Paper

Using Least Mean p-Power Algorithm to Correct Channel Distortion in MC-CDMA Systems

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Abstract—This work focuses on adaptive Broadband Radio Access Network (BRAN) channel identification and on downlink Multi-Carrier Code Division Multiple Access (MC-CDMA) equalization. We use the normalized BRAN C channel model for 4G mobile communications, distinguishing between indoor and outdoor scenarios. On the one hand, BRAN C channel parameters are identified using the Least Mean *p*-Power (LMP) algorithm. On the other, we consider these coefficients in the context of adaptive equalization. We provide an overview and a mathematic formulation of MC-CDMA systems. According to these fundamental concepts, the equalizer technique is investigated analytically to compensate for channel distortion in terms of the bit error rate (BER). The numerical simulation results, for various signal-to-noise ratios and different *p* threshold, show that the presented algorithm is able to simulate the BRAN C channel measured with different accuracy levels. Furthermore, as far as the adaptive equalization problem is concerned, the results obtained using the zero-forcing equalizer demonstrate that the algorithm is adequate for some particular cases of threshold *p*.

Keywords—adaptive equalization, adaptive identification, BER, BRAN C, LMP, MC-CDMA system, ZF.

1. Introduction

The need to develop more efficient wireless communication systems, offering higher data rates, is prevalent today. Different channel accessing techniques exist, such as frequency division multiple access (FDMA), time division multiple access (TDMA), code division multiple access (CDMA) or orthogonal frequency division multiple access (OFDMA). The mix of CDMA and OFDMA offers us a multi carrier-code division multiple access (MC-CDMA) technique which is a good candidate to meet the requirements stated. In the case of very high-speed wireless access of 100 Mbps to 1 Gbps, the channel is severely frequency-selective due to the presence of many interfering paths with different time delays, as well as due to equipment imperfection and presence of noise.

To remedy the perturbation introduced by the transmission channel, it is necessary to identify the distortion and to implement an equalization device. However, the calculation of equalizer coefficients requires knowledge of the parameters of the transmission channel's impulse response parameters, i.e. identification.

There are different identification techniques that can be implemented. In this work we use the LMP algorithm [1]–[3] for radio channel identification. Recently, adaptive algorithms are receiving increasing attention, and are widely studied in various works [1]–[7]. There are several applications, such as interference cancelation, spectral subtraction, wireless localization, adaptive beamforming, and channel equalization [2], in which these can be used. In this paper we address the application of the LMP algorithm in identification of the BRAN C channel and in downlink MC-CDMA equalization. However, LMP is a stochastic gradient-based adaptive filtering algorithm, which uses the p-power of error as the adaptation cost, and it is robust to outliers when $p < 2$ [1], [3]. Here, we address the application of the presented algorithm in the context of adaptive equalization of MC-CDMA systems. However, MC-CDMA offers a high bit rate and high capacity transmission, and is one of the most promising techniques for future mobile communications. Indeed, MC-CDMA is actually a fusion of CDMA and OFDM techniques. MC-CDMA is an effective scheme that reduces such problems as spectral limitation and distortions due to multipath channels.

The principle of MC-CDMA systems is that the multi-carrier transmission combines with frequency domain spreading, and the original data stream from a user is spread with this user's specific code, in this case the Walsh-Hadamard code, in the frequency domain but not in the time domain. Each symbol is transmitted simultaneously in a number of subcarriers. However, in digital communication, synchronization between the transmitter and the receiver is considered to constitute a major problem. Synchronization errors cause the loss of orthogonality between subcarriers and considerably degrade performance, especially when a large number of subcarriers exists, provoked by wireless environments. There are many different propagation paths caused by obstacles in the channels, such as buildings, mountains and walls between the transmitter and receiver [8]–[9]. To compensate for the degradation of the transmitter signal, it is necessary to identify the origin of the distortion and to apply the equalization technique. In this paper, we use the zero forcing (ZF) equalizer after channel identification, to correct channel distortion. However, we have considered a practical frequency selective fading channel, such as BRAN C [10]–[11] normalized for MC-CDMA systems, exited by non-Gaussian sequences, for different SNR and fixed data inputs. The performance of the presented algorithm and equalizer is demonstrated in terms of effectiveness of BRAN C channel identification on the one hand, and BER degradation of downlink MC-CDMA equalization on the other.

