BLIND CHANNEL ESTIMATION IN MIMO-OFDM SYSTEMS USING SEMI-DEFINITE RELAXATION

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ABSTRACT

A new blind channel estimation technique for multiple-input multiple-output orthogonal frequency-division multiplexing (MIMO-OFDM) systems is proposed. It estimates the channel parameters in the time domain jointly for all subcarriers instead of doing this in the frequency domain independently for each subcarrier. This results in a substantially improved parsimony of the channel parameterization along with the ability to use coherent processing across the subcarriers. It is shown that using semi-definite relaxation (SDR), our channel estimation problem can be transferred to a convex form and then solved efficiently using modern convex optimization tools.

***Index Terms*—** Blind channel estimation, space-frequency coding, MIMO-OFDM systems, semi-definite relaxation

1. INTRODUCTION

Space-time coding (STC) techniques used in MIMO wireless systems are known to offer substantially improved transmission rate and immunity to fading as compared to single-antenna systems [1]. In particular, orthogonal space-time block codes (OSTBCs) [2] represent an attractive choice because they achieve full diversity at low decoding complexity. Space-time coded MIMO systems can also be used in conjunction with the orthogonal frequency-division multiplexing (OFDM) scheme, and this allows to combine the advantages of multi-antenna and multi-carrier transmissions [3]. However, the performance of such MIMO-OFDM systems critically depends on the quality of the channel state information (CSI) available at the receiver. Although training-based approaches are commonly used for channel estimation in multi-antenna systems, a promising recent trend is to estimate the channel using spectrally efficient *blind* techniques [4]-[9].

Most of the blind estimation methods can only deal with flat fading channels; see, for example, [4] and [5]. There are also several blind methods for identifying frequency-selective MIMO channels (for example, see [6] and references therein) which do not assume any space-time coding and, therefore, are not able to take advantage of the orthogonal structure of the codes used. There are several promising approaches to channel estimation in space-time coded MIMO-OFDM systems [7]-[10]. However, the techniques of [7] and [8] are only applicable to the case of two transmit and one receive antennas, while the approach of [9] generally requires the number of receive antennas to be not less than the number of transmit antennas[1]. Obviously, the latter restriction may be critical for the downlink mode. The semiblind approach of [10] requires to transmit pilot symbols for a part of subcarriers used. Another common approach to channel estimation in MIMO-OFDM systems is to estimate flat fading channels at each subcarrier independently in the frequency domain [11]. However, this method does not enable coherent processing across the subcarriers and may suffer from a high computational cost in the case when the total number of subcarriers is large.

Below, we propose an approach that is free of the aforementioned drawbacks of the earlier methods. Our technique is applicable to any numbers of transmit and receive antennas and it efficiently exploits the orthogonal structure of the underlying space-frequency code. Moreover, it uses coherent processing across the subcarriers to estimate the channel in the time domain.

2. BACKGROUND

The input-output relationship for a point-to-point MIMO system with N transmit and M receive antennas and frequency-selective finite impulse response (FIR) multipath channel with $L+1$ efficient taps can be expressed in the time domain as [1]

$$\mathbf{Z}(n) = \sum_{l=0}^{L} \mathbf{\Phi}(n-l)\mathbf{G}_l + \mathbf{E}(n) \tag{1}$$

where $\mathbf{Z}(n)$ is a $T \times M$ matrix of the received data whose (p,m)th entry $[\mathbf{Z}]_{p,m}(n)$ is the sample received during the pth burst via the mth receive antenna at the nth time interval, $\mathbf{\Phi}$ is a $T \times N$ matrix of the transmitted data, T is the number of

[1] For specific types of codes the approach of [9] is also applicable when the number of receive antennas is lower than the number of transmit antennas.

