Interference Cancellation Based on Divergence Minimization for MIMO-OFDM Receivers

Carles Navarro Manchón*, Gunvor E. Kirkelund†, Bernard Fleury+†, Preben Mogensen*, Luc Deneire+‡, Troels B. Sørensen* and Christian Rom§

*Department of Electronic Systems, Aalborg University
†Forschungszentrum Telekommunikation Wien (FTW), Vienna, Austria
‡Université de Nice, Sophia Antipolis
§Centre National de la Recherche Scientifique
I3S, UMR 6070, France
†Infineon Technologies Denmark A/S
Alfred Nobels Vej 25, DK-9220 Aalborg, Denmark

Abstract—In this paper, we present a novel iterative receiver for MIMO-OFDM systems with synchronous interferers. The receiver is derived based on the Kullback-Leibler divergence minimization framework, and combines channel estimation, interference cancellation and residual noise estimation in an iterative manner. By using both the pilot and data symbols, the channel estimator improves the accuracy of the estimates in each iteration, which leads to a more effective interference cancellation and data detection process. A performance evaluation based on Monte-Carlo simulations shows that the proposed scheme can effectively mitigate the effect of interferers, and operates very close to the single-user performance even in severe interference scenarios.

I. Introduction

Orthogonal Frequency Division Multiplexing (OFDM) has become the selected transmission technique for several recent wireless standards, such as the IEEE standard for local and metropolitan area networks (better known as WiMAX) [1], or the 3GPP UTRA Long Term Evolution (LTE) [2]. Its ability to cope with time-dispersive channels while allowing for receivers with low complexity, its ability to easily integrate multiple antenna techniques and its flexibility in terms of bandwidth usage and resource allocation are some of the advantages that have motivated its selection.

In OFDM, the transmission bandwidth is divided into multiple narrowband subcarriers. By the addition of a proper cyclic prefix (CP), these subcarriers become fully orthogonal and experience frequency flat fading conditions in time-invariant channels [3]. This allows for simple equalization of the signal at the receiver, while keeping a high spectral efficiency due to the use of orthogonal overlapping subcarriers. In OFDM systems with frequency re-use, however, the signal transmitted from other cells may create co-channel interference which, if not correctly treated, can induce a severe degradation of the receiver performance, especially at the cell edge.

Much work has been done in interference cancellation techniques for OFDM, as in [4]–[6]. These methods, however, assume perfect knowledge of the channel at the receiver. In [7], a minimum mean-squared error interference rejection combiner (MMSE-IRC) for OFDM receivers with multiple antennas is proposed. The combiner parameters are estimated using a discrete-Fourier-transform-based robust MMSE instantaneous correlation estimator, which is therefore sensitive to the leakage effect [8] when the channel delays are not perfectly aligned with the receiver sampling grid.

In our latest work, we proposed an iterative pilot-based channel estimator for OFDM systems with synchronous interferers and super-imposed pilots [9]. In this work, we propose an iterative receiver performing channel estimation, interference cancellation and residual noise variance estimation. Our receiver is derived by applying the Kullback-Leibler (KL) divergence minimization (DM) principle, which was presented in [10] for multiuser detection in a code-division multiple access scenario. The channel estimator combines the information available from the pilot symbols with information from soft-decisions on the data symbols, thus outperforming typical schemes using only the pilot symbols. Furthermore, the channel estimation error is taken into account in the interference cancellation and detection process by estimating the covariance of the channel estimates and the residual noise covariance.

The remainder of the paper is organized as follows. The signal model for our considered scenario is presented in Section II. In Section III, the DM framework is briefly introduced, and the proposed iterative receiver is derived. Its performance is assessed by means of Monte-Carlo simulations in Section IV and finally some concluding remarks are provided in Section V.

The following notation will be used throughout the paper. Vectors are represented by boldface lowercase letters, while matrices are denoted as boldface uppercase letters; (·)T and (·)H denote respectively the transpose and conjugate transpose of a vector; tr{·} denotes the trace operation, and diag{·} represents a diagonal matrix with the elements of vector x; A ⊗ B denotes the Kronecker product of matrices A and B; IN represents the N × N identity matrix; x ∝ y denotes direct proportionality, i.e., x = αy, and x ∝ y denotes
exponential proportionality, i.e., \( \exp[x] = \exp[\beta + y] \), for arbitrary constants \( \alpha \) and \( \beta \); finally, \( E_q \{ f(x) \} \) represents the expectation of the function \( f(x) \) with respect to the probability distribution \( q_x(x) \) of \( x \).

