Joint Channel Estimation and Decision Directed Decoding for OFDM-IDMA Systems over Sparse Channels

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Joint Channel Estimation and Decision Directed Decoding for OFDM-IDMA Systems over Sparse Channels

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***Abstract*—Combining Orthogonal Frequency Division Multiplexing (OFDM) and Interleave Division Multiple Access IDMA (OFDM-IDMA) in the mobile radio environment has been proven to be a promising multiple access scheme for wireless communications thanks to its low decoding complexity and potential for achieving a high spectral efficiency over severe frequency selective channels. Channel estimation accuracy is crucial for the coherent demodulation in OFDM systems. In this paper, we consider this issue where our aim is to exploit some structural properties of the channel response in the aim of higher estimation accuracy. This work is concerned with sparse channels in the temporal domain. Our aim is mainly to show that by associating a simple denoising processing, accounting for the channel sparsity, within the joint channel estimation decision directed decoding scheme, a better tradeoff between performance and complexity is achieved. More precisely, an MST (Most Strong Taps) algorithm is incorporated within a Maximum Likelihood solution using the Space Alternating Generalized Expectation Maximization (SAGE-ML) algorithm [1]. Simulation results have shown the superiority of SAGE-ML with MST in terms of Mean Squared Error (MSE) and Bit Error Rate (BER) compared to the SAGE-ML not exploiting the channel sparsity.**

I. Introduction

Interleave Division Multiple Access (IDMA) [2], is a recent multiple access technique where interleavers are the only means to separate users. This technique has been shown to mitigate interference due to the multiple access simultaneously achieving a high spectral efficiency. In fact interleavers are used, rather than spreading sequences in Coded Division Multiple Access (CDMA), to allow the receiver to remove the Multiple Access Interference (MAI). For each user, an iterative detection algorithm is processed, known as Chip-By-Chip detection.

One challenging problem is that of equalization which becomes more and more serious when the system bandwidth grows and when the frequency selectivity is accentuated due to the multipath effects. These drawbacks call for relevant schemes of modulation and for advanced processing at the receiver. The OFDM scheme indeed avoids Inter Symbol Interference (ISI) by the use of guard temporal intervals. Also, it greatly simplifies the equalization task by dividing the occupied highly frequency selective channel into sufficiently narrow subbands to have almost flat frequency responses.

The OFDM systems however call for a precise channel estimate. Especially in multiple access, it is crucial for reliable decoding and interference cancellation. Channel estimation is commonly carried out using pilot symbols which are known at the receiver side. In the case of OFDM-IDMA systems, the channel estimation is performed iteratively exploiting the structure of IDMA receivers. Channel estimation for OFDM-IDMA systems has been conducted in many works. For example in [3] channel response on pilot subcarriers are first calculated using the Least Squares (LS) algorithm and the responses on the other subcarriers are computed using a linear interpolation. In [4], channel estimation exploits the structure of IDMA receivers to iteratively provide a reliable channel estimate.

In this paper, the Maximum Likelihood solution using the Space Alternating Generalized Expectation Maximization (SAGE) algorithm is studied. This scheme is based on pilots and hard decisions on decoded data symbols, and is referred to as SAGE-ML [4]. To initialize the SAGE algorithm, a pilot-based coarse channel estimate is first derived. In this work, a special attention is given to channels characterized by a sparse structure in the temporal domain. We indeed propose to exploit the sparsity property in order to denoise the channel estimation. More precisely, an MST (Most Strong Taps) [5] detection algorithm is used and compared to a threshold-based detection scheme [6]. Channel estimation is performed in two stages. At the first stage, we perform a coarse estimation of the channel using a block-type estimation (one pilot OFDM block). Two algorithms are then discussed and compared, the LS and the LS using Successive Interference Cancellation (SIC) referred to as LS-SIC. Once the coarse estimate is derived, we move to the second stage which iterates between data decoding (based on channel estimate) and channel estimation updating through SAGE-ML (based on decoded data). Exploiting the channel sparsity, we inculde the MST algorithm where two versions are envisaged, in both the coarse and decision directed stages. The first MST version works under the assumption that the number of the resolved paths is known at the receiver and the other one blindly performs MST using a threshold.