bursts, $\mathbf{G}_l$ is the lth $N \times M$ complex channel matrix that corresponds to the lth tap, and $\mathbf{E}$ is a $T \times M$ matrix of noise. We assume that the noise is both spatially and temporally white with variance of σ^2 per complex dimension. After serial-to-parallel conversion, we get at the transmitter side K parallel data streams of length N_0 where K is the number of complex information symbols prior to encoding and N_0 is the number of orthogonal subcarriers. These symbol streams are then space-frequency encoded using the same orthogonal code by mapping them onto a sequence of $T \times N$ matrices $\{\mathbf{X}(i)\}$ where i is the frequency index [1]. It is known [12] that due to the inverse Fourier transform at the transmitter and Fourier transform at the receiver, the frequency-selective fading channel can be converted to N_0 parallel flat fading channels. Then, (1) turns to the following frequency-domain input-output matrix relation

$$\mathbf{Y}(i) = \mathbf{X}(i)\mathbf{H}_i + \mathbf{V}(i) \tag{2}$$

where i is the subcarrier index. The relationships among $\mathbf{Y}(i)$, $\mathbf{X}(i)$, $\mathbf{H}_i$ and $\mathbf{V}(i)$ and their time-domain counterparts $\mathbf{Z}(n)$, $\mathbf{\Phi}(n)$, $\mathbf{G}_l$ and $\mathbf{E}(n)$ are discussed in [1].

Let us introduce the following operators

$$\overline{[\mathbf{Y}]}_{p,m} \triangleq \begin{bmatrix} \mathrm{Re}([\mathbf{Y}]_{p,m}) & -\mathrm{Im}([\mathbf{Y}]_{p,m}) \\ \mathrm{Im}([\mathbf{Y}]_{p,m}) & \mathrm{Re}([\mathbf{Y}]_{p,m}) \end{bmatrix} \tag{3}$$

$$\underline{\mathbf{Y}} \triangleq \begin{bmatrix} \mathrm{vec}\{\mathrm{Re}(\mathbf{Y})\}^T & \mathrm{vec}\{\mathrm{Im}(\mathbf{Y})\}^T \end{bmatrix}^T \tag{4}$$

for any complex-valued matrix $\mathbf{Y}$ where $\mathrm{vec}\{\cdot\}$ is the vectorization operator that stacks all columns of a matrix on the top of each other, $\mathrm{Re}(\cdot)$ and $\mathrm{Im}(\cdot)$ denote the real and imaginary parts, and $(\cdot)^T$ denotes the transpose. Using the so-called oversampled fast Fourier transform (FFT) matrix $\mathbf{F}$ (which is built from the first $L+1$ columns of N_0-point normalized FFT matrix) and (3)-(4), we can establish a compact linear relation between the channel parameters in the frequency and time domains as

$$\mathbf{h}' = \sqrt{N_0}\left(\overline{\mathbf{F}} \otimes \mathbf{I}_{MN}\right)\mathbf{g}' \tag{5}$$

where $\mathbf{h}' \triangleq \left[\mathbf{h}_0^T \dots \mathbf{h}_{N_0-1}^T\right]^T$, $\mathbf{g}' \triangleq \left[\mathbf{g}_0^T \dots \mathbf{g}_L^T\right]^T$, $\mathbf{I}_P$ is the $P \times P$ identity matrix, $\mathbf{h}_i \triangleq \underline{\mathbf{H}_i}$, $i = 0, \dots N_0 - 1$, $\mathbf{g}_l \triangleq \underline{\mathbf{G}_l}$, $l = 0, \dots, L$, and $\otimes$ stands for the Kronecker matrix product. Assume that prior to encoding, K complex information symbols $\mathbf{s}_i = [s_{i1}, s_{i2}, ..., s_{iK}]^T$ corresponding to the ith subcarrier are zero-mean mutually uncorrelated random variables. Also we assume that each space-frequency code matrix $\mathbf{X}(i)$ has the properties of an OSTBC [2]. Then, we can rewrite the input-output model (2) for each subcarrier as [5]