II. SIGNAL MODEL

We consider a MIMO-OFDM system with \( M \) transmit antennas and a receiver with \( N \) receive antennas, as depicted in Fig. 1. Transmit antennas \( 1, \ldots, M_d \) transmit the signal of interest, while antennas \( M_d + 1, \ldots, M \) are regarded as interferers. We assume that all transmitters in the system are perfectly synchronized in time and use the same frequency resources. For the \( m^{th} \) transmitter, the information bits \( b_m(k) \), \( k = 1, \ldots, K_b, m \) are encoded, yielding a stream of coded bits \( c_m(k), k = 1, \ldots, K_c, m \), which is modulated onto a set of QAM/QPSK symbols denoted by \( x_{d,m}(k), k = 1, \ldots, K_d \). The data symbols are then multiplexed with a sequence of pilot symbols \( x_p,m(k), k = 1, \ldots, K_p \), resulting in the transmitted symbols sequence \( x_m(k), k = 1, \ldots, K \). The transmitted symbols are then OFDM modulated by means of an inverse fast Fourier transform (IFFT) and the insertion of a cyclic prefix. We assume that the sets of pilot subcarriers \( \mathcal{P} = \{ p_1, \ldots, p_{K_p} \} \) and data subcarriers \( \mathcal{D} = \{ d_1, \ldots, d_{K_d} \} \) are the same for all transmitters, and hence

\[
x_m(k) = \begin{cases} x_{p,m}(i), & \text{if } k \in \mathcal{P} \\ x_{d,m}(i), & \text{if } k \in \mathcal{D} \end{cases}.
\]

(Note that \( \mathcal{P} \cap \mathcal{D} = \{1, \ldots, K\} \) and \( \mathcal{P} \cap \mathcal{D} = \emptyset \). \( K \) denotes the total number of subcarriers in the system, while \( K_p \) and \( K_d \) denote the number of pilot and data subcarriers respectively.

The signal received at each of the antenna ports is OFDM demodulated by removing the cyclic prefix and performing a fast Fourier transform (FFT). Assuming that the channel is static during one OFDM symbol and that the cyclic prefix is longer than the maximum excess delay of the channel, the signal received at the \( k^{th} \) subcarrier of receive antenna \( n \) reads

\[
r_n(k) = \sum_{m=1}^{M} h_{nm}(k) x_m(k) + w_n(k) \tag{2}
\]

where \( h_{nm}(k) \) denotes the channel frequency response from transmitter \( m \) to receive antenna \( n \) at subcarrier \( k \) and \( w_n(k) \) is additive white Gaussian noise (AWGN) with variance \( \sigma_w^2 \). The received signal at all subcarriers in all receive antenna ports can be expressed in vector-matrix notation as

\[
r = \sum_{m=1}^{M} H_m x_m + w. \tag{3}
\]

In the above expression, \( r = \begin{bmatrix} r_1^T, \ldots, r_N^T \end{bmatrix}^T \), \( H_m = \begin{bmatrix} \text{diag}(h_{1m}), \ldots, \text{diag}(h_{Nm}) \end{bmatrix}^T \), \( x_m = \begin{bmatrix} x_m(1), \ldots, x_m(K) \end{bmatrix}^T \) and \( w = \begin{bmatrix} w_1(1), \ldots, w_1(K), \ldots, w_N(1), \ldots, w_N(K) \end{bmatrix}^T \). Furthermore, \( r_n = \begin{bmatrix} r_n(1), \ldots, r_n(K) \end{bmatrix}^T \), \( h_{nm} = \begin{bmatrix} h_{nm}(1), \ldots, h_{nm}(K) \end{bmatrix}^T \) and we also define \( h_m = \begin{bmatrix} h_{1m}^T, \ldots, h_{Nm}^T \end{bmatrix}^T \).

III. PROPOSED RECEIVER

In this section, our proposed iterative receiver with channel estimation and interference cancellation is presented. First, the general DM principle is briefly explained, followed by the application to our specific scenario. Finally, some remarks on implementation issues are given.

