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# PREAMBLE-BASED FBMC/OQAM CHANNEL ESTIMATION WITHOUT GUARD SYMBOLS

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A PREPRINT

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## ABSTRACT

Intrinsic interference is known to present a challenge for signal processing tasks in systems employing offset quadrature amplitude modulation-based filter bank multicarrier (FBMC/OQAM) for transmission. In channel estimation, in particular, this otherwise called self interference will corrupt the pilot symbols, thus preventing accurate estimation, unless special means, such as inserting null guard symbols between the training and the information part, are employed, with a consequent loss in spectral efficiency. Iterative procedures that alternately estimate the channel and the interfering data symbols have been proposed to tackle this problem. In this pre-print, these are re-visited, emphasizing the most challenging case of channels of high frequency selectivity that has been studied very little in this respect. The approach followed here capitalizes on the analytical structure of the problem, providing closed-form expressions and efficient ways of computation, and is inspired by the analogy of the intrinsic interference with the interference between information and pilot symbols arising in super-imposed training. Preamble-based estimation is considered, with both Gauss-Markov and linear minimum mean squared error (LMMSE) criteria, and no simplifying assumption is made on the relative (with the FBMC symbol duration) frequency selectivity of the channel. Simulation results with realistic channel models are reported and discussed.

**Keywords** Channel estimation · Filter bank multicarrier (FBMC) · Intrinsic interference · Offset quadrature amplitude modulation (OQAM) · Super-imposed training

## 1 Introduction

Offset quadrature amplitude modulation-based filter bank multicarrier (FBMC/OQAM) did not succeed in the competition for the 5th generation (5G) modulation waveform [1], despite its numerous advantages over the classical cyclic prefix-based orthogonal frequency division multiplexing (CP-OFDM) scheme [2]. A major challenge in practically all signal processing tasks in FBMC/OQAM systems is how to effectively deal with the so-called intrinsic interference effect [2]. In channel estimation, in particular, this presents a challenge due to the contamination it causes to training pilots from neighboring (control or information) symbols and it has been widely studied in the FBMC community [2, Chapter 11], in both the preamble- and scattered pilots-based configurations. Means to mitigate or even avoid the contamination of the pilots in preamble-based methods consist of inserting guard FBMC symbols between the pilots and the rest of the frame, which are almost always null (all zeros) and serve to protect the pilots from being interfered by other neighboring symbols [3]. Whether it be in classical methods that rely on the commonly made assumption of low channel delay spread [3] or in more recent work that relaxes this assumption and hence applies in channels of any frequency selectivity [4], the insertion of guard symbols certainly entails a reduction in bandwidth efficiency (which becomes more severe in view of the inadequacy of just one or two guards in practice [3]).

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It is therefore necessary to research alternative methods that can reduce or even avoid altogether the need for guard symbols. Such schemes are of an iterative nature, alternating, in a decision-directed manner, between channel estimation and interfering symbol detection. [3] reviews methods of this kind for systems that meet the low frequency selectivity assumption. Extensions to the highly frequency selective case have been recently proposed in [5, 6]. This problem is re-visited here based on our earlier formulation and results [7, 4], which allows the derivation of detailed and insightful analytical expressions for the steps of the iterative procedure. The analysis will also reveal a possible complication, which has not been made explicit in earlier related works [8, 5, 6] due to their restriction to the exponential channel model for their simulations. This brief note serves to reporting preliminary results and observations on ideas and methods that will be presented elsewhere in more detail.

Since the methods relying on the simplifying low frequency selectivity assumption can be seen as special cases of [4], it should be also of interest to re-visit earlier iterative schemes of this category [3] from the viewpoint of the present contribution.