$$\mathbf{y}_i = \mathbf{A}(\mathbf{h}_i)\underline{\mathbf{s}_i} + \mathbf{v}_i\,, \quad i = 0, ..., N_0 - 1 \tag{6}$$

where $\mathbf{y}_i \triangleq \underline{\mathbf{Y}(i)}$, $\mathbf{v}_i \triangleq \underline{\mathbf{V}(i)}$, $\mathbf{A}(\mathbf{h}_i) \triangleq [\underline{\mathbf{C}_1\mathbf{H}_i} \cdots \underline{\mathbf{C}_{2K}\mathbf{H}_i}]$, and the matrices $\{\mathbf{C}_k\}_{k=1}^{2K}$ are the OSTBC basis matrices for $\mathbf{X}(i)$ which are known at the receiver [5]. The model (6) can be expressed in a more compact form as

$$\mathbf{y}' = \tilde{\mathbf{A}}(\mathbf{h}')\mathbf{s}' + \mathbf{v}' \tag{7}$$

where $\mathbf{y}' \triangleq \left[\mathbf{y}_0^T \ \dots \ \mathbf{y}_{N_0-1}^T\right]^T$, $\mathbf{s}' \triangleq \left[\underline{\mathbf{s}_0}^T \ \dots \ \underline{\mathbf{s}_{N_0-1}}^T\right]^T$, and $\mathbf{v}' \triangleq \left[\mathbf{v}_0^T \ \dots \ \mathbf{v}_{N_0-1}^T\right]^T$ are the real vectors that integrate the received data, transmitted data, and noise, respectively, for all subcarriers, and

$$\tilde{\mathbf{A}}(\mathbf{h}') \triangleq \begin{bmatrix} \mathbf{A}(\mathbf{h}_0) & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{A}(\mathbf{h}_1) & & \mathbf{0} \\ \vdots & & \ddots & \vdots \\ \mathbf{0} & \cdots & \mathbf{0} & \mathbf{A}(\mathbf{h}_{N_0-1}) \end{bmatrix}.$$

The size of the matrix $\tilde{\mathbf{A}}(\mathbf{h}')$ is $2MTN_0 \times 2KN_0$. Regardless of the value of $\mathbf{h}'$, the following orthogonality property holds:

$$\tilde{\mathbf{A}}^T(\mathbf{h}')\tilde{\mathbf{A}}(\mathbf{h}') \triangleq \mathbf{D}^2 = \mathrm{diag}\{\|\mathbf{h}_0\|^2 \ \dots \ \|\mathbf{h}_{N_0-1}\|^2\} \otimes \mathbf{I}_{2K} \tag{8}$$

where $\|\cdot\|$ is the vector 2-norm or matrix Frobenius norm. As $\tilde{\mathbf{A}}(\mathbf{h}')$ is linear in $\mathbf{h}'$, there exists a unique matrix $\mathbf{\Psi}$ such that

$$\mathrm{vec}\{\tilde{\mathbf{A}}(\mathbf{h}')\} = \mathbf{\Psi}\mathbf{h}'\,. \tag{9}$$

Also, defining the covariance matrix of the received data as $\mathbf{R} \triangleq \mathrm{E}\{\mathbf{y}'\mathbf{y}'^T\}$ where $\mathrm{E}\{\cdot\}$ stands for expectation, and using the fact that the symbol streams and noise are mutually uncorrelated at each subcarrier, we have

$$\mathbf{R} = \tilde{\mathbf{A}}(\mathbf{h}')\mathbf{\Lambda}_{\mathbf{s}'}\tilde{\mathbf{A}}^T(\mathbf{h}') + \frac{\sigma^2}{2}\mathbf{I}_{2MTN_0} \tag{10}$$