The remainder of the paper is organized as follows. Section II provides OFDM-IDMA system model. Section III discusses the joint channel estimation and decision directed decoding scheme. Section IV introduces channel estimation exploiting sparsity. Numerical results are presented in Section V, followed by a conclusion in Section VI.

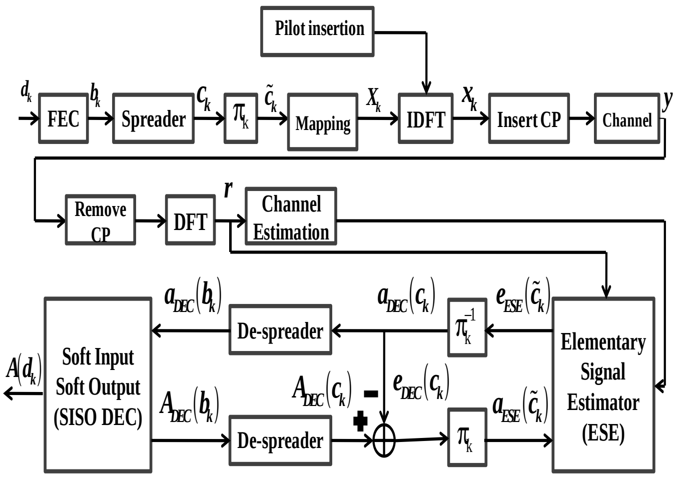

Fig. 1. OFDM-IDMA Transmitter and Receiver Structures

II. System Model

We consider an OFDM-IDMA system [7] with simultaneous K users. Fig. 1 shows the transmitter and the receiver structures for user k.

A. Transmitter

As presented in Fig. 1, the transmitter is divided in two parts one for the Multiple Access scheme (IDMA) and the other for OFDM.

Let's focus on the transmitter for user k. Firstly, the information input d_k is encoded by a Forward Error Correction (FEC) code and then spreaded by a spreading sequence which may be the same for all users. Then the sequence of chips c_k is interleaved using a specific interleaver π_k to separate users. This operation is the key feature of IDMA since it represents the only means to separate users. After symbol mapping, the symbols X_k modulate the subcarriers via an N_c-point Inverse Discrete Fourier Transform (IDFT) module to obtain the time domian signal x_k. After appending the Cyclic Prefix (CP) with length N_g at the beginning of x_k, we obtain an OFDM symbol which is transmitted over Multipath Fading channel. We assume the channel is static over some OFDM symbols. Let $h_k = [h_k(0), h_k(1), ..., h_k(N_a - 1)]$ be the channel impulse response where N_a is the maximum channel memory length (over users).

The output of the multipath channel can be written as

$$y = \sum_k y_k + z = \sum_k h_k \otimes x_k + z, \tag{1}$$

where $\otimes$ denotes the convolution process and z are samples of the additive noise, assumed Gaussian, white with mean zero and variance σ^2 per dimension.

Assuming that the duration of the CP is longer than the maximum channel memory N_a, the received signal after OFDM demodulation over the j^{th} sub-channel can be expressed as

$$r(j) = \sum_k H_k(j) X_k(j) + Z(j), \tag{2}$$

where $H_k(j) = \sum_{l=0}^{N_a-1} h_k(l) . e^{-i2\pi jl/N_c}$ the k^{th} channel frequency response over subcarrier-j , $Z(j)$ is the Discrete Fourier Transform (DFT) of $z(j)$ which is also a centered complex white Gaussian noise with variance σ^2 in each dimension.

B. Receiver

The receiver iteratively removes the interference caused by the Multiple Access for each user by the *Elementary Signal Estimator* (ESE) module which exchanges and updates soft estimate of the information bits with the *Soft Input Soft Output Decoder* (SISO DEC) in a turbo manner.