## 2 System model and problem statement

The (baseband) output of an FBMC/OQAM synthesis filter bank (SFB) can be written as [2]

$$s(l) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} a_{m,n} g_{m,n}(l) \quad (1)$$

where, at the frequency-time (FT) point  $(m, n)$ ,  $m$  is the subcarrier index and  $n$  the FBMC symbol index,  $a_{m,n}$  are (real) OQAM symbols,  $M$  is the (even) number of subcarriers, and

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

with  $g$  being the employed prototype filter impulse response (assumed symmetric and of unit energy) of length  $L_g$ , and  $\phi_{m,n} = (m+n)\frac{\pi}{2} + mn\pi$ . Moreover, usually  $L_g = KM$ , with  $K$  being the overlapping factor. The corresponding noisy output of a channel with impulse response  $\mathbf{h} = [h(0) \ h(1) \ \cdots \ h(L_h-1)]^T$  will be

$$y(l) = \sum_{k=0}^{L_h-1} h(k)s(l-k) + w(l), \quad (2)$$

with  $w(l)$  assumed to be zero mean white Gaussian noise with variance  $\sigma^2$ . Let the  $n=0$  transmitted FBMC symbol consist of pilots. Hence the channel estimation will rely on the output of the analysis filter bank (AFB) at time 0. With no simplifying assumptions (like those made in the works reviewed in [3]) on the channel delay spread relative to the FBMC symbol duration, and assuming perfect time and frequency synchronization, the AFB output at any FT point  $(p, q)$ ,  $y_{p,q}$ , can be expressed as in [4, Eq. (3)]. Making the (quite common in the FBMC literature though not true in practice) assumption that interference only comes from the immediate neighbors (in time), one can write the following for the AFB output at time 0 [7]:

$$\mathbf{y} = (\mathbf{\Gamma} + \mathbf{\Gamma}^{(0,1)})\mathbf{h} + \boldsymbol{\eta}, \quad (3)$$

where  $\mathbf{y} = [y_{0,0} \ y_{1,0} \ \cdots \ y_{M-1,0}]^T$ ,  $\boldsymbol{\eta}$  is the frequency-domain noise with zero mean and covariance matrix  $\sigma^2\mathbf{B}$ , and the  $M \times L_h$  matrices  $\mathbf{\Gamma}$  and  $\mathbf{\Gamma}^{(0,1)}$  represent the transceiver responses at time 0, with ideal channel, to the pilot FBMC symbol (at time 0) and the information FBMC symbol at time 1, respectively (cf. [4, 7] for detailed expressions). More specifically,  $\mathbf{\Gamma} = \mathcal{G}\mathbf{A}_0$ , where the  $M \times ML_h$  matrix  $\mathcal{G}$  only depends on the SFB and AFB definitions and  $\mathbf{A}_0 = \mathbf{I}_{L_h} \otimes \mathbf{a}_0$ , with  $\mathbf{a}_0$  denoting the OQAM pilots, transmitted at time 0. Similarly,  $\mathbf{\Gamma}^{(0,1)} = \mathcal{G}^{(0,1)}\mathbf{A}_1$ , with the  $M \times ML_h$  matrix  $\mathcal{G}^{(0,1)}$  containing the transceiver characteristic from time 1 to time 0 and  $\mathbf{A}_1 = \mathbf{I}_{L_h} \otimes \mathbf{a}_1$ , where  $\mathbf{a}_1$  stands for the OQAM symbols transmitted at time 1, assumed i.i.d. with zero mean and power  $\sigma_a^2$  [7]. The Gauss-Markov estimation of  $\mathbf{h}$ , without the commonly made simplifying assumptions on the channel delay spread, as well as the corresponding mean squared error (MSE)-optimal training design problem were studied in [4]. However, it was assumed (as in most of the preamble-based FBMC/OQAM channel estimation works) that the pilot FBMC symbol is followed by at least one all zeros (null) FBMC symbol,  $\mathbf{a}_1 = \mathbf{0}$ , which serves as a guard protecting the pilots from being interfered by the data part of the frame. Although the results of [4] overcome the problems arising from the low frequency selectivity assumption made in the preamble-based FBMC/OQAM channel estimation literature, there is still the need to address the bandwidth loss incurred by the transmission of the guard symbol(s). It is the aim of this pre-print to make a preliminary investigation of this problem using the above formulation.

