Blind Channel Shortening for SIMO Space-Time Channels Using Linear Prediction in OFDM Systems

A. S. Menezes†, C. M. Panazio‡, J. M. T. Romano†

***Abstract*— In this paper, we make use of a blind adaptive linear predictor for channel shortening in single input multiple output (SIMO) channels. We compare our approach to the so-called MERRY blind channel shortener. We assess through simulations that our proposed approach provides faster convergence rate and it better exploits the spatio-temporal diversity present in the SIMO channels.**

***Index Terms*— OFDM, Blind Channel Shortening, Predictor, SIMO, SOS, MERRY.**

I. INTRODUCTION.

Multicarrier modulation is an attractive technique for high-speed signal transmission and is currently used in many standards, such as wireless local area networks (IEEE 802.11a/g/n), wireless metropolitan area networks (IEEE 802.16), digital video broadcasting (DVB) and digital audio broadcasting (DAB), power line communications (PLC) and digital subscribe line (DSL).

Several low-cost implementations of multicarrier modulation, such as orthogonal frequency division multiplexing (OFDM) and discrete multitone (DMT), make use of an inverse fast Fourier transform (IFFT) for the modulation and a fast Fourier transform (FFT) for the demodulation to create orthogonal sub-carries. However, the orthogonality between sub-carries is compromised in dispersive channels and both interblock and intercarrier interference (IBI and ICI) may appear. By inserting a cyclic prefix (CP) longer than the channel impulse response, both types of interference can be canceled and the effect of the channel can be represented by a single complex-valued coefficient on each sub-carrier. This channel distortion can be easily compensated through a bank of one-tap equalizers in the frequency domain. It can be obtained by means of simple channel estimation techniques with training sequences or with pilot sub-carries. For highly dispersive channels, the required CP is lengthy and the insertion of a long CP reduces the system throughput. One way of minimizing such impairment is to make use of a channel-shortening equalizer. Such technique aims to provide an effective channel, which is the convolution of the channel with the equalizer, whose length is smaller than the CP.

†A. S. Menezes and J. M. T. Romano are with the Signal Processing for Communications Laboratory, School of Electrical and Computer Engineering, State University of Campinas (UNICAMP), Brazil CP 6101, CEP 13083970. Phone: +55 19 37883857 Fax: +55 19 32891395 e-mails: (alam, romano)@decom.fee.unicamp.br

‡ C. M. Panazio is with Laboratory of Communications and Signals, Faculty of Electrical Engineering, Escola Politécnica of the University of São Paulo, cpanazio@lcs.poli.usp.br

The adaptation of such equalizer can be done in a supervised way, when a training sequence is available, or in a blind mode where we exploit some of the signal characteristics that are known *a priori* at the receiver. The main attractive of the blind approach is that it does not need the transmission of a training sequence and hence it may provide a larger system capacity.

There are many different blind criteria [1]. Notwithstanding, most of the usual criteria, like decision-directed (DD) and constant modulus (CM) [1], are not suitable in time-domain for multicarrier-modulation. This is due to the absence of a finite alphabet and also to the fact that the transmitted signal approaches a Gaussian distribution. Other criteria based on second order statistics (SOS) have been specially tailored to this context as [2] and [3]. The MERRY (Multicarrier Equalization by Restoration of Redundance) [3] exploits the redundancy inserted by the CP to achieve channel equalization. Although the MERRY algorithm is simple to implement and is globally convergent in the SISO case, it only updates the equalizer coefficients once per block and thus it may take more time to converge than other techniques that iterates at sample rate.

In this paper, we propose to use a blind adaptive linear predictor for channel shortening in single input multiple output (SIMO) channels context. We assess through simulations that, when compared to the MERRY algorithm, our proposed approach provides faster convergence rate and better exploits the spatio-temporal diversity present in the SIMO channels.

This paper is organized as follows. In Section II, we describe the system model. Section III presents our proposed approach based on the linear predictor for SIMO channels. In section IV we describe the MERRY algorithm and discuss its drawbacks in the SIMO context. Section V states how to assess the system performance. Simulation results are shown in Section VI. Finally, the conclusions and perspectives are stated in VII.

II. SYSTEM MODEL.

The baseband system model in figure 1 depicts one transmit antenna and 2 receiver antennas for clarity, but in general we assume the use of P receiver antennas, representing a generic SIMO channel. Each of the N sub-carriers modulates a QAM signal. Modulation is performed via inverse fast Fourier transform (IFFT) and demodulation is accomplished via FFT.