The remainder of the paper is organized as follows. The problem is formulated in Section 2. The MC-CDMA system and the equalizer used are described in Section 3. In Section 4, an overview of the LMP algorithm is presented. Numerical simulation results and analyses are considered in Section 5. Finally, the study is concluded in Section 6.

2. Problem Formulation

The BRAN adaptive channel identification problem, as illustrated in Fig. 1, is considered with a discrete time model. One common application of such a solution is linked with the use of adaptive filters to identify an unknown system, such as the impulse response of an unknown communications channel.

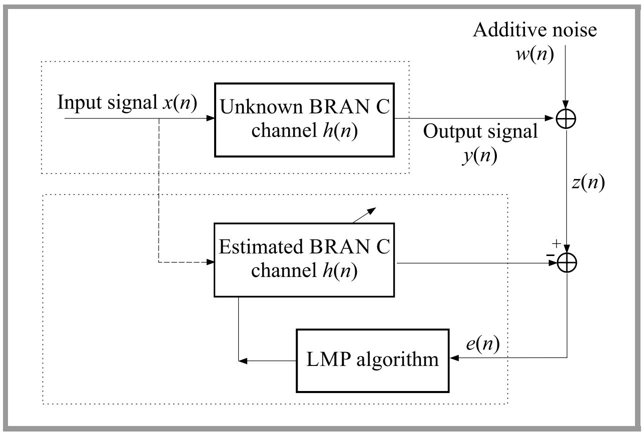

Fig. 1. Adaptive system identification configuration.

Typically, a digital communication channel can be modeled as a finite impulse response filter with an additive noise source. Specifically, the received signal at sample n is:

$$z(n) = \sum_{i=0}^{L-1} h(i)x(n-i) + w(n) \ , \tag{1}$$

where:

$$h = \left[h_0, h_1, \ldots, h_{L-1}\right]$$

and

$$x(n) = \left[x(n), x(n-1), \ldots, x(n-L+1)\right]$$

denotes channel coefficient, with L size, and input signal vector $x(n)$, respectively. $w(n)$ is additive Gaussian noise. The impulse response of the system model is chosen to minimize the mean square error.

For this system we assume that:

- the input sequence $x(n)$ is independent and identically distributed (i.i.d.) zero mean and non-Gaussian,
- the measurement noise sequence $w(n)$ is as assumed zero mean, i.i.d., Gaussian and independent of $x(n)$ with an unknown variance,
- the adaptive filter has the same number of taps as the unknown system represented by $h(n)$.

The problem statement is to identify the parameters of the system $h(n)_{(n=1,\ldots,L)}$ using the LMP algorithm, for various SNR levels and different thresholds p, in order to exploit these coefficients in an adaptive equalization problem. The purpose is to compensate the fading channel, in MC-CDMA systems, in terms of the BER.

3. MC-CDMA System Description

3.1. MC-CDMA Systems

The MC-CDMA signal originates from the concatenation of direct sequence spectrum spreading and multi-carrier modulation operations. However, as it is the case with the OFDM signal, the MC-CDMA signal can be generated by an inverse fast Fourier transform (IFFT) performed on the spreading code chips. Thus, the choice of spreading codes is fundamental. The complex symbol a_i of each user i is, firstly, multiplied by each chip $c_{i,k}$ of the Walsh-Hadamard spreading code, and then applied to the modulator of the multicarriers. Each subcarrier transmits an element of information multiplied by a code chip of that subcarrier (an overview of MC-CDMA systems can be found in [6], [12]–[14]).