where $\mathbf{\Lambda}_{\mathbf{s}'} \triangleq \mathrm{E}\{\mathbf{s}'\mathbf{s}'^T\}$ is a diagonal matrix known at the receiver [5]. Multiplying (10) from the right by $\tilde{\mathbf{A}}(\mathbf{h}')\mathbf{D}^{-1}$ and using (8), we have

$$\mathbf{R}\tilde{\mathbf{A}}(\mathbf{h}')\mathbf{D}^{-1} = \tilde{\mathbf{A}}(\mathbf{h}')\mathbf{D}^{-1}\mathbf{\Lambda} \tag{11}$$

where $\mathbf{\Lambda} \triangleq \left(\mathbf{\Lambda}_{\mathbf{s}'}\mathbf{D}^2 + \frac{\sigma^2}{2}\mathbf{I}_{2KN_0}\right)$. As $\tilde{\mathbf{A}}(\mathbf{h}')\mathbf{D}^{-1}$ has orthonormal columns and $\mathbf{\Lambda}_{\mathbf{s}'}$ and $\mathbf{D}^2$ both are diagonal matrices, (11) can be considered as the characteristic equation for the data covariance matrix $\mathbf{R}$. This implies that the diagonal elements of $\mathbf{\Lambda}$ are the $2KN_0$ largest eigenvalues of $\mathbf{R}$ and the columns of $\tilde{\mathbf{A}}(\mathbf{h}')\mathbf{D}^{-1}$ are the corresponding eigenvectors.

3. BLIND CHANNEL ESTIMATION

Consider the following constrained optimization problem

$$\max_{\mathbf{Q}} \ \mathrm{tr}\{\mathbf{Q}^T\mathbf{R}\mathbf{Q}\} \qquad \text{s.t.} \qquad \mathbf{Q}^T\mathbf{Q} = \mathbf{I}_{2KN_0} \tag{12}$$

where $\mathbf{Q}$ is any $2MTN_0 \times 2KN_0$ real matrix with $MT > K$. For the solution of this problem ($\mathbf{Q}_*$), we have $\mathrm{range}\{\mathbf{Q}_*\} = \mathrm{range}\{\tilde{\mathbf{A}}(\mathbf{h}')\}$ and $\mathrm{tr}\{\mathbf{Q}_*^T\mathbf{R}\mathbf{Q}_*\} = \mathrm{tr}\{\mathbf{\Lambda}\}$ [5], where $\mathrm{tr}\{\cdot\}$ and $\mathrm{range}\{\cdot\}$ stand for the matrix trace and column range, respectively. Let us replace $\mathbf{Q}$ by $\tilde{\mathbf{A}}(\tilde{\mathbf{h}})\tilde{\mathbf{D}}^{-1}$ in (12) where $\tilde{\mathbf{h}}$ is the vector of optimization variables and $\tilde{\mathbf{D}}$ is obtained from (8) by replacing $\mathbf{h}'$ with $\tilde{\mathbf{h}}$. With such a replacement, the constraint in the resulting problem will be always satisfied and, therefore, it can be dropped. Then, we obtain the following unconstrained optimization problem

$$\max_{\tilde{\mathbf{h}}} \operatorname{tr}\{\tilde{\mathbf{D}}^{-1}\tilde{\mathbf{A}}^T(\tilde{\mathbf{h}})\mathbf{R}\tilde{\mathbf{A}}(\tilde{\mathbf{h}})\tilde{\mathbf{D}}^{-1}\}. \tag{13}$$

Clearly, the maximum of the objective function in (13) can not exceed that in (12) because of a particular structure of $\mathbf{Q}$ in (13). Inserting (10) into (13) and using (11), we have

$$\operatorname{tr}\{\tilde{\mathbf{D}}^{-1}\tilde{\mathbf{A}}^T(\tilde{\mathbf{h}})\mathbf{R}\tilde{\mathbf{A}}(\tilde{\mathbf{h}})\tilde{\mathbf{D}}^{-1}\}\Big|_{\tilde{\mathbf{h}}=\mathbf{h}'} = \operatorname{tr}\{\mathbf{\Lambda}\}. \tag{14}$$

Therefore, the maxima of the objective functions in both problems (12) and (13) coincide. Hence, the true channel vector $\mathbf{h}'$ belongs to the subspace of all vectors that maximize (13).