In order to transform the linear convolution of the transmitted symbol with the channel into a circular convolution, a CP of length ν is insert at the beginning of each OFDM

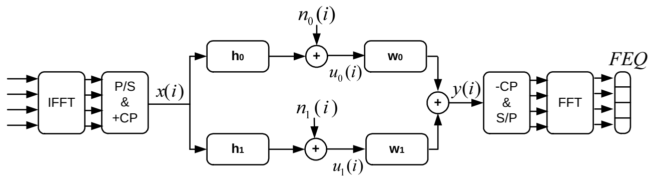

Fig. 1. System Model. (I)FFT (inverse) fast Fourier transform, P/S: parallel to serial, S/P: serial to parallel, +CP: add cyclic prefix, -CP: remove cyclic prefix, FEQ: frequency-domain equalizer.

symbol. Generally, the order of ν is a value between $\frac{N}{16}$ and $\frac{N}{4}$ [4]. A circular convolution is equivalent to a point-wise multiplication in the frequency domain. This can be equalized by the FEQ (frequency domain equalizer), which is a bank of complex scalars. In order to have a circular convolution, the channel length must be no longer than the CP length. If we cannot comply with such constraint, channel shortening is performed by a time-domain equalizer (TEQ) whose coefficients are represented by $\mathbf{w}$.

After the CP insertion, the last ν samples are identical to first ν samples in the k^{th} symbol, i.e.:

$$x\,(Mk+i) \;=\; x\,(Mk+i+N) \quad i \in \{0,\, ...,\, \nu-1\} \tag{1}$$

where $M = N + \nu$ is the total symbol duration and k is the symbol index. The data received by the p^{th} antenna is modeled by

$$u_p(i) = \mathbf{h}_p^T \mathbf{x}(i) \;+\; n_p(i), \tag{2}$$

where $\mathbf{h}_p = [h_p(0)\;\; h_p(1)\;\; \ldots\;\; h_p(L_h-1)]^T$ is the sub-channel, $\mathbf{x}(i) = [x(i)\;\; x(i-1)\;\; \ldots\;\; x(i-L_h+1)]^T$ is the transmitted signal, $n_p(i)$ is the additive white Gaussian noise and L_h is the length of the p^{th} sub-channel.

The p^{th} TEQ output is given by

$$y_p(i) = \mathbf{w}_p^T \mathbf{u}_p \tag{3}$$

where $\mathbf{w}_p = [w_p(0)\;\; w_p(1)\;\; \ldots\;\; w_p(L_w-1)]^T$ is the sub-equalizer, $\mathbf{u}_p(i) = [u_p(i)\;\; u_p(i-1)\;\; \ldots\;\; u_p(i-L_w+1)]^T$ is the input of the p^{th} sub-equalizer and L_w is its length.

The equalized data, fed to the demodulating FFT, is given by

$$y(i) = \sum_{p=0}^{P-1} y_p(i) = \sum_{p=0}^{P-1} \mathbf{w}_p^T \mathbf{u}_p = \mathbf{w}^T \mathbf{u} \tag{4}$$

where

$$\mathbf{w}^T \;=\; \left[\mathbf{w}_0^T\,,\; \mathbf{w}_1^T\,,\; \ldots\,,\; \mathbf{w}_{P-1}^T\right] \tag{5}$$

and

$$\mathbf{u}(i) \;=\; \left[\mathbf{u}_0^T\,(i)\;,\; \mathbf{u}_1^T\,(i)\;,\; \ldots\;,\; \mathbf{u}_{P-1}^T\,(i)\right]^T \tag{6}$$

Each of the P channels has L_h taps, each of the P sub-equalizers has L_w taps, and each of the effective channel $\mathbf{c}_p = \mathbf{h}_p \star \mathbf{w}_p$ has L_c taps, where $L_c = L_h + L_w - 1$ and $\star$ denotes linear convolution.

III. THE PROPOSED TECHNIQUE

According to the Gardner's work [5], identification of both magnitude and phase of a communication channel with second order statistics (SOS) is possible if we explore the cyclostationary properties of the modulated signals. SOS-based blind techniques can be divided in two approaches, namely subspace methods and linear prediction methods. In this paper we use the second method in an adaptive framework.

Given the equation (2), we can rewrite it in the vector form

$$\mathbf{u}_f(i) = \sum_{\lambda=0}^{L_h-1} \mathbf{h}(\lambda) x(i-\lambda) + \mathbf{n}(i) \tag{7}$$

where $\mathbf{u}_f(i) = [u_0(i)\; u_1(i)\; \ldots u_{P-1}(i)\,]^T$ is the vector of P received samples at time i by the P antennas. The vector $\mathbf{n}(i) = [n_0(i)\; n_1(i)\; \ldots n_{P-1}(i)\,]^T$ corresponds to the P noise samples and $\mathbf{h}(\lambda) = [h_0(\lambda)\; h_1(\lambda)\; \ldots\; h_{P-1}(\lambda)]^T \;\; , \lambda \in \{0,\, 1,\, \ldots,\, L_h-1\}$, is the vector with the λ^{th} samples of each sub-channel. The equation (7) describes a SIMO system.

