Joint Channel Estimation / Data Detection in MIMO-FBMC/OQAM Systems – A Tensor-Based Approach

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***Abstract*—Filter bank-based multicarrier (FBMC) systems have been considered as a prevalent candidate for replacing the long established cyclic prefix (CP)-based orthogonal frequency division multiplexing (CP-OFDM) in the physical layer of next generation communications systems. In particular, offset quadrature amplitude modulation (OQAM)-based FBMC has received increasing attention due to, among other features, its potential for maximum spectral efficiency. It suffers, however, from an intrinsic self-interference effect, which complicates signal processing tasks at the receiver, including synchronization, channel estimation and equalization. In a multiple-input multiple-output (MIMO) configuration, the multi-antenna interference has also to be taken into account. (Semi-)blind FBMC/OQAM receivers have been little studied so far and mainly for single-antenna systems. The problem of joint channel estimation and data detection in a MIMO-FBMC/OQAM system, given limited or no training information, is studied in this paper through a tensor-based viewpoint in the light of the success of such techniques in OFDM applications. Simulation-based comparisons with CP-OFDM are included, for realistic transmission models.**

I. Introduction

Filter bank-based multicarrier (FBMC) systems have been considered as a prevalent candidate for replacing the long established orthogonal frequency division multiplexing (OFDM) in the physical layer of next generation communications systems [6]. The potential of FBMC transmission stems from its increased ability to carrying a flexible spectrum shaping, along with a major increase in spectral efficiency and robustness to synchronization requirements, features of fundamental importance in the envisaged networks. A particular type of FBMC, known as FBMC/OQAM (or OFDM/OQAM) system, consisting of pulse shaped OFDM carrying offset quadrature amplitude modulation (OQAM) symbols, has received increasing attention due to, among other features, its potential for maximum spectral efficiency [18]. Notably, it allows a cyclic prefix (CP)-free transmission while offering very good spectral agility and time localization with very important implications in the system design and performance [6]. It suffers, however, from an *intrinsic* inter-carrier/inter-symbol interference (ICI/ISI), which complicates signal processing tasks at the receiver, including synchronization, channel estimation and equalization [18]. Although FBMC/OQAM research has been rapidly advancing in the last decade or so, resulting in a number of well performing techniques for receiver design, (semi-)blind FBMC/OQAM methods have been very little studied so far (e.g., [25]) and mainly for the single-antenna case. Interestingly, (semi-)blind multiple-input multiple-output (MIMO) techniques have been recently considered as a potential solution to the pilot contamination problem in massive MIMO FBMC-based configurations [17].

Tensor models and methods have been extensively studied for communications applications [1], including system modeling and receiver design of single-input multiple-output (SIMO) and MIMO systems, both in a general [20] and a multicarrier and/or spread spectrum [5], [7], [8], [19], [22], [27]–[29] setup (see [9] for more references). The inherent ability of tensor models to capture the relations among the various system's dimensions, in a way that is *unique* under mild conditions and/or constraints, has been exploited in problems of jointly estimating synchronization parameters, channel(s), and transmitted data symbols. Tensorial approaches have proved their unique advantages not only in their 'natural' applications in (semi-) blind receivers [7] but also in the design of training-based high performance receivers for challenging scenarios [20], [21]. Notably, in OFDM applications [7], performance close to that with perfect knowledge of the system parameters has been achieved.

In the light of their successful application in OFDM (semi-) blind estimation problems, tensor-based techniques are considered here in the context of MIMO-FBMC/OQAM systems. The problem of joint channel estimation and data

The research leading to these results was funded by the European Union's H2020 Framework Programme (H2020-MSCA-ITN-2014) under grant agreement No. 642685 MacSeNet.

Part of this work was done while the first author was visiting the Group Science, Engineering and Technology, at KULeuven-Kulak, Belgium.

ISBN 978-0-9928626-7-1 © EURASIP 2017

detection, given limited or no training information, is revisited through a tensorial approach. The main difficulties come from the intrinsic interference effect and the lack of a guard interval (CP), which challenge the receiver design even under the commonly made simplifying assumption of channels of low selectivity, also adopted in this paper. Simulations-based comparisons with CP-OFDM are included, for realistic transmission models.