Let $e(\bullet)$, $a(\bullet)$ and $A(\bullet)$ in Fig. 1 denote the *extrinsic*, the *a priori* and the *a posteriori Log Likelihood Ratios* (LLRs), respectively. The ESE computes the extrinsic information $e_{ESE}(\tilde{c}_k)$ using the received signal, this information is then desinterleaved by π_k^{-1} to obtain $a_{DEC}(c_k)$ and despreaded and fed to the SISO DEC as the a priori information $a_{DEC}(b_k)$ about the bit of interest. The decoder exploits this LLR to compute the a posteriori LLR $A_{DEC}(b_k)$ based on the code structure. After substracting $a_{DEC}(c_k)$ from the spreaded version of $A_{DEC}(b_k)$, the obtained $e_{DEC}(c_k)$ are interleaved again and fed to the ESE as the a priori LLR $a_{ESE}(\tilde{c}_k)$ which are used to update the signal statistics.

The ESE and the SISO DEC perform the overall process for a predetermined number of iterations. At the final iteration hard decisions are made $\hat{d}_k$ using the sign of $A_{DEC}(d_k)$.

The iterative process is summarized as follows [8].

1) Initialization: $E(X_k(j)) = 0$ **,** $Cov(X_k(j)) = I, \forall k, j$**,**

where $E(\bullet)$ and $Cov(\bullet)$ are respectively the mean and the covariance matrix and I is a 2×2 identity matrix.

2) Main operations:

a) Elementary Signal Estimator (ESE) part: We focus on the detection of $X_k(j)$ for user-k, the demodulated signal over the j^{th} subcarrier is

$$r(j) = H_k(j) X_k(j) + \zeta_k(j), \tag{3}$$

where

$$\zeta_k(j) = \sum_{m \neq k} H_m(j) X_m(j) + Z(j), \tag{4}$$

$\zeta_k(j)$ collects inteference and noise.

To detect $X_k(j)$,we generate

$$\widetilde{r}_k(j) = H_k^*(j) r(j) = |H_k(j)|^2 X_k(j) + \widetilde{\zeta}_k(j), \tag{5}$$

where

$$\widetilde{\zeta}_k(j) = H_k^*(j) \zeta_k(j). \tag{6}$$

We focus on the detection of $X_k^{Re}(j)$. Based on the central limit theorem, $\widetilde{\zeta}_k(j)$ can be approximated by a Gaussian variable. This approximation allows us to generate the extrinsic LLR for $X_k^{Re}(j)$ as [9]

$$e_{ESE}\left(X_k^{Re}(j)\right) = 2|H_k(j)|^2 \frac{\widetilde{r}_k^{Re}(j) - E\left(\widetilde{\zeta}_k^{Re}(j)\right)}{Cov\left(\widetilde{\zeta}_k(j)\right)_{1,1}}, \tag{7}$$

where $e_{ESE}\left(X_k^{Re}(j)\right)$ is the *extrinsic* LLR for $X_k^{Re}(j)$, $e_{ESE}\left(X_k^{Im}(j)\right)$ can be computed in a similar way.

We calculate $E\left(\widetilde{\zeta}_k(j)\right)$ and $Cov\left(\widetilde{\zeta}_k(j)\right)$ in eq. (7) as follows

$$\begin{cases} E\left(\widetilde{\zeta}_k(j)\right) & = H_k^*(j)\, E\left(\zeta_k(j)\right), \\ Cov\left(\widetilde{\zeta}_k(j)\right) & = R_k^T(j)\, Cov\left(\zeta_k(j)\right) R_k(j), \end{cases} \tag{8}$$

where ^{T} is the transpose operator and $R_k(j)$ is given by

$$R_k(j) = \begin{pmatrix} H_k^{Re}(j) & -H_k^{Im}(j) \\ H_k^{Im}(j) & H_k^{Re}(j) \end{pmatrix}.$$