It will be useful to recall some more details from [7], namely that

$$\mathcal{G}(0, 1) = \mathbf{S} \begin{bmatrix} \mathbf{G}_0^{(0,1)} & \mathbf{W}\mathbf{G}_1^{(0,1)} & \mathbf{W}^2\mathbf{G}_2^{(0,1)} & \dots & \mathbf{W}^{L_h-1}\mathbf{G}_{L_h-1}^{(0,1)} \end{bmatrix}, \quad (4)$$

where the  $M \times M$  matrix  $\mathbf{S}$  is given by  $\mathbf{S} = \text{diag}(1, -1, 1, -1, \dots, 1, -1)$ ,  $\mathbf{W} = \text{diag}([e^{-jm\frac{2\pi}{M}}]_{m=0}^{M-1})$ , and the  $M \times M$  matrices  $\mathbf{G}_k^{(0,1)}$  are banded and circulant, with eigenvalues  $\Lambda_k^{(0,1)} = \mathbf{F}^H \mathbf{G}_k^{(0,1)} \mathbf{F}$  that are purely imaginary, with  $\mathbf{F}$  being the normalized  $M$ th-order DFT matrix. The following symmetry property of these eigenvalues will also be useful [7, Eq. (15)]:

$$\mathbf{P}\mathbf{Z}^k \Lambda_k^{(0,1)} \mathbf{Z}^{-k} \mathbf{P} = \Lambda_k^{(0,1)}, \quad (5)$$

where

$$\mathbf{P} = \begin{bmatrix} 1 & \mathbf{0}_{1 \times (M-1)} \\ \mathbf{0}_{(M-1) \times 1} & \mathbf{J}_{M-1} \end{bmatrix}$$

with  $\mathbf{J}_m$  being the  $m$ -order antidiagonal (exchange) matrix, and

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

is the downwards circular shift matrix. Moreover,  $\mathbf{S}$  can be also written as  $\mathbf{W}^{M/2}$ , and [7, Eq. (19)]

$$\mathbf{F}^H \mathbf{W}^k = \mathbf{Z}^k \mathbf{F}^H.$$

It is then easy to verify that (4) can be equivalently written as

$$\mathcal{G}^{(0,1)} = \mathbf{F}\mathbf{Z}^{M/2} \begin{bmatrix} \Lambda_0^{(0,1)} & \mathbf{Z}\Lambda_1^{(0,1)} & \mathbf{Z}^2\Lambda_2^{(0,1)} & \dots & \mathbf{Z}^{L_h-1}\Lambda_{L_h-1}^{(0,1)} \end{bmatrix} (\mathbf{I}_{L_h} \otimes \mathbf{F}^H) \quad (6)$$

### 3 Overcoming the need for guard symbols — A super-imposed training approach

Clearly, the presence of the term due to  $\mathbf{a}_1$  in (3) prevents from estimating the channel impulse response (CIR) from  $\mathbf{y}$ . Writing (3) in the equivalent form

$$\mathbf{y} = \mathbf{\Gamma}\mathbf{h} + \underbrace{\mathbf{\Gamma}^{(0,1)}\mathbf{h}}_{\mathbf{u}} + \boldsymbol{\eta} = \mathbf{\Gamma}\mathbf{h} + \mathbf{u} \quad (7)$$

shows that the problem is basically similar to that addressed in [4] but with the composite “noise” term here also involving the unknown CIR and information symbols. Thus, it would make sense to get a first CIR estimate from (7) using Gauss-Markov estimation based on the covariance of  $\mathbf{u}$ ,

$$\mathbf{C}_{\mathbf{u}} = E(\mathbf{u}\mathbf{u}^H),$$

where the expectation is with respect to both the channel and data statistics. It can be shown (cf. Appendix A) that

$$\mathbf{C}_{\mathbf{u}} = \sigma^2 \mathbf{F} \underbrace{\left[ \rho^2 \mathbf{P} \left( \sum_{k=0}^{L_h-1} \sigma_k^2 |\Lambda_k^{(0,1)}|^2 \right) \mathbf{P} + \Lambda_0 \right]}_{\Lambda_{\mathbf{u}}} \mathbf{F}^H, \quad (8)$$