II. System Model

Consider a system based on FBMC/OQAM with $N_{\rm T}$ transmit and $N_{\rm R}$ receive antennas. The synthesis filter bank (SFB) output at the transmit (Tx) antenna t is given by [10]

$$s^{(t)}(l) = \sum_{m=0}^{M-1} \sum_{n} d_{m,n}^{(t)} g_{m,n}(l), \qquad (1)$$

where (m,n) refers to the mth subcarrier and the nth FBMC symbol, $d_{m,n}^{(t)}$ are *real* (Pulse Amplitude Modulation (PAM)) symbols, M is the (even) number of subcarriers, and

$$g_{m,n}(l) = g\left(l - n\frac{M}{2}\right) e^{\jmath \frac{2\pi}{M} m \left(l - \frac{L_g - 1}{2}\right)} e^{\jmath \varphi_{m,n}},$$

with g being the employed prototype filter impulse response (assumed of unit energy) with length L_g, and $\varphi_{m,n} = (m+n)\frac{\pi}{2} - mn\pi$. Moreover, usually $L_g = KM$, with K being the overlapping factor. Let $\boldsymbol{H}^{(r,t)} = \begin{bmatrix} H_0^{(r,t)} & H_1^{(r,t)} & \cdots & H_{M-1}^{(r,t)} \end{bmatrix}^{\rm T}$ be the frequency response of the channel from the Tx antenna t to the receive (Rx) antenna r, assumed invariant in time. Assume, as usual, that the noise signals at different Rx antennas are zero mean white Gaussian with variance σ^2 and uncorrelated with each other (i.e., temporally and spatially white noise). Under the common assumption of a (relatively to M) low channel delay spread, the analysis filter bank (AFB) output at the Rx antenna r and at the (p,q) frequency-time (FT) point can be written as [10]

$$y_{p,q}^{(r)} = \sum_{t=1}^{N_{\rm T}} H_p^{(r,t)} c_{p,q}^{(t)} + w_{p,q}^{(r)}, \qquad (2)$$

where $w_{p,q}^{(r)}$ denotes the corresponding noise component, known to be also zero mean Gaussian of variance σ^2 but correlated in both time and frequency and

$$c_{p,q}^{(t)} = d_{p,q}^{(t)} + \jmath \sum_{(m,n)\in\Omega_{p,q}} \langle g \rangle_{m,n}^{p,q} d_{m,n}^{(t)} \qquad (3)$$

is the "virtual" transmitted symbol (or pseudo-symbol) consisting of the corresponding transmitted symbol plus the (imaginary) interference from its *first-order* FT neighborhood $\Omega_{p,q}$. The interference weights $\langle g \rangle$ are known to follow the symmetry pattern [10]

$$\begin{matrix} (-1)^p\delta & -\beta & (-1)^p\delta \\ -(-1)^p\gamma & d_{p,q} & (-1)^p\gamma \\ (-1)^p\delta & \beta & (-1)^p\delta \end{matrix} \qquad (4)$$

with the horizontal and vertical directions denoting time and frequency, respectively, and the constants $\gamma > \beta > \delta > 0$ being *a-priori* computable from g (cf. [10] for details).

Let each Tx antenna transmit N FBMC symbols and let $\boldsymbol{D}^{(t)} = [d_{m,n}^{(t)}] \in \mathbb{R}^{M\times N}$ denote the corresponding frame of PAM data. The corresponding AFB output at the rth Rx antenna can then be written as the $M \times N$ matrix

$$\boldsymbol{Y}^{(r)} = [y_{m,n}^{(r)}] = \sum_{t=1}^{N_{\rm T}} {\rm diag}(\boldsymbol{H}^{(r,t)})\boldsymbol{C}^{(t)} + \boldsymbol{W}^{(r)}, \qquad (5)$$

where $\boldsymbol{C}^{(t)} = [c_{m,n}^{(t)}] = \begin{bmatrix} \boldsymbol{c}_0^{(t)} & \boldsymbol{c}_1^{(t)} & \cdots & \boldsymbol{c}_{N-1}^{(t)} \end{bmatrix} \in \mathbb{C}^{M\times N}$ collects the virtual symbols for Tx antenna t and $\boldsymbol{W}^{(r)} = [w_{m,n}^{(r)}]$. One can readily see that the intrinsic interference effect as desribed in (4) can be compactly expressed as follows