The following vector represents the concatenation of all sub-equalizer input vectors:

$$\mathbf{U}_{f_{L_w}}(i) \;=\; \left[\mathbf{u}_f^T(i)\;\; \mathbf{u}_f^T(i-1)\ldots \mathbf{u}_f^T(i-L_w+1)\right]^T \tag{8}$$

This vector can be obtained by:

$$\mathbf{U}_{f_{L_w}}(i) = \boldsymbol{H}\mathbf{X}_{L_h+L_w-1}(i) \quad + \mathbf{N}_{L_w}(i) \tag{9}$$

where $\mathbf{X}_{L_h+L_w-1}(i) = [x(i)\;\; x(i-1)\ldots x(i-L_h-L_w+2)]^T$ is the transmitted signal vector and $\mathbf{N}_{L_w}(i) = \left[\mathbf{n}^T(i)\;\; \mathbf{n}^T(i-1)\;\; \ldots\;\; \mathbf{n}^T(i-L_w+1)\right]^T$ is the associated noise vector. The matrix $\boldsymbol{H}$ is the channel convolution matrix, which is a $L_wP \times\; L_h + L_w - 1$ block-Toeplitz matrix given by

$$\boldsymbol{H} \;=\; \begin{bmatrix} \mathbf{h}(0) & \cdots & \mathbf{h}(L_h-1) & & 0 \\ & \ddots & & \ddots & \\ 0 & & \mathbf{h}(0) & \cdots & \mathbf{h}(L_h-1) \end{bmatrix} \tag{10}$$

An estimate of the transmitted signal is obtained by filtering the received sample vector by the equalizer, as follows:

$$\widehat{x}(i-d) \;=\; \mathbf{F}_{L_w}^H \mathbf{U}_{f_{L_w}}, \tag{11}$$

where d is the equalization delay and $\mathbf{F}_{L_w}^H$ is the $L_wP \times 1$ vector given by

$$\mathbf{F}_{L_w} \;=\; \left[\mathbf{w}_f^H(0)\;\; \mathbf{w}_f^H(1)\;\ldots\;\; \mathbf{w}_f^H(L_w-1)\right]^H \tag{12}$$

where $\mathbf{w}_f(l) = \left[\mathbf{w}_0^T(l)\;\; \mathbf{w}_1^T(l)\;\ldots\;\mathbf{w}_{P-1}^T(l)\right]^T$.

In the absence of additive noise, perfect equalization is attainable according to the Bezout Identity [6], with the constraint that the P sub-channels have no common zeros. So that is possible to obtain a zero-forcing (ZF) equalizer that leads to the following result

$$\mathbf{F}_{L_w}^H \boldsymbol{H} \;=\; [\mathbf{0}_{1\times d}\; 1\; \mathbf{0}_{1\times L_h+L_w-d-2}] \tag{13}$$

Based on the assumption of absence of additive noise, it can be shown that, for $d = 0$, the ZF equalizer corresponds to a multichannel forward linear predictor [7] for which the adaptive implementation is presented in the following.

Let us define the multichannel forward prediction error as

$$\begin{aligned} \mathbf{e}_f(i) &= \mathbf{u}_f(i) - \boldsymbol{A}^H_{L_w-1}\mathbf{U}_{f_{L_w-1}}(i-1) \\ &= \begin{bmatrix}\boldsymbol{I}_P & -\boldsymbol{A}^H_{L_w-1}\end{bmatrix}\mathbf{U}_{f_{L_w}}(i) \end{aligned} \tag{14}$$

where $\boldsymbol{A}_{L_w-1}$ is the $(L_w-1)P \times P$ matrix with the optimal multichannel forward prediction error coefficients and $\boldsymbol{I}$ is a *P X P* identity matrix. The *P X 1* forward prediction error variance matrix is shown [6] to be given by:

$$E\left\{\mathbf{e}_f(i)\mathbf{e}_f^H(i)\right\} = \sigma_x^2\mathbf{h}(0)\mathbf{h}^H(0) \tag{15}$$

Both $\boldsymbol{A}_{L_w-1}$ and $E\left\{\mathbf{e}_f(i)\mathbf{e}_f^H(i)\right\}$ can be extracted from the autocorrelation matrix of the received signal $\mathbf{U}_{f_{L_w}}$. It is shown in [6] that the following relation holds:

$$\begin{bmatrix}\boldsymbol{I}_P & -\boldsymbol{A}^H_{L_w-1}\end{bmatrix}\boldsymbol{H} = \mathbf{h}(0)\begin{bmatrix}1 & 0 & \ldots & 0\end{bmatrix} \tag{16}$$

The above equation can be rewritten in the following from:

$$\mathbf{h}^{\#}(0)\begin{bmatrix}\boldsymbol{I}_P & -\boldsymbol{A}^H_{L_w-1}\end{bmatrix}\boldsymbol{H} = \begin{bmatrix}1 & 0 & \ldots & 0\end{bmatrix} \tag{17}$$

where $\mathbf{h}^{\#}(0) = \mathbf{h}^H(0)\big/\|\mathbf{h}(0)\|^2$.