A. The Divergence Minimization principle

Let \( \Phi \) denote a vector including as components all the unknown parameters to be estimated and \( p(\Phi | r) \) be the posterior probability density function (pdf) of \( \Phi \) given an observation \( r \). The DM framework approximates \( p(\Phi | r) \) by an auxiliary pdf \( q(\Phi) \) minimizing the KL divergence [11]

\[
D\left(p(\Phi) \bigg|\bigg| q(\Phi) \right) = \int d\Phi q(\Phi) \log \frac{q(\Phi)}{p(\Phi | r)}.
\]

In our application, we are interested in estimating the desired transmitted signals \( x_1, \ldots, x_{M_d} \). To achieve this reliably, we need estimates of the channel transfer functions \( h_1, \ldots, h_M \), the interfering signals \( x_{M_d+1}, \ldots, x_M \) and the inverse of the noise covariance matrix \( \Sigma_w^{-1} \), with \( \Sigma_w = E \{ w w^H \} \). Therefore, the set of parameters to be estimated is \( \Phi = \{ \Sigma_w^{-1}, h_1, \ldots, h_M, x_1, \ldots, x_M \} \), while the observation vector \( r \) is given by (3). In order to obtain a solution that can be computed with tractable complexity, we define an auxiliary function \( q(\Phi) \) that factorizes according to

\[
q(\Phi) = q_{\Sigma_w^{-1}}(\Sigma_w^{-1}) \prod_{m=1}^{M} q_{h_m}(h_m) q_{x_m}(x_m). \tag{5}
\]
The auxiliary function is iteratively updated by minimizing the KL divergence in (4) with respect to one of the factors in (5) while keeping the rest fixed. By alternatively updating the different factors, the KL divergence is minimized and the auxiliary distribution \( q(\Phi) \) approximates the true posterior pdf \( p(\Phi | r) \). More details about the formal principles of the DM framework can be found in [10].

In the following, the updating steps of \( q(\Phi) \) with respect to the different parameters are described. The algorithm assumes initial distributions \( q_0^{[i]}(\Sigma^{-1}) \), \( q_0^{[m]}(h_m) \) and \( q_0^{[c]}(x_m) \), where the superindex \( (\cdot)^{[i]} \) indicates the \( i \)th updating step.

### B. Update of the channel gain distributions

When updating the channel distribution \( q_{h_m}(h_m) \) in the \((i+1)\)th updating step, the distributions \( q_{w_m}^{[i]}(\Sigma^{-1}) \), \( q_{x_m}^{[i]}(x_m) \) are kept fixed. By alternatively updating \( h_m \) and \( q_{h_m}^{[i]}(h_m) \), the rest are treated as constants. The updated distribution \( q_{h_m}^{[i+1]}(h_m) \) is obtained by solving the minimization problem:

\[
\text{minimize } D(q_{h_m}(h_m) || q_{h_m}^{[i]}(h_m)) \mid p(h_m) \text{ subject to } q_{h_m}(h_m) \in \mathbb{R}^N, (6)
\]

which leads to the solution

\[
q_{h_m}^{[i+1]}(h_m) \propto p(h_m) \cdot \exp \left[ E_{q_{h_m}^{[i]}} \left( E_{q_{h_m}} \left( \log p(r | \Phi) \right) \right) \right]
\]

where \( p(h_m) \) denotes the prior distribution of \( h_m \). The log-likelihood function in (7) reads

\[
\log p(r | \Phi) \propto \sum_{m=1}^{M} H_m x_m = \sum_{m=1}^{M} H_m x_m.
\]

By assuming that the prior distribution of \( h_m \) is Gaussian with zero mean and covariance matrix \( \Sigma_{h_m} = E \{ h_m h_m^T \} \), the marginalizations in (7) lead to an updated distribution which is also Gaussian, with pdf

\[
q_{h_m}^{[i+1]}(h_m) \propto \exp \left[ - (h_m - h_m^{[i+1]})^T \Sigma_{h_m}^{[i+1]^{-1}} (h_m - h_m^{[i+1]}) \right].
\]

The mean value is given by

\[
h_m^{[i+1]} = \Sigma_{h_m}^{[i]} + \bar{X}_{m}^{[i]} \Sigma_{w_m}^{[i]^H} \{ \Sigma_{w_m}^{[i]} \}^{-1} B_{m}^{[i]} - \bar{X}_{m}^{[i]} \Sigma_{w_m}^{[i]} \{ \Sigma_{w_m}^{[i]} \}^{-1} (r - \sum_{j \neq m} \bar{X}_{j}^{[i]} x_j)
\]

and the covariance is

\[
\Sigma_{h_m}^{[i+1]} = \Sigma_{h_m}^{[i]} + \bar{X}_{m}^{[i]} \Sigma_{w_m}^{[i]} \{ \Sigma_{w_m}^{[i]} \}^{-1} B_{m}^{[i]} - \bar{X}_{m}^{[i]} \Sigma_{w_m}^{[i]} \{ \Sigma_{w_m}^{[i]} \}^{-1} (r - \sum_{j \neq m} \bar{X}_{j}^{[i]} x_j)
\]