where  $\rho^2 = \frac{\sigma_s^2}{\sigma_n^2}$  is the signal-to-noise ratio at the SFB input,  $|\Lambda_k^{(0,1)}|^2$  stands for the (diagonal) matrix of the squared magnitudes of the entries of  $\Lambda_k^{(0,1)}$ , and  $\sigma_k^2$ ,  $k = 0, 1, \dots, L_h - 1$  are the powers of the CIR taps, assumed uncorrelated with each other. Given that the matrix in parentheses above is diagonal, one can also write

$$\text{diag}(\Lambda_{\mathbf{u}}) = \rho^2 \mathbf{P} \text{diag} \left( \sum_{k=0}^{L_h-1} \sigma_k^2 |\Lambda_k^{(0,1)}|^2 \right) + \text{diag}(\Lambda_0), \quad (9)$$

where  $\text{diag}(\Lambda)$  gives the vector of the diagonal entries of  $\Lambda$ . Thus, a first estimate of the CIR vector can be computed from (7) as follows

$$\hat{\mathbf{h}}_{(0)} = \tilde{\mathbf{\Gamma}}^\dagger \tilde{\mathbf{y}}, \quad (10)$$

where  $\dagger$  stands for Moore-Penrose pseudo-inversion,  $\tilde{\mathbf{\Gamma}} = \Lambda_{\mathbf{u}}^{-1/2} \mathbf{F}^H \mathbf{\Gamma}$ , and  $\tilde{\mathbf{y}} = \Lambda_{\mathbf{u}}^{-1/2} \mathbf{F}^H \mathbf{y}$ .

<sup>2</sup>Equivalently (given the purely imaginary nature of  $\Lambda_k^{(0,1)}$ ),  $|\Lambda_k^{(0,1)}|^2 = -\Lambda_k^{(0,1)2}$ .

One can then substitute for  $\mathbf{h}$  in (7),

$$\mathbf{y} - \Gamma \hat{\mathbf{h}}_{(0)} = \Gamma^{(0,1)} \hat{\mathbf{h}}_{(0)} + \boldsymbol{\eta} = \mathcal{G}^{(0,1)} \mathbf{A}_1 \hat{\mathbf{h}}_{(0)} + \boldsymbol{\eta},$$

to compute an estimate of  $\mathbf{a}_1$ . This can be easily done by writing the latter equation in the equivalent form:

$$\underbrace{\mathbf{y} - \Gamma \hat{\mathbf{h}}_{(0)}}_{\mathbf{y}_{(0)}} = \underbrace{\mathcal{G}^{(0,1)} (\hat{\mathbf{h}}_{(0)} \otimes \mathbf{I}_M)}_{\mathcal{G}_{(0)}} \mathbf{a}_1 + \boldsymbol{\eta} \quad (11)$$

and solving for  $\mathbf{a}_1$ :

$$\hat{\mathbf{a}}_{1(0)} = \mathcal{Q} \left( \mathcal{G}_{(0)}^{-1} \mathbf{y}_{(0)} \right), \quad (12)$$

where  $\mathcal{Q}(\cdot)$  is the projection onto the closest OQAM constellation point. In view of (6)  $\mathcal{G}_{(0)}$  can be written as

$$\mathcal{G}_{(0)} = \mathbf{F} \mathbf{S} \sum_{k=0}^{L_h-1} \mathbf{Z}^k \boldsymbol{\Lambda}_k^{(0,1)} \hat{h}_0(k) \mathbf{F}^H$$

and hence

$$\mathcal{G}_{(0)}^{-1} \mathbf{y}_{(0)} = \mathbf{F} \left( \sum_{k=0}^{L_h-1} \mathbf{Z}^k \boldsymbol{\Lambda}_k^{(0,1)} \hat{h}_0(k) \right)^{-1} \mathbf{S} \mathbf{F}^H \mathbf{y}_{(0)}.$$