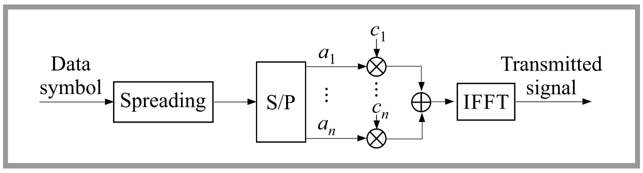

Fig. 2. Transmitter of downlink MC-CDMA systems.

Figure 2 shows the MC-CDMA modulator in a scenario where the spreading code has a length L_c equal to the number of subcarriers N_p, based on the hypothesis of L_c being equal to N_p, and the expression of the signal transmitted at the output of the modulator is given by:

$$x = \frac{1}{\sqrt{N_p}} Ca \ , \tag{2}$$

where matrix C represents the spreading codes:

$$\mathrm{C} = \left[c_0, c_1, \ldots, c_{N_u-1}\right] = \begin{bmatrix} c_{0,0} & \cdots & c_{N_u-1,0} \\ c_{0,1} & \cdots & c_{N_u-1,1} \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ c_{0,L_c-1} & \cdots & c_{N_u-1,L_c-1} \end{bmatrix}, \quad (3)$$

where $c_i = [c_{i,0}, c_{i,1}, \ldots, c_{i,L_c-1}]^T$.

When N_u users are active, the multi-user downlink MC-CDMA signal received at the input of the receiver, denoted by $r(t)$, is:

$$r(t) = \frac{1}{\sqrt{N_p}} \sum_{p=0}^{P-1} \sum_{k=0}^{N_p-1} \sum_{i=0}^{N_u-1} \times \Re\{\beta_p e^{j\theta_p} a_i c_{i,k} e^{2j\pi(f_0+k/T_c)(t-\tau_p)}\} + n(t) . \quad (4)$$

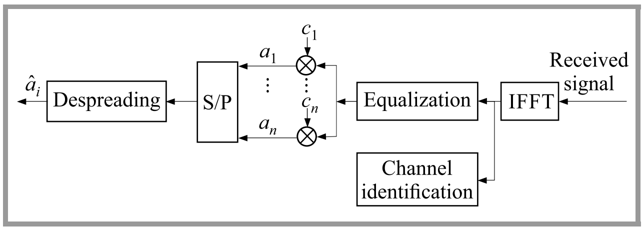

Fig. 3. Receiver of downlink MC-CDMA systems.

In Fig. 3 we represent the receiver for downlink MC-CDMA systems. After equalization, the expression of the signal s_k is given in a vector form, by the following expression:

$$s = \mathrm{G}r = \mathrm{GHC}a + \mathrm{G}n , \quad (5)$$

where $\mathrm{H} = \mathrm{diag}[h_0, \ldots, h_{N_p-1}]$ represents the complex channel frequency response.

The matrix $\mathrm{G} = \mathrm{diag}\left[g_0, \ldots, g_{N_p-1}\right]$ represents the diagonal matrix composed of the equalization of coefficients g_k equalization, or, in a scalar form, by:

$$s_k = g_k h_k \left(\sum_{i=0}^{N_u-1} c_{i,k} a_i \right) + g_k n_k . \quad (6)$$

After despreading and threshold detection, the data symbol of the user detected corresponds to the sign of the scalar produced between the vector of the received equalized signals, s, and the user-specific spreading code i, c_i^T, that is:

$$\widehat{a}_i = < c_i^T, s > = \sum_{k=0}^{N_p-1} c_{i,k} s_k . \quad (7)$$

Using Eqs. (6) and (7), the general expression of the symbol detected for i user is given by the following equation:

$$\begin{aligned} \widehat{a}_i &= \sum_{q=0}^{N_u-1} \sum_{k=0}^{N_p-1} c_{i,k} (g_k h_k c_{q,k} a_q + g_k n_k) \\ &= \underbrace{\sum_{k=0}^{N_p-1} c_{i,k}^2 g_k h_k a_i}_{U \quad (i=q)} + \underbrace{\sum_{q=0}^{N_u-1} \sum_{k=0}^{N_p-1} c_{i,k} c_{q,k} g_k h_k a_q}_{M \quad (i \neq q)} \\ &\quad + \underbrace{\sum_{k=0}^{N_p-1} c_{i,k} g_k n_k}_{N} , \end{aligned} \quad (8)$$

where the terms U, M and N of Eq. (8) are, respectively, the signal of the considered user, signals of other users (multiple access interferences) and the noise pondered by the equalization coefficient and by spreading the code of the chip.

If we suppose that the spreading codes are orthogonal, i.e.:

$$c_i^T c_q = \sum_{k=0}^{N_p-1} c_{i,k} c_{q,k} = 0 , \quad \forall \; i \neq q , \quad (9)$$

Equation (8) will become:

$$\widehat{a}_i = \underbrace{\sum_{k=0}^{N_p-1} c_{i,k}^2 g_k h_k a_i}_{U} + \underbrace{\sum_{k=0}^{N_p-1} c_{i,k} g_k n_k}_{N} . \quad (10)$$

The probability of binary error is written as [15]:

$$\begin{aligned} P_e &= P_r \left\{ X < 0 | \Re(a) = +\sqrt{E_a} \right\} \\ &= \frac{1}{2} \mathrm{erfc} \left(\frac{E\{X\}}{\sqrt{2\mathrm{var}\{X\}}} \right) , \end{aligned} \quad (11)$$

with X being the decision variable equal to $\Re(\widehat{a})$ for a given value of a.

The mean $E(X)$ of the decision variable, conditional upon h_k is written as:

$$\begin{aligned} E\{X\} &= \Re \left\{ \sum_{k=0}^{L_c-1} c_{i,k}^2 g_k h_k \right\} \sqrt{E_a} \\ &= \sqrt{E_a} \frac{1}{L_c} \sum_{k=0}^{L_c-1} \Re\{g_k h_k\} \underset{L_c \to \infty}{\longrightarrow} 0 , \end{aligned} \quad (12)$$

and the variance of the decision variable is:

$$\begin{aligned} \mathrm{Var}\{X\} &= E \left[\left(\sum_{k=0}^{L_c-1} c_{i,k} \Re\{g_k n_k\} \right)^2 \right] \\ &= \frac{1}{L_c} \sum_{k=0}^{L_c-1} |g_k|^2 \frac{E\{n_k^2\}}{2} . \end{aligned} \quad (13)$$

The power P_U of the information bearing component U is:

$$P_U = E[UU^*] = \frac{\sum_{k=0}^{L_c-1} |g_k h_k|^2}{L_c^2} \sigma_a^2 \ . \tag{14}$$

The power P_N of the signal's noise component is:

$$P_N = E[NN^*] = \frac{1}{L_c} \sum_{k=0}^{L_c-1} |g_k|^2 \sigma_{n_k}^2 \ . \tag{15}$$

The SNR of the MC-CDMA signal after despreading as a function of the length of the spreading codes L_c is:

$$\frac{P_U}{P_N} = \frac{\sum_{k=0}^{L_c-1} |g_k h_k|^2 \sigma_a^2}{L_c \sum_{k=0}^{L_c-1} |g_k|^2 \sigma_{n_k}^2} \ . \tag{16}$$

3.2. Equalization of MC-CDMA Systems using ZF

The goal of ZF is to minimize the peak distortion of the equalized channel, i.e. the inverse of the channel is applied to the received signal the restored signal is defined as:

$$g_k = \frac{1}{h_k} \ . \tag{17}$$

The estimated received symbol, $\widehat{a_i}$ of symbol a_i of the user i is:

$$\widehat{a_i} = \sum_{k=0}^{N_p-1} c_{i,k}^2 a_i + \sum_{k=0}^{N_p-1} c_{i,k} \frac{1}{h_k} n_k \ . \tag{18}$$