The rightmost term of (17) is indeed the ideal combined channel equalizer response corresponding to *d=0*. Hence, the ideal ZF equalizer is obtained of (17) and is given by

$$\mathbf{F}^H_{L_w} = \mathbf{h}^{\#}(0)\begin{bmatrix}\boldsymbol{I}_P & -\boldsymbol{A}^H_{L_w-1}\end{bmatrix} \tag{18}$$

Based on the solution described above, an adaptive version has been derived in [6]. The forward prediction error vector is estimated at each iteration and the forward prediction coefficients matrix is updated with the least mean square (LMS) algorithm. The estimation of the forward prediction error matrix (15) can be carried out by

$$\boldsymbol{E}_f(i) = \lambda\boldsymbol{E}_f(i) + (1-\lambda)\mathbf{e}_f(i)\mathbf{e}_f^H(i) \tag{19}$$

where $0 \ll \lambda < 1$ acts as a forgetting factor.

The adaptive procedure developed in [7] and used in this paper can be then summarized as follows:

A. *Initialization* i = *0*

The forward prediction error matrix is initialized with $\boldsymbol{E}_f(0) = \delta\boldsymbol{I}_P$ and $\boldsymbol{A}_{L_w-1}(0) = \mathbf{0}$.

B. *For* i = *1, 2, 3,* $\cdots$

$$\mathbf{e}_f(i) = \begin{bmatrix}\boldsymbol{I}_P & -\boldsymbol{A}^H_{L_w-1}\end{bmatrix}\mathbf{U}_{f_{L_w}}(i) \tag{20}$$

$$\mathbf{A}_{L_w-1}(i+1) = \mathbf{A}_{L_w-1}(i) + \mu\mathbf{U}_{f_{L_w}}\mathbf{e}_f^H(i) \tag{21}$$

C. *Estimation of* ***h(0)***

An estimate $\widehat{\mathbf{h}}(0)$ of $\mathbf{h}(0)$ is obtained taking the column of (19) with the largest norm.

D. *Obtaining the ZF equalizer.*

$$\mathbf{F}_{L_w}(i) = \begin{bmatrix}\boldsymbol{I}_P \\ -\boldsymbol{A}_{L_w-1}\end{bmatrix}\frac{\widehat{\mathbf{h}}(0)}{\left\|\widehat{\mathbf{h}}(0)\right\|} \tag{22}$$

IV. ANALYSIS OF MERRY ALGORITHM IN THE SIMO CONTEXT.

The MERRY algorithm [3] assumes that a CP is used in the transmission and that the source sequence is white before the CP insertion. If the effective channel is no longer than CP and in the absence of noise, then the last sample in the received symbol will be equal to the last sample in the received CP of the symbol. This characteristic can be seen in the following example. Consider three transmitted OFDM symbols as depicted in figure 2.

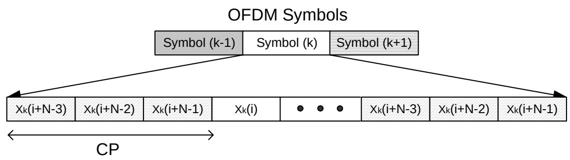

Fig. 2. Three transmitted OFDM symbols.

In the absence of noise and given that the channel has $\mathbf{h}_0 = [1 \quad 1 \quad 1]^T$, $L_h = 3$, P = 1 and the CP has length L_h, we have the received signal after the convolution as represented in figure 3.

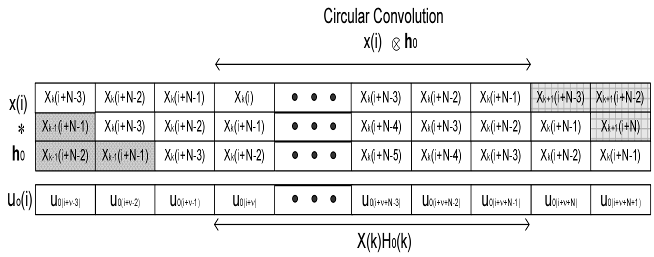

Fig. 3. Transmitted OFDM symbols and convolution with the channel $\mathbf{h}_0$.