Then one can go back to (7) and re-estimate the CIR vector given the estimated  $\mathbf{a}_1$ :

$$\hat{\mathbf{h}}_{(1)} = \check{\check{\Gamma}}_{(0)}^\dagger \check{\check{\mathbf{y}}}, \quad (13)$$

with  $\check{\check{\Gamma}}_{(0)} = \boldsymbol{\Lambda}_0^{-1/2} \mathbf{F}^H (\Gamma + \mathcal{G}^{(0,1)} \hat{\mathbf{A}}_{1(0)})$  and  $\check{\check{\mathbf{y}}} = \boldsymbol{\Lambda}_0^{-1/2} \mathbf{F}^H \mathbf{y}$ , then use the new CIR estimate to re-estimate  $\mathbf{a}_1$ ,

$$\hat{\mathbf{a}}_{1(1)} = \mathcal{Q} \left( \mathcal{G}_{(1)}^{-1} \mathbf{y}_{(1)} \right), \quad (14)$$

and go on alternating between channel estimation and data detection until convergence. It should be noted that such an alternating procedure has been also proposed in [8] to perform OFDM channel estimation with super-imposed training.

## 4 Simulation results — Discussion

A closer look, however, at (9) may reveal a possible complication with the above procedure. Indeed, as shown in Fig. 1a for the case of the PHYDYAS filter bank [2] with  $M = 32$  and  $K = 4$ ,  $|\boldsymbol{\Lambda}_k^{(0,1)}|^2$  can be very close to zero at the middle region of the spectrum for sufficiently high  $k$  and hence channels of high frequency selectivity. Thus, for channels with power profiles like the one of the Veh-A model depicted in Fig. 1b (for sub-carrier spacing of 15 kHz), the matrix  $\boldsymbol{\Lambda}_u$  (and hence  $\mathbf{C}_u$ ) will be ill-conditioned at high signal-to-noise ratio (SNR) values. This is made apparent in Fig. 2b, where the condition number of this matrix (for OQPSK input, of  $\sigma_a^2 = 1$ ) is plotted with respect to SNR. Observe that the condition starts worsening at around 10 dB hence it should not be surprising that it is at this SNR value that the estimation performance of (10) starts deteriorating (Fig. 2a).<sup>3</sup> Nevertheless, it is suggested from this example that two iterations of the above procedure may suffice for its convergence, to an error floor, however, which is significantly higher than that achieved with the method of [4] with one guard FBMC symbol.

Things are quite different for channel power profiles that do not promote those  $\boldsymbol{\Lambda}_k^{(0,1)}$ 's with large  $k$  and hence avoid the serious ill-conditioning of  $\boldsymbol{\Lambda}_u$ . Such is the exponential channel model, which has been exclusively used to experimentally support the iterative methods of [6, 5]. Indeed, as shown in Fig. 3b for an exponential channel model of the form of Fig. 3a, the ill-conditioning effect is much less severe. Fig. 4 confirms that the iterative procedure performs well in such scenarios. Indeed, at the 3rd iteration, a performance similar to the one with a guard symbol is attained, while the 4th iteration improves even beyond that. This should not be surprising in view of the fact that in reality there is non-negligible interference from the non-adjacent FBMC symbol(s), hence the error floor exhibited even in the presence of a guard.

To overcome the above complications for more general (not exponential) propagation scenarios, an appropriate regularization needs to be incorporated. An obvious solution of this kind is to adopt LMMSE estimators instead. The results for the exponential and Veh-A scenarios are shown in Fig. 5a and 5b, respectively. Clearly, the performance has been improved compared to Fig. 2a, albeit not at very high SNR values. Further research is needed to come up with a more appropriate regularization that would result in high performance for any scenario and would be free from the need to have a-priori knowledge of the channel and noise statistics. Effectively coping with synchronization impairments in such a context is also under investigation.