$$\boldsymbol{C}^{(t)} = \boldsymbol{D}^{(t)} + \jmath\left[\beta \boldsymbol{E}\boldsymbol{D}^{(t)} + \boldsymbol{S}(-\gamma\boldsymbol{D}^{(t)}\bar{\boldsymbol{E}} + \delta\bar{\boldsymbol{Z}}\boldsymbol{D}^{(t)}\tilde{\boldsymbol{E}})\right], \qquad (6)$$

where $\boldsymbol{S} = {\rm diag}(1,-1,1,-1,\ldots,1,-1)$ is of order M, $\boldsymbol{E}$ is the circulant $M \times M$ matrix

$$\boldsymbol{E} = \begin{bmatrix} 0 & 1 & 0 & 0 & \cdots & 0 & -1 \\ -1 & 0 & 1 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \ddots & \cdots & \ddots & \vdots \\ 1 & 0 & 0 & \cdots & 0 & -1 & 0 \end{bmatrix},$$

while $\bar{\boldsymbol{E}}$ and $\tilde{\boldsymbol{E}}$ are similarly structured Toeplitz $N \times N$ matrices:

$$\bar{\boldsymbol{E}} = \begin{bmatrix} 0 & 1 & 0 & 0 & \cdots & 0 & 0 \\ -1 & 0 & 1 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \ddots & \cdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 0 & -1 & 0 \end{bmatrix},$$

$$\tilde{\boldsymbol{E}} = \begin{bmatrix} 0 & 1 & 0 & 0 & \cdots & 0 & 0 \\ 1 & 0 & 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \ddots & \cdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 0 & 1 & 0 \end{bmatrix}.$$

Letting

$$\boldsymbol{Z} = \begin{bmatrix} \boldsymbol{0}_{1\times(M-1)} & 1 \\ \boldsymbol{I}_{M-1} & \boldsymbol{0}_{(M-1)\times 1} \end{bmatrix}$$

denote the $M \times M$ matrix of circular downwards shifting, $\bar{\boldsymbol{Z}}$ can be expressed as

$$\bar{\boldsymbol{Z}} = \boldsymbol{Z} + \boldsymbol{Z}^{-1},$$

which is also circulant. Note that $\boldsymbol{D}^{(t)} = \Re\{\boldsymbol{C}^{(t)}\}$.

Remarks.

1) As it is common, it is here assumed that the frame is preceded and followed by inactive inter-frame gaps, which can be taken as FBMC symbols of all zeros, thus resulting in negligible interference among frames [10].
2) Although FBMC/OQAM has proved to be more robust than CP-OFDM to imperfect frequency synchronization [2], incorporating a carrier frequency offset (CFO) into its signal model can be seen to be less straightforward [15], especially when considering a frequency-domain model as in (5). For the sake of simplicity, and

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in order to concentrate on joint data/channel estimation, perfect synchronization is assumed in the following.

III. Joint Channel Estimation / Data Detection

Stacking the $N_{\rm R}$ matrices (5) in the $MN_{\rm R} \times N$ matrix

$$\boldsymbol{Y}_2 = \left[\begin{array}{cccc} (\boldsymbol{Y}^{(1)})^{\rm T} & (\boldsymbol{Y}^{(2)})^{\rm T} & \cdots & (\boldsymbol{Y}^{(N_{\rm R})})^{\rm T} \end{array} \right]^{\rm T}, \quad (7)$$

one can write (see also [5], [7])

$$\begin{aligned} \boldsymbol{Y}_2 &= \sum_{t=1}^{N_{\rm T}} \left(\left[\begin{array}{c} (\boldsymbol{H}^{(1,t)})^{\rm T} \\ (\boldsymbol{H}^{(2,t)})^{\rm T} \\ \vdots \\ (\boldsymbol{H}^{(N_{\rm R},t)})^{\rm T} \end{array} \right] \odot \boldsymbol{I}_M \right) \boldsymbol{C}^{(t)} + \boldsymbol{W}_2 \\ &= (\boldsymbol{H} \odot \boldsymbol{\Gamma}) \boldsymbol{C} + \boldsymbol{W}_2, \end{aligned} \quad (8)$$