In the above equations, \( \bar{X}_{j}^{[i]} = E_{q_{w_j}^{[i]}} \{ x_j \} \), \( \bar{X}_{j}^{[i]} = I_M \otimes \text{diag}(\bar{x}_j) \), and \( B_{j}^{[i]} = I_M \otimes \text{diag}(\bar{\sigma}_{x_j(1)}, \ldots, \bar{\sigma}_{x_j(K)}) \) with \( \bar{\sigma}_{x_j(k)} = E_{q_{w_j}^{[i]}}(|x_j(k)|^2) - |\bar{x}_j(k)|^2 \). Details on \( (\Omega_{w_m}^{[i]} \})^{-1} \) will be given in the following subsection.

### C. Update of the inverse noise covariance distribution

For the update of the inverse noise covariance distribution \( q_{\Sigma^{-1}}^{[i]}(\Sigma^{-1}) \), the distributions \( q_{x_m}^{[i]}(x_m) \) and \( q_{h_m}^{[i]}(h_m) \) are kept fixed, leading to the following minimization problem:

\[
\begin{align*}
\text{minimize } & D(q_{w_m}^{[i]}(\Sigma^{-1}) || q_{w_m}^{[i]}(\Sigma^{-1})) \mid p(\Sigma^{-1}) \\
\text{subject to } & \int q_{w_m}^{[i]}(\Sigma) d\Sigma = 1 \\
& \Sigma_{w_m}^{[i]} \geq 0.
\end{align*}
\]

Analogously to the channel gain update, the solution of the minimization reads

\[
q_{w_m}^{[i+1]}(\Sigma) \propto p(\Sigma^{-1}) \exp \left[ E_{q_{w_m}^{[i]}} \left( E_{q_{w_m}} \left( \log p(r | \Phi) \right) \right) \right].
\]

After performing the marginalizations with respect to the channel distribution and the transmitted symbols distribution, and assuming \( p(\Sigma^{-1}) \) is a uniform distribution, we obtain an updated distribution given by

\[
q_{w_m}^{[i+1]}(\Sigma^{-1}) \propto |\Sigma^{-1}| \exp \left[ \text{tr} \{ -\Sigma^{-1} C^{[i]} \} \right]
\]

with

\[
C^{[i]} = \sum_{j=1}^{M} (\bar{X}_{j}^{[i]} \Sigma_{h_j}^{[i]} \bar{X}_{j}^{[i]}) \\
+ \sum_{j=1}^{M} B_{j}^{[i]} \Sigma_{h_j}^{[i]} B_{j}^{[i]H} \\
+ \sum_{j=1}^{M} \bar{X}_{j}^{[i]} \Sigma_{h_j}^{[i]} \bar{X}_{j}^{[i]H}.
\]

The above expression has the form of a complex Wishart distribution [12]. Specifically, the matrix \( \Sigma^{-1} \) is Wishart distributed as \( \Sigma^{-1} \sim W_{NK}(NK + 2, C^{[i]}) \), and has mean value

\[
(\Omega_{w_m}^{[i+1]} \})^{-1} = E_{q_{w_m}^{[i+1]}} \{ \Sigma^{-1} \} = \left( \frac{C^{[i]}}{NK + 2} \right)^{-1}
\]

In order to obtain simpler expressions, it can be further assumed that \( \Sigma^{-1} \) represents the covariance matrix of a white Gaussian process with \( \Sigma^{-1} = \sigma_w^{-2} \mathbb{I}_{NK} \). Under these conditions, the corresponding distribution of the reciprocal variance becomes

\[
q_{\sigma^{-2}}^{[i+1]}(\sigma_w^{-2}) \propto (\sigma_w^{-2})^{-NK} \exp \left[ - \sigma_w^{-2} \text{tr} \{ C^{[i]} \} \right]
\]

which is chi-square distributed [12], with mean value

\[
(\sigma_w^{-2})^{[i+1]} = E_{q_{\sigma^{-2}}^{[i+1]}} \{ \sigma_w^{-2} \} = \left( \frac{\text{tr} \{ C^{[i]} \}}{NK + 2} \right)^{-1}.\]
D. Update of the transmitted symbol distributions