The goal of equalization is to extract a_i. After equalization and despreading, SNR of the MC-CDMA signal obtained in Eq. (16) reduces to:

$$\frac{P_U}{P_N} = \frac{\sigma_a^2}{\sum_{k=0}^{L_c-1} \frac{1}{|h_k|^2} \sigma_{n_k}^2} \ . \tag{19}$$

Determination of the subcarrier weighing coefficients is to be performed adaptively, using the LMP algorithm and will be described in Section 4.

4. Adaptive Identification using LMP Algorithm

LMP [1], [3] is one of the most popular adaptive filtering algorithms. With a proper p value, the LMP can outperform the traditional least mean square (LMS) ($p = 2$).
The cost function of the LMP algorithm is [1]:

$$L_{LMP} = |e(n)|^p = |z(n) - h^T(n)x(n)|^p \ , \tag{20}$$

where p is a positive constant value. Furthermore, we can keep the filter stable under impulsive noise conditions when $1 < p < 2$. Gradient descent methods can be used to estimate the filter weights, and an iteration equation can be derived as:

$$\begin{aligned} h(n+1) &= h(n) - \eta \frac{\partial J_{LMP}(n)}{\partial h(n)} \\ &= h(n) - \eta \left[-p|e(n)|^{p-1} \mathrm{sign}(e(n))x(n) \right] \\ &= h(n) + \eta p |e(n)|^{p-1} \mathrm{sign}(e(n))x(n), \end{aligned} \tag{21}$$

where $\mu = p\eta$ is the step size, and

$$\mathrm{sign}(x) = \begin{cases} 1 & \text{if} \quad x > 0 \\ 0 & \text{if} \quad x = 0 \\ -1 & \text{if} \quad x < 0 \end{cases} \ . \tag{22}$$

5. Simulation Results

Performance is evaluated using the normalized mean square error (NMSE):

$$NMSE = \sum_{i=1}^{L} \left[\frac{h(i) - \widehat{h}(i)}{h(i)} \right]^2 \ , \tag{23}$$

where $\widehat{h}(i)$ and $h(i)$, $i = 1, \ldots, L$, are the estimated and real parameters, respectively, in each run.
Table 1 shows a summary of the real model of the BRAN C channel identified using the LMP algorithm presented. The length of this channel is $L = 18$.

Table 1
Delay and magnitudes of 18 targets of BRAN C channel

Delay τ_i [ns]	Mag. A_i [dB]	Delay τ_i [ns]	Mag. A_i [dB]
0	–3.3	230	–3.0
10	–3.6	280	–4.4
20	–3.9	330	–5.9
30	–4.2	400	–5.3
50	0.0	490	–7.9
80	–0.9	600	–9.4
110	–1.7	730	–13.2
140	–2.6	880	–16.3
180	–1.5	1050	–21.2

5.1. Adaptive Identification of BRAN C Channel

Here, an adaptive algorithm, such as LMP is introduced for system identification, It adjusts its coefficients to minimize the mean square error between its output and the output of an unknown system. The goal is to adapt the coefficients of the filter to match, as closely as possible, the response of an unknown BRAN C channel.
Figures 4, 5 and 6 represent the estimations of the BRAN C parameters using LMP, where SNR = 0, 4 and 8 dB, respectively, the data length of non-Gaussian signal input is

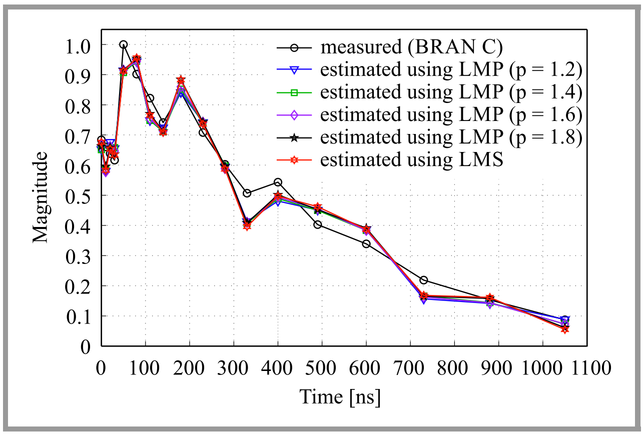

Fig. 4. BRAN C channel identification performance versus parameter threshold p, for SNR = 0 dB.