where $\boldsymbol{W}_2$ is similarly defined, $\boldsymbol{C} = \left[\begin{array}{cccc} (\boldsymbol{C}^{(1)})^{\rm T} & (\boldsymbol{C}^{(2)})^{\rm T} & \cdots & (\boldsymbol{C}^{(N_{\rm T})})^{\rm T} \end{array} \right]^{\rm T}$,

$$\begin{aligned} \boldsymbol{H} &= \left[\begin{array}{cccc} \boldsymbol{H}^{(1,1)} & \boldsymbol{H}^{(2,1)} & \cdots & \boldsymbol{H}^{(N_{\rm R},1)} \\ \boldsymbol{H}^{(1,2)} & \boldsymbol{H}^{(2,2)} & \cdots & \boldsymbol{H}^{(N_{\rm R},2)} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{H}^{(1,N_{\rm T})} & \boldsymbol{H}^{(2,N_{\rm T})} & \cdots & \boldsymbol{H}^{(N_{\rm R},N_{\rm T})} \end{array} \right]^{\rm T}, \\ \boldsymbol{\Gamma} &= \underbrace{\left[\begin{array}{cccc} \boldsymbol{I}_M & \boldsymbol{I}_M & \cdots & \boldsymbol{I}_M \end{array} \right]}_{N_{\rm T} \text{ times}}, \end{aligned}$$

and $\odot$ denotes the Khatri-Rao (columnwise Kronecker) product [23]. If $\boldsymbol{\mathcal{Y}}$ is the $M \times N \times N_{\rm R}$ (i.e., frequency $\times$ time $\times$ space) tensor of received signals with entries $\boldsymbol{\mathcal{Y}}_{m,n,r} = y_{m,n}^{(r)}$, then the matrix $\boldsymbol{Y}_2$ above results from vertically stacking its $N_{\rm R}$ frontal slices and (8) corresponds to its *canonical polyadic decomposition (CPD)* (also known as PARAFAC), of rank $MN_{\rm T}$ [23]. The joint estimation problem can then be stated (using a commonly used notation [23]) as

$$\min_{\boldsymbol{H},\boldsymbol{C}} \|\boldsymbol{\mathcal{Y}} - [\![\boldsymbol{\Gamma}, \boldsymbol{C}^{\rm T}, \boldsymbol{H}]\!]\|_{\rm F}, \quad (9)$$

where $\|\cdot\|_{\rm F}$ stands for the (tensor) Frobenius norm [23] and the noise color has been ignored for the sake of simplicity. Stacking instead (in a vertical fashion) the lateral slices of $\boldsymbol{\mathcal{Y}}$ yields the $MN \times N_{\rm R}$ matrix

$$\boldsymbol{Y}_3 = \left[\begin{array}{cccc} \mathrm{vec}(\boldsymbol{Y}^{(1)}) & \mathrm{vec}(\boldsymbol{Y}^{(2)}) & \cdots & \mathrm{vec}(\boldsymbol{Y}^{(N_{\rm R})}) \end{array} \right] \quad (10)$$

In view of (5) and using analogous arguments as previously, one can write

$$\boldsymbol{Y}_3 = (\boldsymbol{C}^{\rm T} \odot \boldsymbol{\Gamma}) \boldsymbol{H}^{\rm T} + \boldsymbol{W}_3, \quad (11)$$

with $\boldsymbol{W}_3$ constructed as in (10).

The *uniqueness* property of the CPD tensor decomposition, which can be trusted to hold under *mild* conditions [23], can be taken advantage of in the above setup (in a way analogous to that followed in OFDM; see, e.g., [7] etc.) to *blindly* estimate the channel matrix $\boldsymbol{H}$ and recover the virtual symbols $\boldsymbol{C}$ from the tensor of AFB output signals, $\boldsymbol{\mathcal{Y}}$. However, in a multiple-input ($N_{\rm T} \geq 2$) system, the matrix $\boldsymbol{\Gamma}$ has collinear columns and hence a k-rank of 1 [23], which implies that the identifiability of the above CPD model is not guaranteed. In fact, a quite similar formulation was presented, for MIMO-OFDM, in [28], where identifiability was claimed to hold, however based on a proof of questionable validity.[1] A simple way to see that the CPD in (9) does not enjoy uniqueness for $N_{\rm T} > 1$ is the following. Stacking the horizontal slices of the tensor $\boldsymbol{\mathcal{Y}}$ in the $N_{\rm R}N \times M$ matrix $\boldsymbol{Y}_1 = \left[\begin{array}{cccc} \boldsymbol{Y}^{(1)} & \boldsymbol{Y}^{(2)} & \cdots & \boldsymbol{Y}^{(N_{\rm R})} \end{array} \right]^{\rm T}$ results in the following alternative way of writing the CPD,

