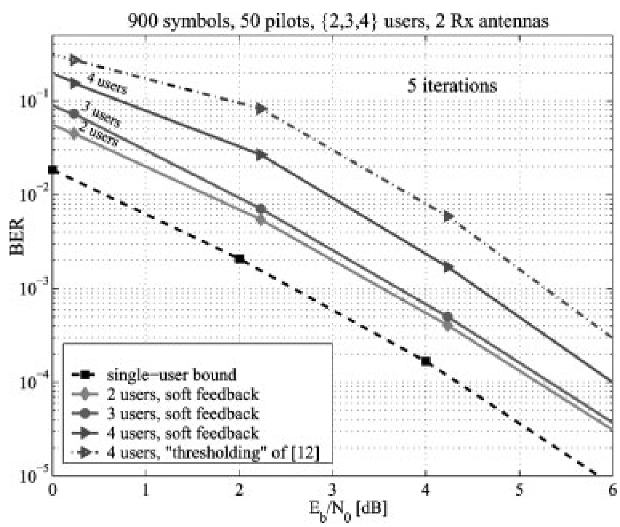

Figure 10. BER for different number of users in the system.

to the two-user case. With a loss of approximately 1 dB the system can accommodate $K = 4$ users (i.e. $\beta = 2$ and $\rho = 0.947$). Theoretical studies [25] show that the number of users can be increased without bound, provided that the average power per user is increased and the total power is appropriately, non-uniformly distributed among the users.

In the setup with four users and two receive antennas (Fig. 10), we compared the performance of soft decision feedback (from the decoders to the channel estimator) with hard decision feedback of 'reliable' symbols only, as proposed in Reference [12]. The symbols are identified as reliable by comparing their $\mathcal{L}^{\text{APP}}$ in every iteration with a certain threshold value. We used the value of 0.5. Estimating the channel using soft estimates of all the symbols yields much better results compared to the case of using hard decisions of several reliable symbols. This difference is more pronounced for lower SNR, in larger systems and in case of transmission with shorter pilot sequences.

6. SUMMARY AND CONCLUSIONS

In this paper, we propose an iterative receiver algorithm for MIMO systems in frequency-selective fading channels. The algorithm performs iterative channel estimation, soft interference cancellation with MMSE post-filtering and soft-in soft-out MAP decoding. The decoder computes extrinsic and *a-posteriori* log-likelihood ratios of coded symbols in each iteration. A novel LMMSE channel estimator, which exploits soft estimates of all the data symbols, is derived. The estimator is initiated by the pilot symbols, and updated in each iteration, using the *a-posteriori* based soft data decisions, obtained from the decoders' output. Two approximate channel estimators, based on LMMSE and LS solution are presented, and their performance is compared by simulations. Simulations show that the two estimators have the same MSE performance after few iterations. Iteration gain allows reduction of pilot sequence length to less than 5% of the total block length. The iterative receiver can accommodate a number of users higher than the number of receive antennas without significant performance loss. The presented scheme with soft feedback of all the data symbols outperforms the equivalent scheme with hard decision feedback of only reliable data symbols, particularly for increased number of users and shorter pilot sequences.

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