The mean and variance of the received signal can be estimated as follows

$$\begin{cases} E\left(r(j)\right) & = \sum_k H_k(j)\, E\left(X_k(j)\right). \\ Cov\left(r(j)\right) & = \sum_k R_k(j)\, Cov\left(X_k(j)\right) R_k^T(j) + \sigma^2 I. \end{cases} \tag{9}$$

b) DEC part : The DECs provide A Posteriori Probability (APP) decoding using the output of the ESE as the a priori LLRs. With QPSK signaling, the outputs of DEC-k are extrinsic LLRs for $\left\{X_k^{Re}(j)\right\}$ and $\left\{X_k^{Im}(j)\right\}$ which will be used to update the mean and the variance of each chip as follows

$$\begin{cases} E\left(X_k(j)\right) & = \tanh\left(\frac{e_{DEC}\left(X_k^{Re}(j)\right)}{2}\right) + i\tanh\left(\frac{e_{DEC}\left(X_k^{Im}(j)\right)}{2}\right), \\ Cov\left(X_k(j)\right) & = \begin{pmatrix} 1-\left(E\left(X_k^{Re}(j)\right)\right)^2 & 0 \\ 0 & 1-\left(E\left(X_k^{Im}(j)\right)\right)^2 \end{pmatrix}, \end{cases} \tag{10}$$

assuming that the extrinsic LLRs for the real and imaginary parts of $X_k(j)$ are uncorrelated .

III. Joint channel estimation and decision directed decoding

In this section, we consider the Maximum Likelihood solution using the Space Alternating Generalized Expectation Maximization (SAGE) algorithm [4]. This algorithm is based on pilots and hard decisions on decoded data symbols, and is referred to as SAGE-ML. To initialize the SAGE algorithm, a pilot based coarse channel estimate is derived. For this, we reserve the first S_p OFDM symbols for pilot transmission while the following $S-S_p$ OFDM symbols contain information data.

A. Coarse Channel Estimation

After OFDM modulation and pilot insertion, users transmit their signals over a frequency selective block fading channels. In the following, we consider two algorithms for coarse estimation, the first is the Least Squares (LS) estimator and the second is the LS estimator with Successive Iterference Cancellation (SIC).

1) Per-user LS Estimation: Using the received signal and the transmitted pilot symbols, while ignoring the interference from the other users, we rewrite the received signal N_c samples for user k as

$$r_k[s] = X_{k,p}[s]\, H_k[s] + \zeta_k[s], \tag{11}$$

where $\zeta_k[s]$ collects the interference plus noise and $X_{k,p}[s]$ is $N_c \times N_c$ diagonal matrix collecting pilot symbols for $s = 0, ..., S_p - 1$ and $H_k[s]$ the k^{th} user channel frequency response.

The channels frequency responses LS estimates are given by

$$\hat{H}_k[s] = X_{k,p}^{-1}[s]\, r_k[s]. \tag{12}$$

If more than one pilot OFDM symbol is transmitted, averaging is used to further improve performance, i.e., $\hat{H}_k = {}^1\!/_{S_p} \sum_{s=0}^{S_p-1} \hat{H}_k[s]$.

2) Per-user SIC based LS Estimation: In this algorithm, we attempt to decrease the effect of interference due to the multiple access. By estimating one user channel, and removing his component from the interference term, the interference will decrease while going through the users. This procedure is repeated for a predetermined number of iterations as follows

- Initialization : $\hat{r}[s] = r[s]$.
- For each iteration i :

for $k = 1, ..., K$

if $i = 0$:

$$\hat{H}_k^{(i)}[s] = UU^H X_{k,p}^{-1}[s]\, \hat{r}[s], \tag{13}$$

$$\hat{r}[s] = \hat{r}[s] - X_{k,p}[s]\, \hat{H}_k^{(i)}[s], \tag{14}$$

else

$$\hat{r}[s] = \hat{r}[s] + X_{k,p}[s]\, \hat{H}_k^{(i-1)}[s], \tag{15}$$

$$\hat{H}_k^{(i)}[s] = UU^H X_{k,p}^{-1}[s]\, \hat{r}[s], \tag{16}$$

$$\hat{r}[s] = \hat{r}[s] - X_{k,p}[s]\, \hat{H}_k^{(i)}[s], \tag{17}$$

where U is an $N_c \times N_g$ matrix collecting the first N_g columns of the $N_c \times N_c$ DFT matrix and ^{H} is the Hermetian operator. This procedure implicitely uses the fact that CP length is larger than the channel memory.