Analogously to the other updates, when updating the distribution \( q_{x_m}(x_m) \), the distributions \( q_{x_m}^{[i]}(x) = \prod_{j \neq m} q_{x_j}^{[i]}(x_j) \), \( q_{h}^{[i]}(h) = \prod_{j=1}^{M} q_{h_j}^{[i]}(h_j) \) and \( q_{\Sigma_w^{-1}} \) are kept fixed, and the update is achieved by solving

\[
\begin{align*}
\text{minimize} & \quad D\left(q_{x_m}(x_m) \bigg| \bigg| q_{x_m}^{[i]}(x_m) \bigg| \bigg| q_{\Sigma_w^{-1}}(\Sigma_w^{-1}) \right) \left\| p(\Phi|\rho) \right\| \\
\text{subject to} & \quad \sum_{x_m} q_{x_m}(x_m) = 1 \\
& \quad q_{x_m}(x_m) \geq 0.
\end{align*}
\]

The solution to (19) reads

\[
q_{x_m}^{[i+1]}(x_m) \propto p(x_m) \cdot \exp \left[ \mathbb{E}_{q_{h_j}^{[i]}} \left\{ \mathbb{E}_{q_{x_j}^{[i]}} \left\{ \log p(\rho|\Phi) \right\} \right\} \right]
\]

Since no prior information on the transmitted data symbols is available (we assume that the receiver has perfect information on the pilot symbols), a uniform prior distribution is assumed, and \( p(x_m) \) can be removed from (20). After marginalizing with respect to the fixed distributions, the updating step is given by

\[
q_{x_m}^{[i+1]}(x_m) \propto \exp \left[ 2\sigma_w^{-2} \sum_{k=1}^{K} \sum_{n=1}^{N} \sum_{j=1}^{M} \right. \\
\left. h_{nm}^{[i]} \gamma_{nm}(k) \mathbb{I}_{K} \mathbb{I}_{K}, \right]
\]

\[
\gamma_{nm}(k) = r_{nm}(k) - \sum_{j \neq m} h_{nj}^{[i]}(k) \hat{x}^{[i]}(k)
\]

\[
- \frac{1}{2} \left( h_{nm}^{[i]}(k) \hat{x}^{[i]}(k) + \frac{x_{m}^{[i]} + \Sigma_{h_m}(k,k)}{h_{nm}^{[i]}(k)} \right),
\]

where we have assumed that \( \Sigma_{w}^{-1} = \sigma_w^{-2} \mathbb{I}_{N_K} \), as in (18). As it can be observed in the above expressions, the updated distribution is obtained by cancelling the signal contribution from other transmitters. Also, the covariance of the channel estimates, \( \Sigma_{h_m} \), is taken into account. From the updated distribution, the values of \( \hat{x}_{m}^{[i+1]} \) and \( B_{m}^{[i+1]} \) are calculated to be used in the updates of the inverse noise covariance and the channel gain distributions. When the last iteration of the algorithm is reached, the distributions \( q_{x_m}(x_m) \), \( m = 1, \ldots, M_d \) are used to obtain soft estimates of the coded symbols, which are fed to the channel decoder in order to detect the information bits.

E. Implementation Issues

1) Order of the updates: While the DM framework allows to obtain the update rules for each of the distributions minimizing the KL divergence with respect to the true posterior distribution, there is so far no formal way of determining the optimal updating sequence. Therefore, this has to be determined by performing a performance evaluation of the different possible updating orderings by, e.g., Monte-Carlo simulations. In this work, we opt to evaluate the following scheme:

1) Update \( q_{h_m}(h_m) \), \( m = 1, \ldots, M \).
2) Update \( q_{x_m}(x_m) \), \( m = 1, \ldots, M \).
3) Update \( q_{\Sigma_w^{-1}} \).

The above sequence of updates represents a full iteration of the receiver. Although there is no evidence of this scheme being optimal, simulation results shown in the next section confirm the good performance of a receiver using this design.

2) Initialization: Although the convergence of the DM receiver is ensured due to the minimization performed at each update step, the receiver might converge to different stationary points depending on the initial values used in the algorithm. It is therefore of crucial importance to initialize the iterative receiver properly. In this work, we choose to initialize the channel estimates with a linear minimum mean-squared error (LMMSE) channel estimator using only the signal received at pilot subcarriers. The expression of the LMMSE channel estimates for channel \( h_m \) reads

\[
h_m^{[0]} = \Sigma_{h_m} h_m \cdot \Phi^{-1} r_p
\]

where \( \Sigma_{w} = \mathbb{E}(w_p w_p^H) \), \( \Sigma_{h_m} h_m = \mathbb{E}(h_m h_m^H) \) and \( \Sigma_{h_p,j} = \mathbb{E}(h_{p,j} h_{p,j}^H) \). The subindex \( p \) in matrices and vectors indicates that only elements corresponding to the pilot subcarriers are taken. The initial values for the covariance of the channel estimates are taken from the prior channel covariance, i.e., \( \Sigma_{h_m}^{[0]} = \Sigma_{h_m} \).