The MERRY algorithm cost function [3] is given by

$$J_{MERRY}(\mathbf{w}, \Delta) = E\left\{|y(i+\Delta) - y(i+N+\Delta)|^2\right\} \tag{23}$$

where Δ is a delay, which corresponds to the boundaries between successive OFDM blocks after equalization. The adaptive algorithm is obtained by the stochastic gradient descent of (23) and by applying a power constraint into the equalizer coefficients, in order to avoid the trivial solution $\mathbf{w} = \mathbf{0}$:

For symbol $k = 0, 1, 2, \cdots$,

$$\begin{aligned} \widetilde{\mathbf{u}}(k) &= \mathbf{u}(Mk+\nu-1+\Delta) - \mathbf{u}(Mk+\nu-1+N+\Delta) \\ e_M(k) &= \mathbf{w}^T(k)\widetilde{\mathbf{u}}(k) \\ \widehat{\mathbf{w}}(k+1) &= \mathbf{w}(k) - \mu_M e_M(k)\widetilde{\mathbf{u}}^*(k) \\ \mathbf{w}(k+1) &= \frac{\widehat{\mathbf{w}}(k+1)}{\left\|\widehat{\mathbf{w}}(k+1)\right\|} \end{aligned} \tag{24}$$

where $\mathbf{w}$ and $\mathbf{u}$ are defined in the equations (5) and (6) respectively.

The gradient descent algorithms are sensitive to the filter coefficients initialization, specially for blind techniques. For the $P = 1$ case, a standard initialization is a "center-spike" initialization in which the adaptive filter coefficients are equal to zero with exception of the center coefficient that is set to one, i.e., $\mathbf{w}_i = [0, \ldots, 0, 1, 0, \ldots, 0]^T$. For $P > 1$, one of the sub-equalizers can be initialized with a center-spike and the rest of the equalizer coefficients can all be set to zeros. Given this type of initialization and considering the cases where $L_h \leq CP$, we can shown that the MERRY algorithm will not move from initialization because the true gradient is zero unless L_h is longer than the CP.

The optimal value of Δ is the one that minimizes (23). Since the transmission delay is equal to zero, the value of Δ is equal to the delay generated by the center-spike. In this case, the error can be written as

$$e_M(k) = [0 \ldots 1 \ldots 0,\ \mathbf{0}_1,\ \mathbf{0}_2,\ \ldots,\ \mathbf{0}_{P-1}]\,\widetilde{\mathbf{u}}(k) \tag{25}$$

$$\widetilde{\mathbf{u}}(k) = [\zeta_0,\ \ldots,\ \gamma_{Center\ Spike},\ \zeta_{Lw},\ \ldots,\ \zeta_{PLw-1}] \tag{26}$$

where ζ_i is a random variable with zero mean and $\gamma_{Center\ Spike} = n_0(Mk+\nu-1+\Delta) - n_0(Mk+N+\nu-1+\Delta)$ is the difference between two uncorrelated zero mean Gaussian noise in the position of the center spike. Then, we have

$$\begin{aligned} e_M(k) &= \mathbf{w}^T \widetilde{\mathbf{u}}(k) \\ &= n_0(Mk+\nu+\Delta) - n_0(Mk+N+\nu+\Delta) \end{aligned} \tag{27}$$

The true gradient of (24) is given by

$$E\left\{e_M(k)\widetilde{\mathbf{u}}^*(k)\right\} = \left[0 \ldots, 2\sigma_n^2, 0,\ \ldots 0\right]^T, \tag{28}$$

where all elements are equal to zero except the element in the center-spike position, $2\sigma_n^2$. Then, it holds for the first iteration, given by:

$$\begin{aligned} \widehat{\mathbf{w}}(1) &= \mathbf{w}(0) - \mu_M \mathrm{E}\{e_M(k)\widetilde{\mathbf{u}}^*(k)\} \\ &= [0,\ \ldots 0, 1 - 2\mu\sigma_n^2,\ 0,\ \mathbf{0}_1,\ \mathbf{0}_2,\ \ldots,\ \mathbf{0}_{P-1}]^T \end{aligned} \tag{29}$$

and

$$\begin{aligned} \mathbf{w}(1) &= \frac{\widehat{\mathbf{w}}(1)}{\left\|\widehat{\mathbf{w}}(1)\right\|} \\ &= [0 \ldots 1 \ldots 0,\ \mathbf{0}_1,\ \mathbf{0}_2,\ \ldots,\ \mathbf{0}_P]^T \end{aligned} \tag{30}$$

and so on for the other iterations.