$$\boldsymbol{Y}_1 = (\boldsymbol{H} \odot \boldsymbol{C}^{\rm T}) \boldsymbol{\Gamma}^{\rm T} + \boldsymbol{W}_1, \quad (12)$$

or equivalently

$$\boldsymbol{Y}_1 = \sum_{t=1}^{N_{\rm T}} \left[\begin{array}{c} (\boldsymbol{H}^{(1,t)})^{\rm T} \\ (\boldsymbol{H}^{(2,t)})^{\rm T} \\ \vdots \\ (\boldsymbol{H}^{(N_{\rm R},t)})^{\rm T} \end{array} \right] \odot (\boldsymbol{C}^{(t)})^{\rm T} + \boldsymbol{W}_1 \quad (13)$$

Clearly, there is no way to identify $\boldsymbol{H}$ and $\boldsymbol{C}$ from the above (unless additional information is made available). However, in the SIMO case, (12) yields

$$\boldsymbol{Y}_1 = \boldsymbol{H} \odot \boldsymbol{C}^{\rm T} + \boldsymbol{W}_1, \quad (14)$$

which shows that the channel and (virtual) symbol matrices can be determined (up to scaling ambiguity) through a *Khatri-Rao factorization (KRF)* of $\boldsymbol{Y}_1$ (e.g., [20]).[2] Nevertheless, such a solution approach fails to offer an interpretation of the common iterative schemes of joint channel / data estimation as outlined in Remark 1) below. On the other hand, assuming (as in [7]) non-perfect frequency synchronization, involving nonzero CFOs (different per Tx antenna [7] and/or user in a multiple access scenario [22]), the corresponding factor matrix can be assumed to be of full k-rank, which leads to the generic condition

$$M + \min(N, MN_{\rm T}) + \min(N_{\rm R}, MN_{\rm T}) \geq 2MN_{\rm T} + 2 \quad (15)$$

In practice, where N would probably be larger than $MN_{\rm T}$, this simplifies to $N_{\rm R} \geq M(N_{\rm T} - 1) + 2$. For the SIMO scenario, this becomes $N_{\rm R} \geq 2$, which simply requires the spatial dimension to be nontrivial. Using appropriate precoding at the transmitter can result in more flexible identifiability conditions (e.g., not requiring an excessively large number of receive antennas) and algorithms; see, e.g., [7], [13].

A. An ALS view of the joint channel estimation / data detection procedure

The problem in (9) can then be solved with the aid of the classical alternating least squares (ALS) algorithm [23], iteratively alternating between the conditional updates (cf. (8), (11))[3]

$$\boldsymbol{C} = (\boldsymbol{H} \odot \boldsymbol{\Gamma})^{\dagger} \boldsymbol{Y}_2 \quad (16)$$

[1] Involving the inverse of the rank-deficient matrix $\boldsymbol{\Gamma}^{\rm T}\boldsymbol{\Gamma}$.

[2] See also Proposition 3.1 in [24], which ensures uniqueness of the CPD when one of its factors ($\boldsymbol{\Gamma} = \boldsymbol{I}_M$) is known and of full column rank. Furthermore, applying Proposition 3.2 of [24], while making the common assumption that $N \gg M \gg N_{\rm R}$, leads to the trivial requirement that $N_{\rm R} \geq 1$.