To simplify (13), let us rewrite its objective function as

$$\begin{aligned}&\operatorname{tr}\{\tilde{\mathbf{D}}^{-1}\tilde{\mathbf{A}}^T(\tilde{\mathbf{h}})\mathbf{R}\tilde{\mathbf{A}}(\tilde{\mathbf{h}})\tilde{\mathbf{D}}^{-1}\}\\ &= \operatorname{vec}\{\tilde{\mathbf{A}}(\tilde{\mathbf{h}})\tilde{\mathbf{D}}^{-1}\}^T(\mathbf{I}_{2KN_0}\otimes\mathbf{R})\operatorname{vec}\{\tilde{\mathbf{A}}(\tilde{\mathbf{h}})\tilde{\mathbf{D}}^{-1}\}.\end{aligned} \tag{15}$$

Using (9), we have

$$\begin{aligned}\operatorname{vec}\{\tilde{\mathbf{A}}(\tilde{\mathbf{h}})\tilde{\mathbf{D}}^{-1}\} &= (\tilde{\mathbf{D}}^{-1}\otimes\mathbf{I}_{2MTN_0})\operatorname{vec}\{\tilde{\mathbf{A}}(\tilde{\mathbf{h}})\}\\ &= (\tilde{\mathbf{D}}^{-1}\otimes\mathbf{I}_{2MTN_0})\mathbf{\Psi}\tilde{\mathbf{h}}.\end{aligned} \tag{16}$$

Substituting (16) to (15), and using some properties of the Kronecker product, we obtain

$$\operatorname{tr}\{\tilde{\mathbf{D}}^{-1}\tilde{\mathbf{A}}^T(\tilde{\mathbf{h}})\mathbf{R}\tilde{\mathbf{A}}(\tilde{\mathbf{h}})\tilde{\mathbf{D}}^{-1}\} = \tilde{\mathbf{h}}^T\mathbf{\Psi}^T(\tilde{\mathbf{D}}^{-2}\otimes\mathbf{R})\mathbf{\Psi}\tilde{\mathbf{h}}. \tag{17}$$

Hence, the optimization problem (13) becomes equivalent to

$$\max_{\tilde{\mathbf{h}}} \ \tilde{\mathbf{h}}^T\mathbf{\Psi}^T(\tilde{\mathbf{D}}^{-2}\otimes\mathbf{R})\mathbf{\Psi}\tilde{\mathbf{h}}. \tag{18}$$

Assume that the channel norms for each subcarrier are known at the receiver. This assumption mathematically corresponds to the following constraint: $\tilde{\mathbf{D}}^2 = \mathbf{D}^2$. Adding this constraint to (18), the latter problem becomes

$$\max_{\tilde{\mathbf{h}}} \tilde{\mathbf{h}}^T\mathbf{\Psi}^T(\tilde{\mathbf{D}}^{-2}\otimes\mathbf{R})\mathbf{\Psi}\tilde{\mathbf{h}} \quad \text{s.t.} \quad \tilde{\mathbf{D}}^2 = \mathbf{D}^2. \tag{19}$$