Once an initial value for the channel estimates is available, estimates of the transmitted symbols can be obtained. In our proposed implementation, these are obtained using a soft-output maximum-likelihood detector (MLD) [13]. From the soft output detector, the initial values \( x_{m}^{[0]} \) and \( B_{m}^{[0]} \) are obtained for \( m = 1, \ldots, M \). With these initial values, the initial estimate of the inverse noise covariance \( (\Omega_{w}^{[0]})^{-1} \) is obtained by using either (16) or (18).

IV. Performance Evaluation

In this section, we evaluate the performance of the proposed channel estimator by means of Monte-Carlo simulations. In order to do so, we define an OFDM system with parameters inspired by the 3GPP Long Term Evolution (LTE) 5 MHz downlink physical layer parameters [2]. The system operates with an FFT size of 512, with 300 active subcarriers, and a frequency spacing of 15 KHz between them. Pilot subcarriers are transmitted in every OFDM symbol, with a frequency spacing of 12 subcarriers (i.e. 600 KHz) between them. The desired and interfering signals have their pilots in the same subcarriers, and perfect synchronization between the transmitters is assumed. Hence, pilots of all transmitted signals overlap in frequency. The pilot sequences are made of random independent and uniformly distributed QPSK symbols. A convolutional code is used for channel coding, with BCJR [14]
decoding at the receiver, and QPSK modulation is employed for the data symbols. We consider a scenario with two single-antenna transmitters, one transmitting the desired signal and the other being an interferer. The receiver has two receive antennas, and the signal-to-interference level per receive antenna branch is 0 dB (i.e., both the desired and interfering signal are received with the same power). The channel responses are generated according to the extended Typical Urban channel model [15], which consists of 9 taps and has a maximum excess delay of 5 μs. Block fading is used, i.e., the channel response is static over the duration of an OFDM symbol, and we assume that the cyclic prefix is long enough to cope with the inter-symbol interference due to multipath propagation.

In Fig. 2, the bit error rate performance of our proposed receiver in the considered scenario is depicted. For comparison’s sake, the performance of a receiver using LMMSE channel estimation and MLD detection (also used as initialization for the DM receiver) is shown, as well as the single-user bound (SUB). As it can be seen, the iterative process greatly improves the performance of the receiver with a few iterations. After the first iteration of the algorithm, the receiver shows a gain of 0.9 dB at 1% BER with respect to the initialization, which is further improved up to a 1.7 dB gain with five iterations. After the first few iterations the receiver converges, achieving a performance which is only slightly more than 2 dB away from the SUB, even in such a strong interference environment.

In Fig. 3, the performances of the DM receiver’s channel estimator and the pilot-based LMMSE channel estimator are compared. As the plot shows, a great improvement in the channel estimates’ accuracy is obtained after just the first iteration. This is due to the increase of information used in the channel estimator: while the LMMSE only makes use of the observations at pilot subcarriers, the DM channel estimator combines those with the estimates at the data subcarriers and the partial information available on the data symbols. In subsequent iterations, the reliability of the information on the data symbols is increased due to the interference cancellation at the detector and the estimate of the noise covariance, leading to an improvement in the channel estimates.

V. CONCLUSION

In this work we have presented a novel iterative receiver for MIMO-OFDM systems with synchronized interferers. The receiver, derived under the DM framework, combines channel estimation, interference cancellation and residual noise estimation in an iterative fashion, and is guaranteed to converge due to the formal principle under which it has been derived. The performance has been assessed by means of Monte-Carlo simulations, showing that our proposed scheme performs very closely to the single-user bound, even with an interference level as high as 0 dB. This is due, in large proportion, to the channel estimator, which combines the information available from the pilot symbols with the information obtained from soft-decisions on the data symbols, allowing to drastically reduce the channel estimates’ error.

ACKNOWLEDGMENT

This work has been partly funded by the FP7-ICT Network of Excellence in Wireless Communications, NEWCOM++ (Contract No. 216715). The authors would also like to thank Infineon Technologies Denmark A/S and Nokia Denmark A/S for the financial support which made this work possible.

REFERENCES