B. Decision Directed Channel Estimation

In this section, we introduce the SAGE algorithm which iteratively computes the ML solution over the $S - S_p$ OFDM data blocks as follows

- Initialization : For each user k and OFDM symbol s, the initially estimated signal is

$$\hat{s}_k^{(0)}[s] = X_k[s]\, \hat{H}_k[s], \tag{18}$$

where $\hat{H}_k[s]$ are the Per-user channel estimates recovered from the first pilot based step, and $X_k[s]$ are hard decisions on decoded symbols using the first estimate of $\hat{H}_k[s]$.

- For each iteration i :
for $k = 1 + [i \, mod \, K]$, and for all s, compute

$$\hat{r}_k^{(i)}[s] = \hat{s}_k^{(i)}[s] + \left(r[s] - \sum_{m=1}^{K} \hat{s}_m^{(i)}[s] \right). \quad (19)$$

$$\begin{aligned} \hat{H}_k^{(i+1)}[s] &= \underset{H_k[s]}{argmin} \left(\left\| \hat{r}_k^{(i)}[s] - X_k[s] H_k[s] \right\|^2 \right) \\ &= X_k^{-1}[s] \hat{r}_k^{(i)}[s]. \end{aligned} \quad (20)$$

We average the estimates over all transmitted OFDM symbols as

$$\hat{H}_k^{(i+1)}[s] = 1/S \sum_{s=0}^{S-1} \hat{H}_k^{(i+1)}[s]. \quad (21)$$

Then we update the signal for user k .

$$\hat{s}_k^{(i+1)}[s] = X_k[s] \hat{H}_k^{(i+1)}[s]. \quad (22)$$

for all m, $m \neq k$

$$\hat{s}_m^{(i+1)}[s] = \hat{s}_m^{(i)}[s]. \quad (23)$$

Since $X_k[s]$ are initially unknown at the receiver, estimates must be used.

The estimates are then updated by the decoders in every iteration using the most recent channel estimates. We perform hard decisions on the decoded symbols so that

$$\hat{X}_k(j) = sign\left(a_{ESE}\left(X_k^{Re}(j)\right)\right) + i.sign\left(a_{ESE}\left(X_k^{Im}(j)\right)\right).$$

IV. Channel Estimation Exploiting Sparsity

A. Most Significant Taps Approach (MST)

In this section, we investigate how incorporating the channel sparsity properties in time domain in order to improve the channel estimation performance. The main idea is to neglect taps of low energy. In fact, in the case of sparse channels, many of the coefficients are with low energy and insignificant amplitude. Therefore, these coefficients estimates are dominated by noise. The main idea is to neglect these taps and hence we keep among the first N_g taps only those with most significant energies as discussed in [5] and presented in Fig. 2. Neglecting the nonsignificant channel taps will reduce the noise perturabtion in the channel estimate, thus improving the channel estimation performance especially at low Signal to Noise Ratio (SNR) .

This processing is carried both during the pilot based stage and during the decision directed estimation.

B. Threshold-based MST

Actually, there are many approaches that exploit the sparsity features of channels in time domain. In the case, where we know the number of the received paths for user k denoted by L_k, the simplest way is to keep only the L_k most significant coefficients within the first N_g corresponding estimate of the channel impulse response. The advantage of this method is that it minimizes the occurence of effective tap missing or false detection of zero taps as effective. It is however worth noting