<sup>3</sup>In this and the other channel estimation examples here, the MSE-optimal OQAM (real-valued) preamble from [4] has been employed.

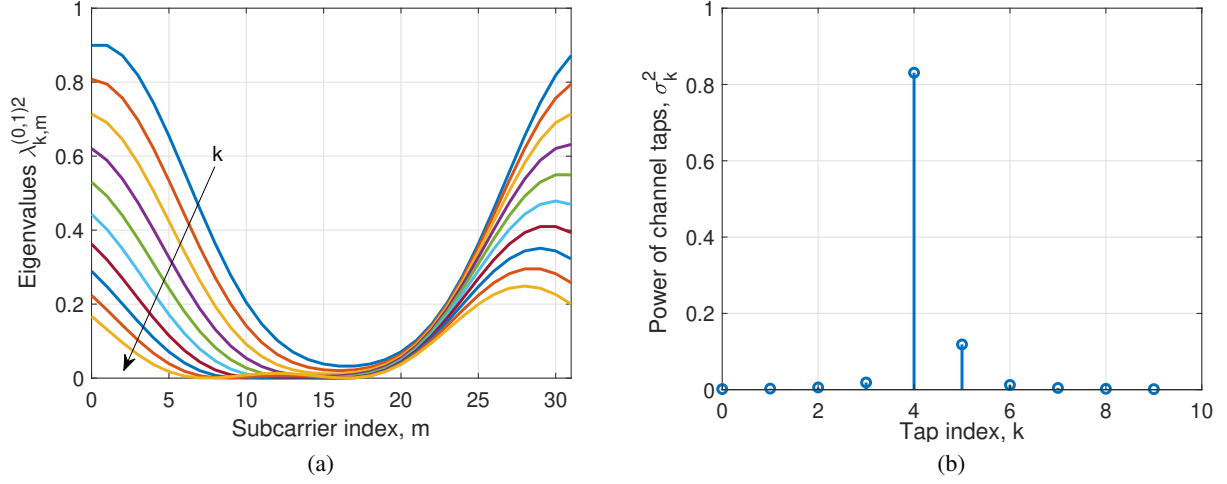


Figure 1: (a) Magnitude squared of the eigenvalues  $\Lambda_k^{(0,1)}$  (b) Powers of channel taps (Veh-A).

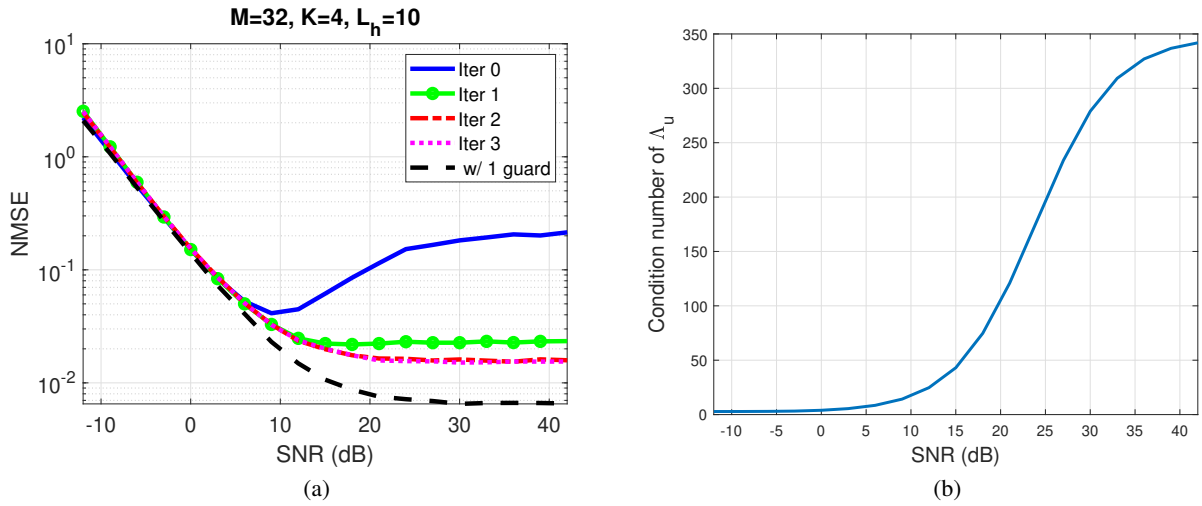


Figure 2: For the scenario of Fig. 1, with OQPSK input: (a) NMSE versus SNR (b) Condition number of  $\Lambda_u$  as a function of SNR.