[3] The fact that one of the three factor matrices is known could justify a characterization of the above problem as a bilinear instead of a trilinear one. To make this explicit, such an ALS algorithm has also been known with the name *bilinear ALS (BALS)* [21].

and
$$\boldsymbol{H} = \left[(\boldsymbol{C}^{\mathrm{T}} \odot \boldsymbol{\Gamma})^{\dagger} \boldsymbol{Y}_3\right]^{\mathrm{T}}, \tag{17}$$

where $(\cdot)^{\dagger}$ stands for the (left) pseudo-inverse. A necessary condition for its existence in (17) is that there are at least as many Rx as Tx antennas. Observe that the permutation ambiguity is trivially resolved in this context because one of the factor matrices, $\boldsymbol{\Gamma}$, is known, similarly with [4]. A straightforward (and common) way to address the scaling ambiguity is through the transmission of a short training preamble.[4] At convergence, and once the complex scaling ambiguity has been resolved, the transmitted symbols can be detected as

$$\boldsymbol{D}^{(t)} = \mathrm{dec}(\Re\{\boldsymbol{C}^{(t)}\}), \quad t = 1, 2, \ldots, N_{\mathrm{T}}, \tag{18}$$

where $\mathrm{dec}(\cdot)$ signifies the decision device for the input constellation. However, this procedure does not exploit the information about $\boldsymbol{D}$ found in the imaginary (interference) part of (6) and can be seen to perform similarly or even somewhat worse than CP-OFDM [9]. A significant performance gain can be achieved by taking advantage of the structure of the intrinsic interference through the inclusion of the steps (18) and (6) between (16) and (17) in each iteration. Of course, the complex scaling ambiguity needs to be resolved first, which can be done by initializing ALS with the training-based estimates as in the simulations reported in the next section.

Another important difference with the corresponding OFDM problem is that the noise at the AFB output is colored and hence the cost function in (9) should be modified accordingly to a *weighted* LS one. Indeed the noise tensor is correlated in two of its three dimensions (time and frequency, not space) with corresponding covariances that can be *a-priori* known and only depend on the constants β, γ, δ. Thus, appropriately modified ALS algorithms can be employed instead (see [9] for details). To keep the presentation simple, no noise correlation will be considered here.

Remarks.

1) One can check that, in a SIMO system, (16) and (17) are in fact nothing but a compact way of re-writing the well-known equations for channel equalization, $c_{p,q} = \frac{1}{N_{\mathrm{R}}} \sum_{r=1}^{N_{\mathrm{R}}} \frac{y_{p,q}^{(r)}}{H_p^{(r,1)}}$, and estimation, $H_p^{(r,1)} = \frac{1}{N} \sum_{q=0}^{N-1} \frac{y_{p,q}^{(r)}}{c_{p,q}}$.[5] It is also of interest to note the similarity of the above ALS procedure with the iterative block algorithms studied in [26] for the solution of the (*bilinear*) blind maximum likelihood source separation problem, especially the so-called *iterative least squares with projection (ILSP)* scheme.
2) In the present context, the identifiability (uniqueness) question should also consider the discrete (in fact, finite) nature of the set of possible values of the $\boldsymbol{C}$ factor. No such uniqueness results are known to exist for general 3-way tensors. Nevertheless, one could consider using arguments analogous to those followed in [26] to show that identifiability is ensured for large enough sets of independent, identically distributed (i.i.d.) input symbols. Indeed, since the factors in (8) are both of full rank, the identifiability condition of [26] applies, whereby it suffices for N to be large enough so that $\boldsymbol{C}$ contains all $\frac{Q^{2M}}{2}$ distinct (up to a sign) M-vectors with entries belonging to the Q^2-QAM constellation. The probability of non-identifiability for $N \gg \frac{Q^{2M}}{2}$ i.i.d. (multicarrier) symbols is shown in [26] to approach zero exponentially fast. For large M and/or Q, the number of symbols required may become unrealistically large. More practical conditions can be found in, e.g., [12], albeit only for constant modulus (e.g., Quadrature Phase-Shift Keying (QPSK) signals).[6] See also [7] for a related upper bound on the probability of non-identifiability for the case of i.i.d. Binary Phase-Shift Keying (BPSK) input. It must be noted, of course, that no such problem was encountered in the simulations run for this work. Moreover, it is known [14] that the imaginary part of $\boldsymbol{C}$ in FBMC/OQAM is close to be Gaussian distributed, providing an extra support to the use of generic rank results that are known to hold for matrices generated by absolutely continuous distributions [7].