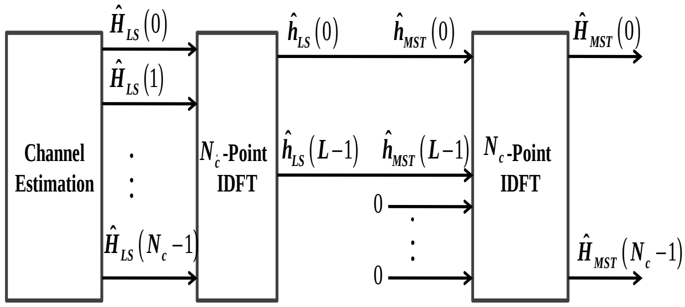

Fig. 2. Block diagram of the MST-based channel estimation

that the assumption that the number of received paths L_k is perfectly known is not realistic. Another way to implement the MST algorithm is to use a threshold on the recovered channel impulse response estimate amplitude. This threshold should be adapted to the channel estimation noise level. In this way, we keep only the coefficients having an energy superior to a predetermined threshold computed using the averaging noise method [6].

In this paper, we assume that the received paths are distributed within the cyclic prefix of the OFDM frame. Hence, the averaged noise level can be obtained by the energy of taps located in the rest of the OFDM frame as follows

$$\hat{\sigma}_k^2 = \frac{1}{N_c - N_g} \sum_{p=N_g}^{N_c-1} \left| \hat{h}_k(p) \right|^2. \quad (24)$$

As shown in equations eq. (13) and eq. (16), the LS-SIC frequency response estimate is truncated to the length of the CP which denoises the channel estimate outside the CP. Therefore, we use the LS estimate to recover $\hat{\sigma}_k^2$ following eq. (24).

After estimating the average noise level, the decision rule for taps inside the CP is given by [6]

$$\hat{h}_k(p) = \begin{cases} \hat{h}_k(p) & if \left| \hat{h}_k(p) \right|^2 > 2.\hat{\sigma}_k^2. \\ 0 & otherwise. \end{cases} \quad (25)$$

V. Numerical Results

For the simulations, we set the number of users to $K = 5$, the spreading factor to 16 using a spreading sequence $s_i = (-1)^i$, $i = 0, 1, ..., 15$ with the same length for all users and no FEC is here performed. The interleavers $[\pi_1, \pi_2, ..., \pi_K]$ are generated randomly. We set M the interleaver block length to $M = 640$ bits to guarantee a good separation of users. At the output of interleavers, the chips are modulated using Quadrature Phase Shift Keying (QPSK) which will be transmitted over $N_c = 256$ subcarriers. One OFDM symbol is dedicated for the pilot-based channel estimation, $S_p = 1$.

The simulations are performed over a block fading multipath channel model. The equivalent discrete channel impulse response for user k is given by

$$h_k(n) = \sum_{l=0}^{N_a-1} \alpha_{l,k} \delta(n-l), \quad (26)$$

where $\alpha_{l,k}$ are zero-mean complex Gaussian random variables with non zero valued coefficients, $\theta_{l,k} = Ce^{-l/\tau_{rms}}$, where C is a variance constant. The non zero valued taps are of number $L_k = 16$ and are uniformly and randomly positioned within the CP with length $N_g = {}^{N_c}/_4$. The root mean square delay spread is set to $\tau_{rms} = {}^{L_k}/_{N_c}$. The channel length N_a is assumed to be no longer than the CP $(N_a \leq N_g)$, and the block fading channel is generated randomly and independently for each user.

For all the simulations in the case of the LS-SIC, we fix the number of iterations at the coarse estimation stage to 3.

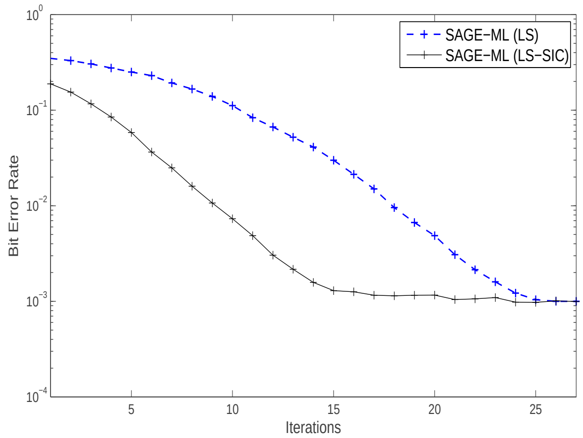

Fig. 3. BER performance for LS and LS-SIC vs number of iterations in the decision directed satge $(E_b/N_0 = 10\,dB)$

In Fig. 3, for $E_b/N_0 = 10\,dB$, we compare the two versions of SAGE-ML, the one that performs the simple LS algorithm with the one that performs the LS with SIC. As shown, SAGE-ML-SIC offers a better performance than the LS saving about 10 iterations to the convergence. This is achieved thanks to the processing performed during the LS-SIC which reduces the interference resulting from the multiple access. Hence, the LS-SIC performs better initial estimate to be used in the decision directed stage.