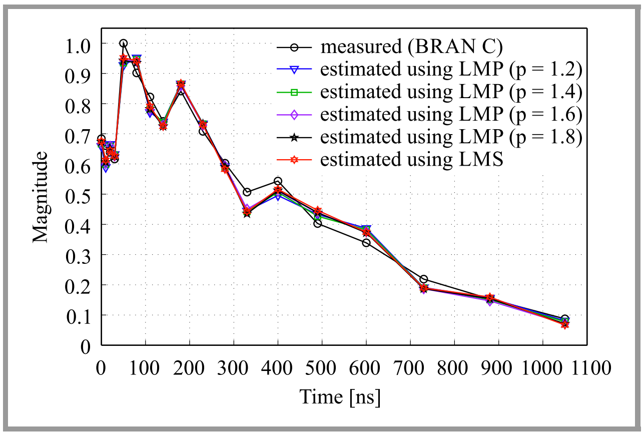

Fig. 5. BRAN C channel identification performance versus parameter threshold p, for SNR = 4 dB.

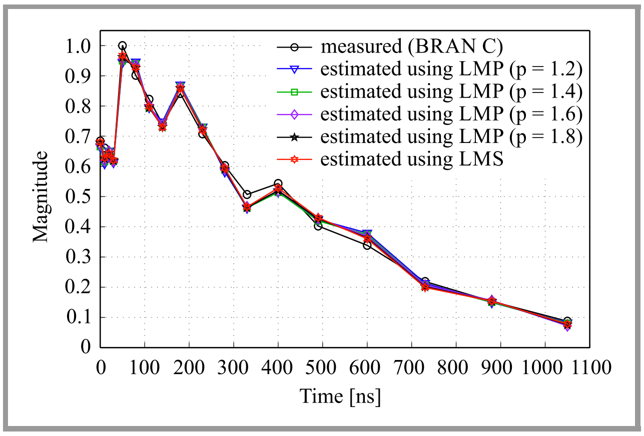

Fig. 6. BRAN C channel identification performance versus parameter threshold p, for SNR = 8 dB.

N = 2048, and for 100 Monte Carlo runs, in order to study the effect of the noise power on the estimated parameters. The parameter, in numerical simulations, is set as $\mu = 0.01$ and various thresholds p are applied.

In a very noisy environment (SNR = 0 dB), Gaussian noise influenced the estimated parameters of the BRAN C channel model (Fig. 4). We would also like to point out a difference between the estimated and true BRAN C parameters, which do not follow the real model in this SNR scenario. Simulation results (Figs. 5 and 6) confirm better accuracy levels, especially when SNR > 4 dB. However, the estimated models, using the standard LMP algorithm, follow the real model of the BRAN C channel and a minor difference is observed. For example, if SNR = 8 dB, we have a perfect agreement between the estimated and measured channel, using all algorithms considered.

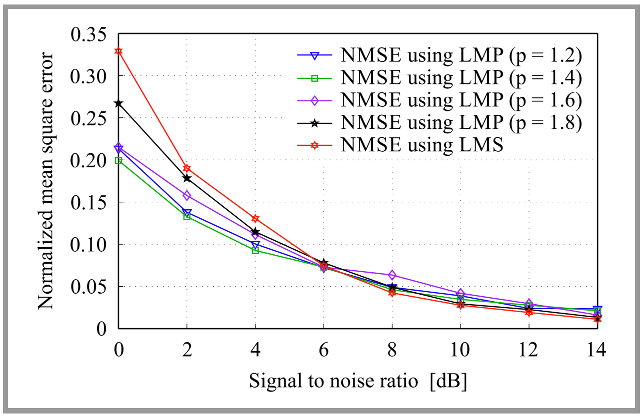

Fig. 7. NMSE values as a function of SNR using the LMP algorithms.