Note that even if the channel norm at some ith subcarrier is unknown, it can be recovered from the eigenvalues of $\mathbf{R}_i$ as $\|\mathbf{h}_i\| = \sqrt{(\operatorname{tr}\{\mathbf{R}_i\} - MT\sigma^2)/\operatorname{tr}\{\mathbf{\Lambda}_{s_i}\}}$; see [5] for further details. Let us express the constraint in (19) explicitly as

$$\tilde{\mathbf{h}}^T\mathbf{S}_i^T\mathbf{S}_i\tilde{\mathbf{h}} = \|\mathbf{h}_i\|^2, \quad i = 0,\ldots,N_0-1$$

where $\mathbf{S}_i$ is the selection matrix built so that $\tilde{\mathbf{h}}^T\mathbf{S}_i^T\mathbf{S}_i\tilde{\mathbf{h}} = \tilde{\mathbf{h}}_i^T\tilde{\mathbf{h}}_i$, and define two positive semi-definite matrices

$$\mathbf{P}^f \triangleq \mathbf{\Psi}^T(\mathbf{D}^{-2}\otimes\mathbf{R})\mathbf{\Psi} \succeq 0, \quad \mathbf{T}_i^f \triangleq \mathbf{S}_i^T\mathbf{S}_i \succeq 0 \tag{20}$$

where the superscript "f" refers to the frequency domain. Both these matrices are known at the receiver. Then, we can rewrite (19) as

$$\max_{\tilde{\mathbf{h}}} \tilde{\mathbf{h}}^T\mathbf{P}^f\tilde{\mathbf{h}} \quad \text{s.t.} \quad \tilde{\mathbf{h}}^T\mathbf{T}_i^f\tilde{\mathbf{h}} = \|\mathbf{h}_i\|^2, \ i = 0,\ldots,N_0-1. \tag{21}$$

The main drawback of this formulation is that it is in the frequency domain and, therefore, the number of the optimization variables (i.e., unknown channel parameters to be estimated) is rather high. However, we can use (5) to transfer the problem to the time domain and, therefore, dramatically reduce the number of channel parameters. Doing so, we obtain an equivalent problem

$$\min_{\tilde{\mathbf{g}}} -\tilde{\mathbf{g}}^T\mathbf{P}^t\tilde{\mathbf{g}} \quad \text{s.t.} \quad \tilde{\mathbf{g}}^T\mathbf{T}_i^t\tilde{\mathbf{g}} = \|\mathbf{h}_i\|^2, \ i = 0,\ldots,N_0-1 \tag{22}$$

where

$$\begin{aligned}\mathbf{P}^t &\triangleq N_0(\overline{\mathbf{F}}^T\otimes\mathbf{I}_{MN})\mathbf{P}^f(\overline{\mathbf{F}}\otimes\mathbf{I}_{MN}) \succeq 0\\ \mathbf{T}_i^t &\triangleq N_0(\overline{\mathbf{F}}^T\otimes\mathbf{I}_{MN})\mathbf{T}_i^f(\overline{\mathbf{F}}\otimes\mathbf{I}_{MN}) \succeq 0\end{aligned}$$

and the superscript "t" refers to the time domain.

Note that in contrast to (21) the problem (22) can not be decoupled for each subcarrier. Therefore, (22) offers a way of *coherent processing* across the subcarriers. Also, (22) provides much more parsimonious channel representation as compared to (21).

The problem (22) is a non-convex quadratically constrained quadratic problem (QCQP) because $-\mathbf{P}^t$ is not positive semi-definite. To reformulate this problem in a convex form, let us define a matrix of new optimization variables $\tilde{\mathbf{G}} \triangleq \tilde{\mathbf{g}}\tilde{\mathbf{g}}^T$ and approximate (22) as

$$\begin{aligned}&\min_{\tilde{\mathbf{G}}} -\operatorname{tr}\{\tilde{\mathbf{G}}\mathbf{P}^t\}\\ &\text{s.t.} \ \operatorname{tr}\{\tilde{\mathbf{G}}\mathbf{T}_i^t\} = \|\mathbf{h}_i\|^2, \ i = 0,\ldots,N_0-1, \ \tilde{\mathbf{G}} \succeq 0.\end{aligned} \tag{23}$$

The approximation made to obtain (23) from (22) is in that a non-convex rank-one constraint $\operatorname{rank}\{\tilde{\mathbf{G}}\} = 1$ has been replaced by a convex positive semi-definite constraint $\tilde{\mathbf{G}} \succeq 0$. This approximation is commonly referred to as *semi-definite relaxation* (SDR).