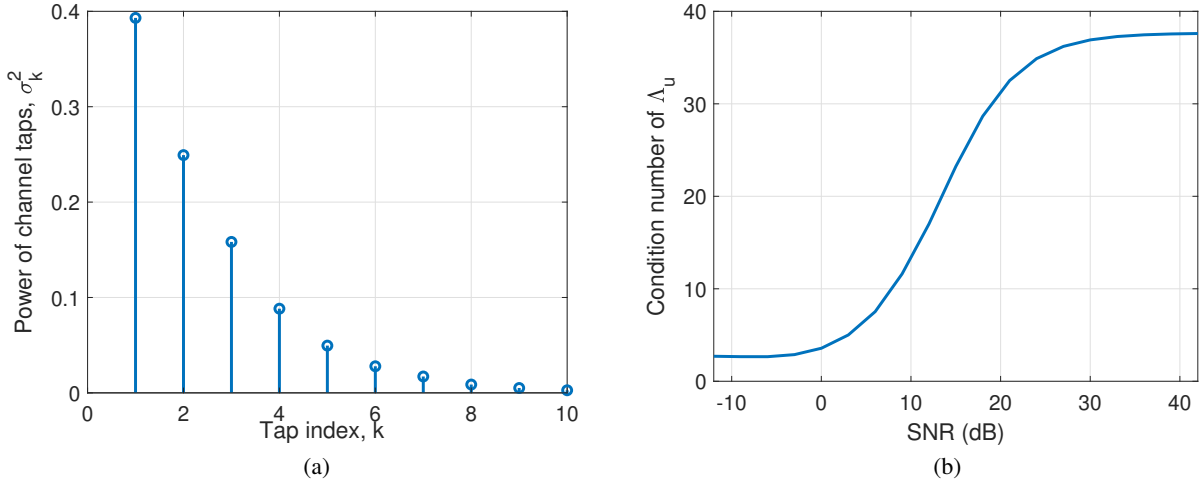


Figure 3: As in Fig. 1, with exponential channel: (a) Power of channel taps (b) Condition number of  $\Lambda_u$  as a function of SNR.

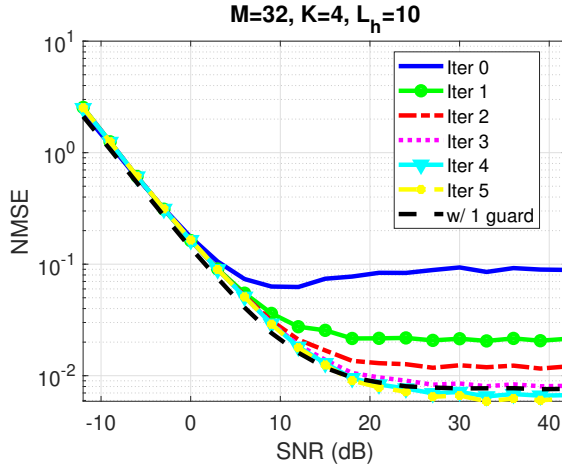


Figure 4: In the scenario of Fig. 3: NMSE versus SNR.