Figure 7 shows the performance of NMSE versus threshold p values for different SNRs. This figure gives us a good idea about the precision of these algorithms in terms of NMSE defined in the Eq. (23). Indeed, in the interval of 0–6 dB, we can note that the standard LMP is more efficient than the traditional LMS ($p = 2$), for all threshold p values, with LMP presenting a higher advantage ($p = 1.4$) than other options within the interval in question. In addition,

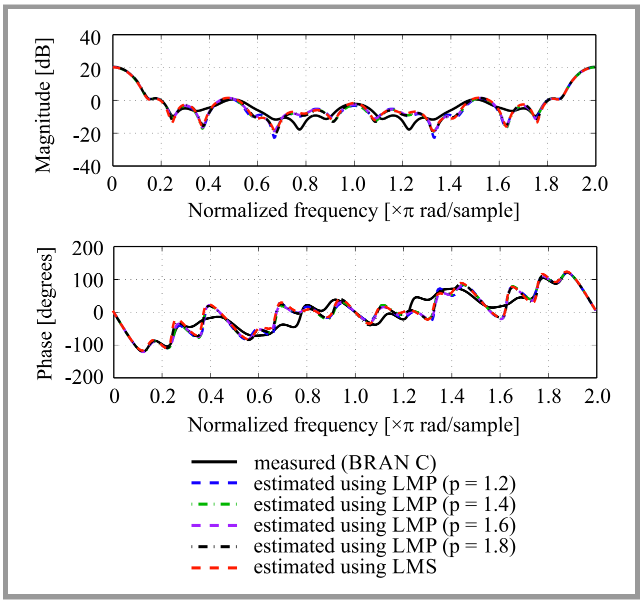

Fig. 8. Estimated magnitude and phase of the BRAN C channel when SNR = 0 dB and N = 2048.

for SNR higher than 6 dB, we observe that the traditional LMS becomes more effective compared to the LMP algorithm. In conclusion, LMP ($p = 1.4$) is very adequate in a noisy environment 0 dB $\leq$ SNR $\leq$ 6 dB. If SNR $>$ 6 dB, we have a minor difference between NMSE obtained using LMP ($p = 1.4$) and that obtained using LMS.

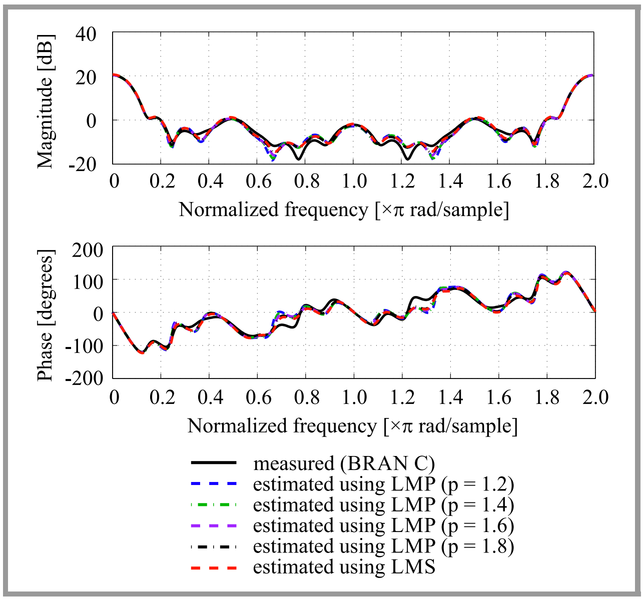

Fig. 9. Estimated magnitude and phase of the BRAN C channel when SNR = 8 dB and N = 2048.