The problem (23) is convex and can be efficiently solved in polynomial time by means of convex optimization tools, such as SeDuMi package [13]. It is worth noting that, although we cannot prove this theoretically, it follows from our simulations that the resulting optimal matrix $\tilde{\mathbf{G}}_*$ obtained from solving (23) is always rank-one. Therefore, the recovery of the optimal vector $\tilde{\mathbf{g}}_*$ from $\tilde{\mathbf{G}}_*$ is straightforward.

4. SIMULATIONS

In each simulation run, the entries of $\mathbf{G}_l$ are independently drawn from a Gaussian distribution with zero mean and variance σ_g^2, and are then kept fixed for this run. It is assumed that $L+1 = 3$, $N_0 = 8$, $N = 3$, $M = 4$, $K = T = 4$, and the full-rate OSTBC of [2] with BPSK symbols is used for space-frequency coding. In each run, 10 data blocks are used to estimate $\mathbf{R}$.

Fig. 1 compares the averaged over subcarriers normalized channel frequency response estimation errors

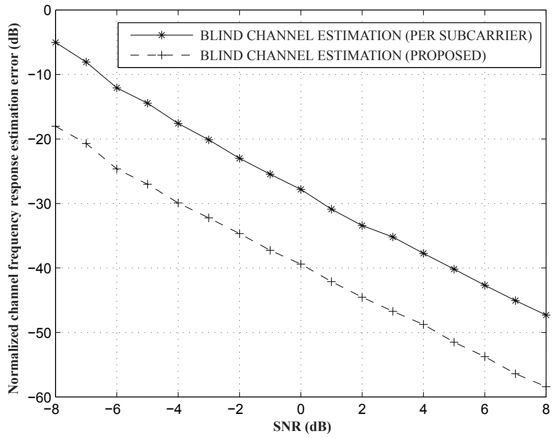

Fig. 1. Normalized channel frequency response estimation error averaged over subcarriers versus SNR.

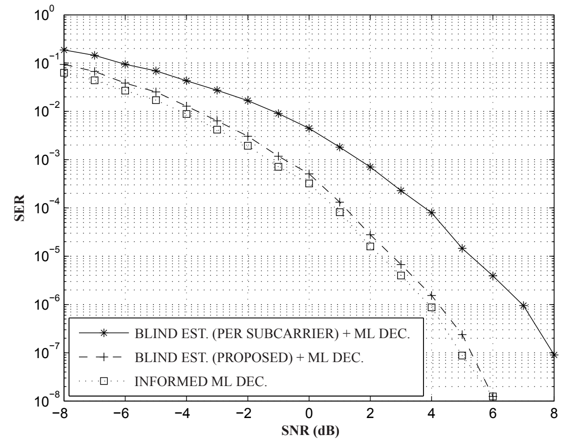

Fig. 2. SERs versus SNR.

$\frac{1}{N_0}\sum_{i=0}^{N_0-1}\|\hat{\mathbf{H}}_i-\mathbf{H}_i\|^2/\|\mathbf{H}_i\|^2$ versus the signal-to-noise ratio (SNR) for the proposed technique and the method of [5] that estimates the channel at the per subcarrier basis.

Fig. 2 shows the symbol error rates (SERs) versus the SNR for these two methods combined with the maximum likelihood (ML) decoder. Additionally, the results for the informed ML decoder are shown in this figure. The latter decoder is assumed to know the channel exactly.

It can be seen that, as expected, the proposed approach substantially outperforms the technique of [5]. From Fig. 2, it follows that the SER performance of our method combined with the ML decoder closely achieves that of the informed ML detector. This performance gain results from a substantially improved parsimony of the channel parameterization along with the ability to use coherent processing across the subcarriers.

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