IV. Numerical Examples

The above approach is evaluated here in a SIMO 1×2 system. The input signal is organized in frames of 53 OFDM (i.e., $N = 106$ FBMC) symbols each, using QPSK modulation. Filter banks designed as in [3] are employed, with $M = 32$ and $K = 4$. With a subcarrier spacing of 15 kHz, the (block fading) PedA channels involved are of length $L_h = 9$ and satisfy the model assumption (2) only very crudely. The results are compared with those for a similar SIMO-OFDM system, using a CP of $\frac{M}{4} = 8$ samples. The results of KRF (cf. (14)) are also included. The estimation performance, in terms of mean squared error (MSE) versus transmit signal to noise ratio (SNR), is shown in Fig. 1(a). In the proposed approach, the *inf*ormed (of the interference structure and input constellation) iterations are initialized with estimates based on MSE-optimal training preambles[7]. FBMC is seen to outperfom CP-OFDM at low (to medium) SNR values (albeit at the cost of a slightly larger number of iterations [9]). Moreover, as expected, jointly estimating the channel and the data symbols brings significant improvement over the training only-based approach ("train." curves). Analogous conclusions can be drawn from the bit error rate (BER) detection performance depicted in Fig. 1(b). Notably, the informed ALS approach is observed to yield results quite close to those obtained when perfect channel

[4]Alternatively ways include appropriate normalization of one of the factors (e.g., [21]) or the transmission of a pilot sequence at one of the subcarriers (e.g., [4], [7]).

[5]The latter is known as Interference Approximation Method (IAM) [10]. In fact, it can be seen that the ALS iterations are equivalent to *maximum-ratio combining (MRC)* operations [11], which may be simplified (e.g., when all (virtual) symbols have the same magnitude) to the above (IAM) expressions (equivalent to *equal-gain combining (EGC)* [11].

[6]Thanks to Dr. M. Sørensen, KULeuven, for pointing out this paper.

[7]consisting of equipowered pseudo-random pilots for CP-OFDM and the optimal PAM preamble (IAM-R) for FBMC [10].

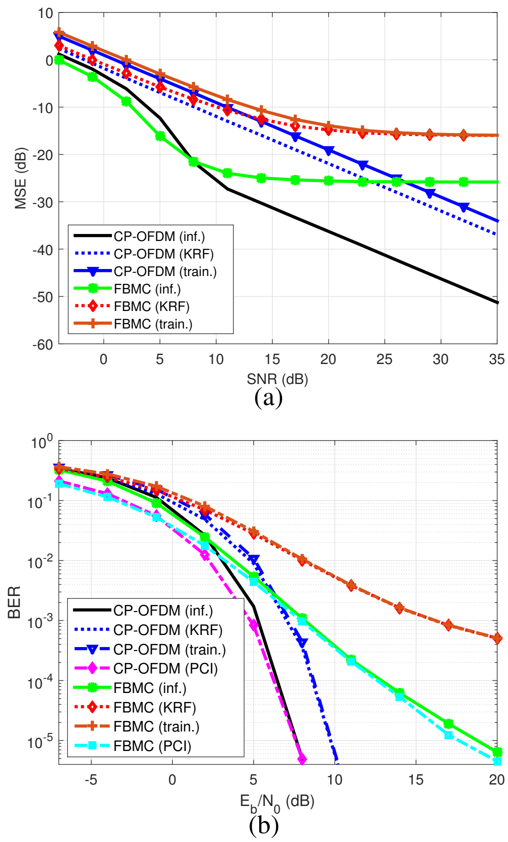

Fig. 1. Performance comparison for a 1×2 system with PedA channels: (a) MSE (b) BER.

information ("PCI") is available. The FBMC curves are seen to *floor* at higher SNR values, resulting in performance losses compared to CP-OFDM at such SNR regimes. This is a typical effect of the residual intrinsic interference which comes from the invalidation of model (2) and shows up in the absence of strong noise [10].

V. Future Work

On-going work aims at taking non-perfect synchronization also into account. Further extensions will include channels of strong frequency- (not satisfying (2)) and time- (e.g., [16]) selectivity, as well as richer configurations involving precoders and space-time/frequency coding (e.g., [13]).

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ISBN 978-0-9928626-7-1 © EURASIP 2017