This shows that in the context where $L_h \leq \nu$, the MERRY algorithm does not move away its coefficients from the initialization. Therefore, it cannot exploit the diversity provided by the SIMO channels. This behavior is verified in the simulations of the section VI.

Other initializations may be used, but there is no guarantee that they will provide additional performance. For instance, let us suppose that $h_0 = 1$ and $h_1 = -1$. If we initialize both sub-equalizers $\mathbf{w}_0$ and $\mathbf{w}_1$ with center spikes, the initialization would be already a solution to (23) but the equalizer output would be constituted only by noise, since the signal is canceled.

V. Performance assessment

In order to assess the performance of each technique, we make use of the SNR measurement proposed in [8]. In this method, the received signal can be partitioned into the desired signal, an IBI component, and noise components. The desired signal and the IBI (interblock interference) components are linear filtered versions of the same transmitted signal by $\mathbf{h}_{eq}^{desired}$ and $\mathbf{h}_{eq}^{IBI}$. These filters are obtained by the following steps:

A. Find the equivalent channel $\widetilde{\mathbf{h}}$

$$\widetilde{\mathbf{h}} = \sum_{p=0}^{P-1} \mathbf{h}_p \star \mathbf{w}_p \tag{31}$$

where $\widetilde{\mathbf{h}} = [\widetilde{h}(0)\ \widetilde{h}(1)\ \ldots\ \widetilde{h}(L_h + L_w - 1)]^T$

B. Find the window $g(k, \rho)$

$$g(k,\rho) = \begin{cases} 1, & \rho \leq k \leq \rho + \nu \\ 0, & otherwise \end{cases} \tag{32}$$

where ρ is an integer value that maximizes the value of $\sum_{k=0}^{L_h+L_w-1} |g(k,\rho)\widetilde{h}(k)|^2$

C. Obtaining $\mathbf{h}_{eq}^{desired}$ and $\mathbf{h}_{eq}^{IBI}$

$$\begin{aligned} h_{eq}^{desired}(k) &= g(k,\rho)\widetilde{h}(k) \\ h_{eq}^{IBI}(k) &= (1 - g(k,\rho))\widetilde{h}(k) \end{aligned} \tag{33}$$

In frequency domain, the desired signal is multiplied by $H_{eq}^{desired}(i) = \sum_{k=0}^{N-1} h_{eq}^{desired}(k)\mathrm{e}^{-j2\pi ki/N}$ and the IBI component is multiplied by $H_{eq}^{IBI}(i) = \sum_{k=0}^{N-1} h_{eq}^{desired}(k)\mathrm{e}^{-j2\pi ki/N}$. Since both desired signal and IBI component are originated by the transmitted signal $x(i)$, their variance in the i^{th} sub-carrier is $\sigma_X^2|H_{eq}^{desired}(i)|^2$ and $\sigma_X^2|H_{eq}^{IBI}(i)|^2$, where σ_X^2 is the variance of the QAM symbols X(i) that are modulated by the IFFT and that generates the transmitted signal $x(k)$. We also assume that the IBI interference can be modeled as a gaussian noise.

The independent noise components $n_p(k)$ with variance σ_n^2/N of each sub-channel are filtered by their respective sub-equalizers. Therefore, the noise variance in frequency domain for the i^{th} sub-carrier is given by $\sigma_n^2 \sum_{p=0}^{P-1} |W_p(i)|^2$, where $W_p(i) = \sum_{k=0}^{N-1} w_p(k)\mathrm{e}^{-j2\pi ki/N}$.

Thus, the SNR for the i^{th} sub-carrier is given by

$$SNR(i) = \frac{\sigma_X^2 \left|H_{eq}^{desired}(i)\right|^2}{\sigma_n^2 \sum_{p=0}^{P-1} |W_p(i)|^2 + \sigma_X^2 \left|H_{eq}^{IBI}(i)\right|^2} \tag{34}$$

We obtain the theoretical bit error rate (BER) values of each sub-carrier using the corresponding SNR values. Finally, the ultimate performance measure is obtained by taking the average BER of all sub-carries.

VI. Simulation Results

In order to evaluate convergence rate and BER, we define two channels groups as shown in table I. The **Group I** presents two minimum phase sub-channels and **Group II** shows two non-minimum phase channels. The simulation parameters are N = 64, $L_w = 15$, the transmitted data is 4 - QAM with $\sigma_X^2 = 2$. In this paper the matched filter bound (MFB) was employed as a benchmark and we assume perfect synchronization.