In all the simulations that follow, we will use the LS-SIC as the coarse estimation algorithm.

In order to compare the effectiveness of the proposed algorithms, we test the effect of the number of iterations at the Decision Directed stage on the performance in terms of the Mean Squared Error (MSE). The MSE is calculated as follows $MSE = E\left(\left\|\hat{H} - H\right\|^2\right)$ and evaluated by replacing the expectation by an average over the trials.

As we can notice in Fig. 4, for $E_b/N_0 = 10\,dB$ all the proposed algorithms converge at 15 iterations. The blue curve presenting the response of the proposed MST with perfect knowledge of the number of paths (Full MST) offers the best performance superpassing the MST with threshold with a gain of about $1.5\,dB$ and the SAGE-ML with a gain of about $5\,dB$ in MSE performance. The obtained results show how exploiting the channel sparsity allows even without any prior knowledge of the number of paths to enhance the performance

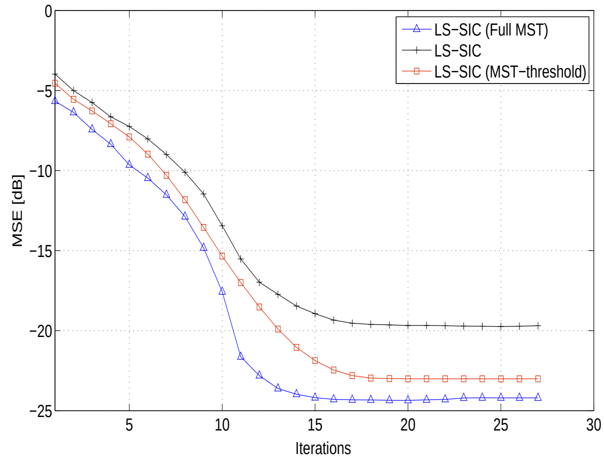

Fig. 4. MSE on the channel frequency response estimate vs iterations for $E_b/N_0 = 10\,dB$

compared to the case not accounting for channel properties and by using a simple processing.

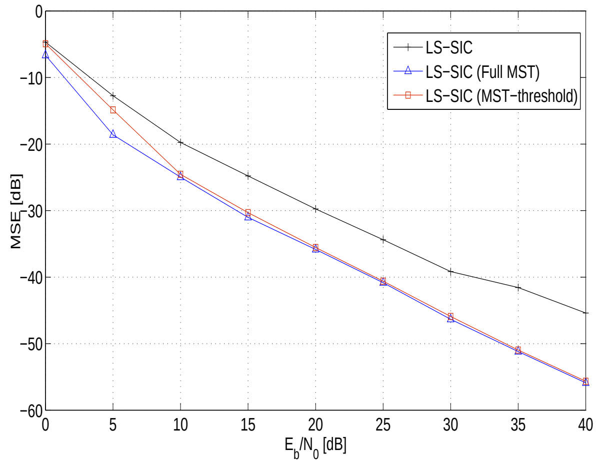

Fig. 5. MSE on the channel frequency response vs E_b/N_0

In Fig. 5, we fix the number of iterations in the decision directed stage to 17 to guarantee the convergence and we compute the MSE using different values of SNR. At low SNR, the Full MST is superpassing the two other proposed algorithms and the threshold-based MST fails to correctly recover all of the original taps because of the noise that corrupts the received paths. At high SNR $(E_b/N_0 > 10\,dB)$, the Full MST and the MST with threshold are able to recover the original number of paths with their original positions that's why it offers the best performance superpassing the LS-SIC with approximately $5\,dB$ in MSE performance which is a proof of the denoising advantage of exploiting the channel sparse structure.