In order to test accuracy in the frequency domain, we represent – in Figs. 8 and 9 – the estimation magnitude and the phase of the impulse response of BRAN C radio channel, for SNR = 0 dB and SNR = 8 dB, respectively, for various thresholds p. From these figures we can conclude that:

- for a high noise environment (SNR = 0 dB), the estimated magnitude and phase follow the real model of BRAN C channel, with a certain difference,
- for SNR $\geq$ 8 dB, the estimated magnitude and phase converge with the real model, with the highest accuracy value.

5.2. Adaptive Equalization of MC-CDMA Systems

As far as the problem of adaptive equalization is concerned, we use the ZF equalizer technique after channel identification to correct channel distortion. The performance is evaluated in terms of BER.

In Fig. 10 we represent the BER estimation of the BRAN C radio channel using the ZF equalizer in MC-CDMA systems, for different SNRs and various thresholds p of the LMP algorithm.

BER simulation for various SNRs differing from 0 to 14 dB, demonstrates that the BER estimated using LMP ($p = 1.4$) and LMS algorithms is more precise and offers better results than in the case of the LMP algorithm. However, if SNR $\geq$ 14 dB and LMP ($p = 1.4$) and LMS algorithms are used, we obtain a 1 bit error if 10^4 bits are received. In the other case ($p = 1.2$, 1.6 and 1.8), we obtain a 1 bit error if 10^3 bits are received, which is an advantage over LMP ($p = 1.6$).

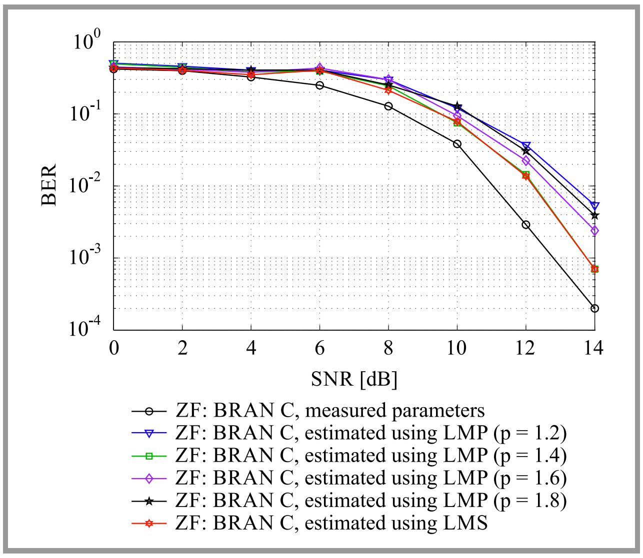

Fig. 10. BER of the estimated and measured BRAN C channel, for different SNR and various thresholds p.

6. Conclusion

In this paper, the BRAN channel identification problem and downlink MC-CDMA equalization have been investigated. We have presented an overview of the LMP algorithm. To illustrate identification performance, we applied this algorithm to the BRAN C channel model for various thresholds p and different SNRs. According to the results of numerical simulations, it has been demonstrated that LMP ($p = 1.4$) is preferred in a very noise environment (0 dB $\leq$ SNR $\leq$ 6 dB), and is more efficient than traditional LMS ($p = 2$) for all thresholds p. Furthermore, where SNR $>$ 6 dB, the LMS algorithm becomes more efficient than LMP with a minor difference, principally in the case of $p = 1.4$. These interesting, identification-related results encouraged us to exploit the estimated BRAN C channel coefficients in the context of adaptive equalization for MC-CDMA systems. Indeed, we have used the ZF equalizer to reduce BER. The results obtained here prove that BER rates estimated using LMP ($p = 1.4$) and LMS algorithms are similar and more precise than other cases involving the use of the LMP algorithm, and, thus, the objective assumed has been reached.

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