Groups	Sub-channels	Coefficients							
I	$\mathbf{h}_0$	0.49	-0.34	0.25	0	0	0	-0.20	0.05
	$\mathbf{h}_1$	0.49	0.39	0.29	0	0	0	0.20	0.15
II	$\mathbf{h}_0$	0.22	-0.27	0.38	0	0	0	-0.22	0.05
	$\mathbf{h}_1$	0.38	0.49	0.44	0	0	0	-0.27	0.16

TABLE I
SUB-CHANNELS COEFFICIENTS

A. Convergence rate

The mean square error (MSE) curves presented in 4 were obtained using ν = 6, SNR= 20dB and the channel defined in **Group I**. In order to make a fair comparison between the techniques, we have applied the MSE defined in the cost function of the MERRY algorithm (23) into the output of the predictor. The MSE curves are obtained by an ensemble average of 150 trials. The adaptations steps of each technique were adjusted to make both of them converge to the same MSE floor.

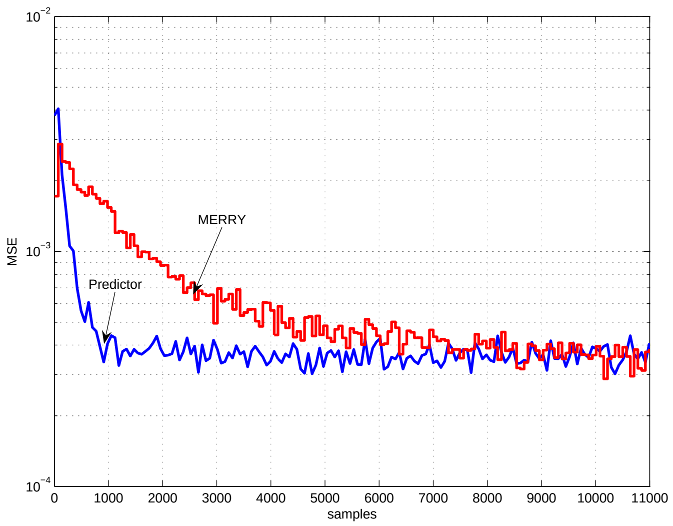

Fig. 4. Convergence curves of the MERRY and Predictor techniques.

For a wireless environment, in which the channels changes significantly every 10 or 20 blocks [4], the MERRY algorithm can have difficulty tracking the changing environment. In this context, the predictor is more advantageous because it is updated at sample rate, besides its faster convergence rate, as shown in figure 4.

B. Minimum phase channels

The BER for both techniques were obtained after the convergence of each algorithm. We have used a small adaptation step to minimize the influence of adaptation noise. The figures 5 and 6 present the results for the channel described in **Group I**, table I.

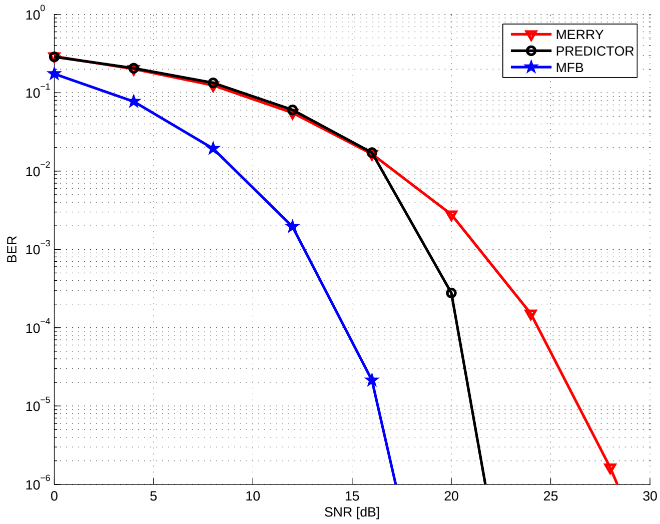

Fig. 5. BER for minimum phase sub-channels and ν = 6.

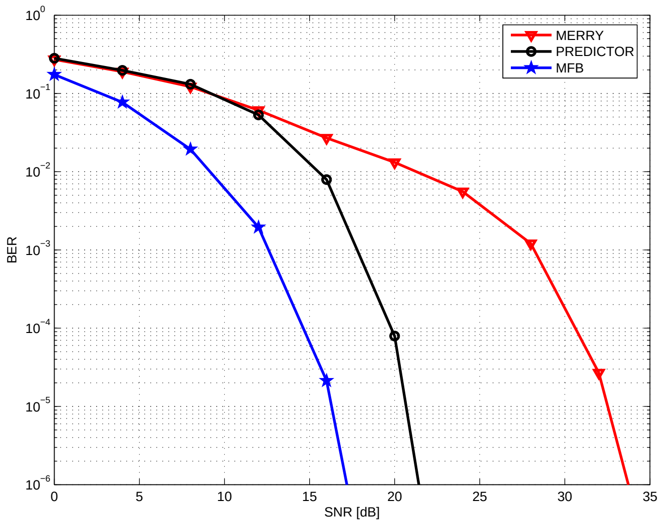

Fig. 6. BER for minimum phase sub-channels and ν = 10.