Fig. 6 shows the performance of the three proposed algorithms in terms of Bit Error Rate (BER) with a fixed SNR $(E_b/N_0 = 10\,dB)$. The Full MST converges at 13 iterations saving about 3 iterations in comparison to the others. The MST

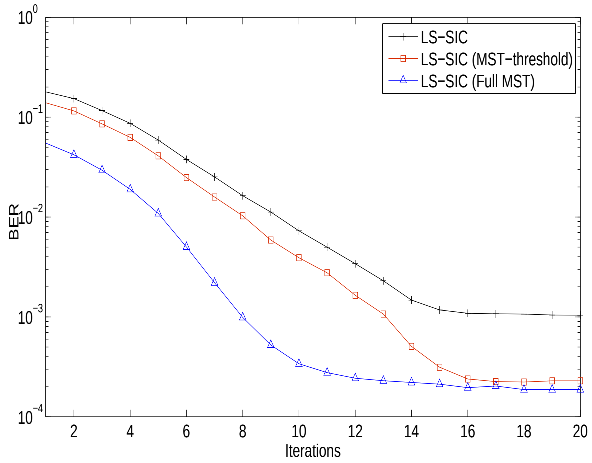

Fig. 6. BER vs Iterations for $E_b/N_0 = 10\,dB$

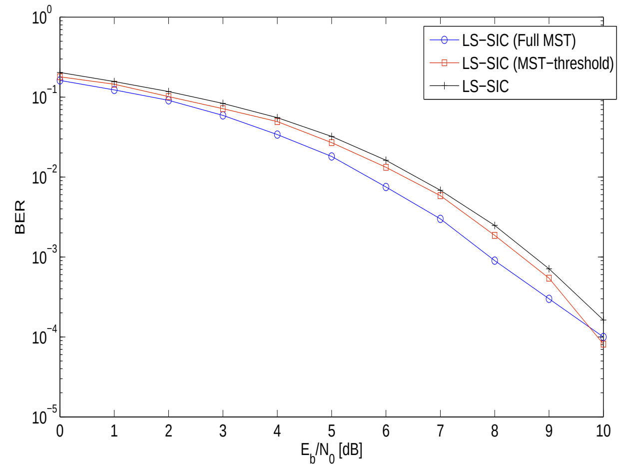

Fig. 7. BER performance for DVB-T standard.

with threshold is always offering better performance than the SAGE-ML and approximately offers the same performance as the Full MST at higher number of iterations.

In Fig. 7, we compare the proposed algorithms over the simplified version of the Digital Video Broadcasting-Terrestrial (DVB-T) channel which its static case with parameters is given by Table 1[10].

Delay (OFDM sample)	Gain	Phase (radians)
0	0.2487	-2.5694
1	0.1287	-2.1208
3	0.3088	0.3548
4	0.4252	0.4187
5	0.4900	2.7201
7	0.0365	-1.4375
8	0.1197	1.1302
12	0.1948	-0.8092
17	0.4187	-0.1545
24	0.3170	-2.2159
29	0.2055	2.8372
49	0.1846	2.8641

TABLE I
THE STATIC CHANNEL IMPULSE RESPONSE OF THE DVB-T

As shown in fig. 7, the MST with its two versions incorporation within the SAGE-ML with LS-SIC outperforms its original version not accounting for channel sparsity. At high SNR the MST-based threshold efficiently recovers the original tap positions offering the same peformance as the Full MST.

VI. CONCLUSION

In this paper, we investigated joint channel estimation and data decoding for OFDM-IDMA systems over sparse channels. The obtained results have shown the benefits from using the algorithms exploiting sparsity features. The study confirmed the potential substantial gain in terms of performance and complexity reduction of exploiting sparsity properties within the joint channel estimation and decision directed decoding scheme.

Further research will concern the use of more sophisticated tools of sparsity processing.

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