## A Proof of (8)

It follows from (7) and (4) that

$$\begin{aligned} \mathbf{C}_u &= \mathcal{G}^{(0,1)} E \left( \mathbf{A}_1 \mathbf{h} \mathbf{h}^H \mathbf{A}_1^H \right) \mathcal{G}^{(0,1)H} + \sigma^2 \mathbf{B} \\ &= \mathcal{G}^{(0,1)} E \left( \mathbf{A}_1 \text{diag}(\sigma_0^2, \sigma_1^2, \dots, \sigma_{L_h-1}^2) \mathbf{A}_1^H \right) \mathcal{G}^{(0,1)H} + \sigma^2 \mathbf{B}, \end{aligned} \quad (15)$$

where it was assumed that the CIR taps are uncorrelated with powers  $\sigma_k^2, k = 0, 1, \dots, L_h - 1$ . From the definition of  $\mathbf{A}_1$  it readily follows that  $\mathbf{A}_1 \text{diag}(\sigma_0^2, \sigma_1^2, \dots, \sigma_{L_h-1}^2) \mathbf{A}_1^H = \text{diag}(\sigma_0^2, \sigma_1^2, \dots, \sigma_{L_h-1}^2) \otimes \mathbf{a}_1 \mathbf{a}_1^H$  and hence its expectation with respect to the data statistics is  $\sigma_a^2 \text{diag}(\sigma_0^2, \sigma_1^2, \dots, \sigma_{L_h-1}^2) \otimes \mathbf{I}_M$ . Substituting in (15) and applying (6) yields after some algebra the following expression for  $\mathbf{C}_u$ :

$$\mathbf{C}_u = \mathbf{F} \mathbf{S} \sigma_a^2 \sum_{k=0}^{L_h-1} \sigma_k^2 \mathbf{Z}^k |\Lambda_k^{(0,1)}|^2 \mathbf{Z}^{-k} \mathbf{S} \mathbf{F}^H + \sigma^2 \mathbf{B}. \quad (16)$$

Obviously, (5) also holds for the squared magnitude of the diagonal matrix  $\Lambda_k^{(0,1)}$ . Using this in (16) along with the fact that pre- and post-multiplying a diagonal matrix with  $\mathbf{S}$  has no effect, and writing  $\mathbf{B} = \mathbf{F} \Lambda_0 \mathbf{F}^H$  leads to (8).

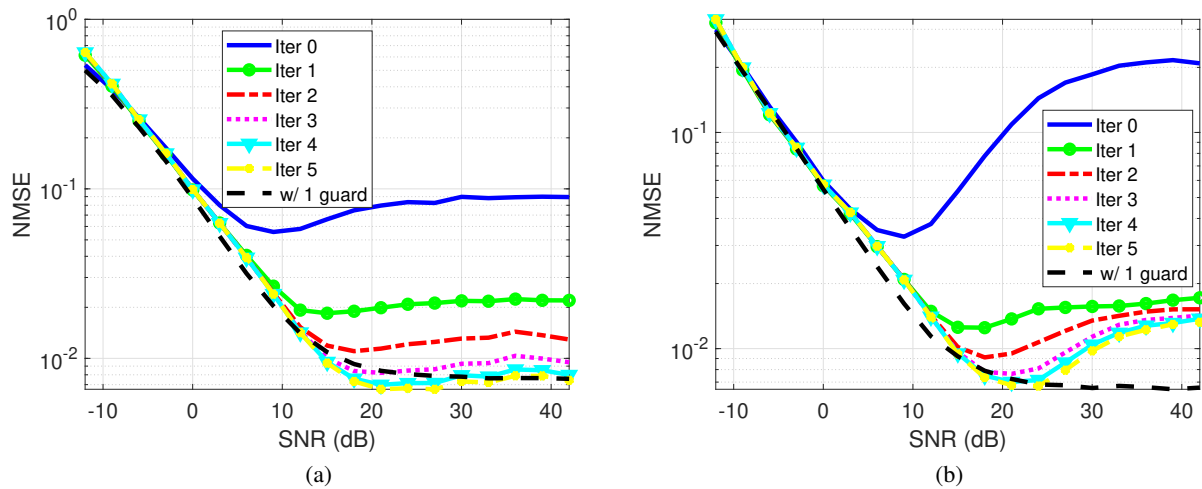


Figure 5: NMSE versus SNR using LMMSE: (a) Exponential (b) Veh-A.

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