In both cases, ν = 6 and ν = 10, the performance superiority of the predictor over the MERRY technique is significative, specially for higher SNR values. With ν = 10, there is no need to shorten the channel. Nevertheless, the diversity in the space-time context is an important parameter to improve the SNR of each sub-carrier and then the BER. As shown in section IV, for $\nu \geq L_h$, the MERRY algorithm does not move away its coefficients from the initialization. On the other hand, the predictor tries to whiten the signal independently of the CP length and, in the process, can exploit the implicity spatio-temporal diversity. Clearly, the fact that both sub-channels are minimum phase, also contributes to the good performance of the predictor.

C. Non-minimum phase channels

We now analyze the BER performance using the non-minimum phase sub-channels described in **Group II**, table I. The results are shown in figures 7 and 8.

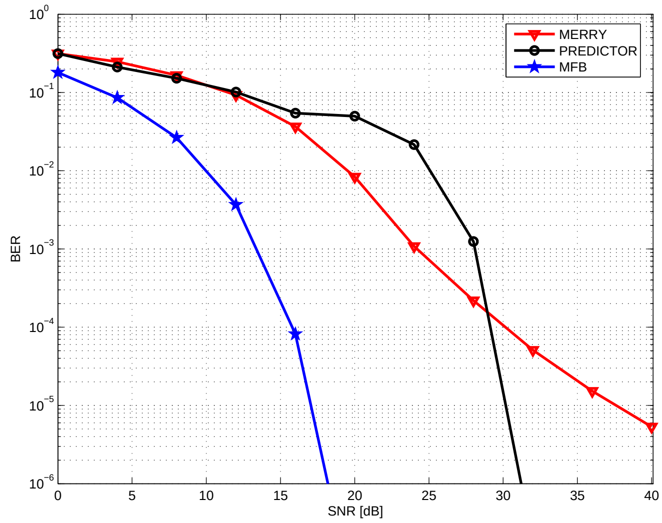

Fig. 7. BER for non-minimum phase sub-channels and ν = 6.

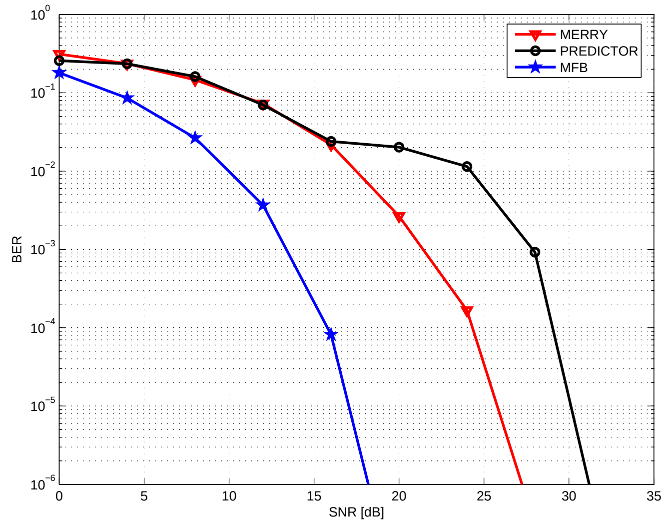

Fig. 8. BER for non-minimum phase sub-channels and ν = 10.

Contrarily to the minimum phase case, the performance of the predictor is considerably degraded in this non-minimum sub-channels scenario (figs. 7 and 8). In the process of equalizing the received signal, the predictor causes a bad combination of the non-minimum phase sub-channels that incurs in a loss of spatio-temporal diversity. This loss is evidenced in fig. 8, where the performance of the predictor is always worse than the MERRY algorithm, although it captures only the first sub-channel.

VII. Conclusions and Perspectives

In this paper, we propose to use a blind adaptive linear predictor to provide channel shortening in a space-time context for OFDM signals.

Compared to the so-called MERRY algorithm, it can offer faster convergence since it operates at sample rate, contrary to the MERRY algorithm, which adapts at OFDM symbol rate.

In terms of channel diversity, which is intrinsically provided by the SIMO channel, the MERRY algorithm may not exploit it when the CP length is larger than the channel length. On the other hand, simulations suggest that the predictor can exploit it on minimum phase channels and then obtain a better BER performance.

The proposed technique suffers from performance loss in non-minimum phase sub-channels due to the minimum phase equalization nature of the predictor. We envisage the use of a cascade forward-backward predictor to overcome such problem. Additionally, the performance analysis over time-varying channel must be examined.

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