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Bit Error Rate Analysis of MC-CDMA Systems with Channel Identification Using Higher Order Cumulants

Mohammed Zidane[1,*], Said Safi[2], Mohamed Sabri[1], and Ahmed Boumezzough[3]
[1]Department of Physics, Faculty of Sciences and Technology, Sultan Moulay Slimane University, Morocco
[2]Department of Mathematics and Informatics, Polydisciplinary Faculty, Sultan Moulay Slimane University, Morocco
[3]Department of Physics, Polydisciplinary Faculty, Sultan Moulay Slimane University, Morocco
*Corresponding author, e-mail: zidane.ilco@gmail.com

Abstract

The aim of this paper is to contribute to study the problems of the blind identification and equalization using Higher Order Cumulants (HOC) in downlink Multi-Carrier Code Division Multiple Access (MC-CDMA) systems. For this problem, two blind algorithms based on HOC for Broadband Radio Access Network (BRAN) channel are proposed. In the one hand, to assess the performance of these approaches to identify the parameters of non minimum phase channels, we have considered two theoretical channels, and one practical frequency selective fading channel called BRAN C, driven by non gaussian signal. In the other hand, we use the Minimum Mean Square Error (MMSE) equalizer technique after the channel identification to correct the channel distortion. Theoretical analysis and numerical simulation results, in noisy environment and for different signal to noise ratio (SNR), are presented to illustrate the performance of the proposed methods.

Keywords: *HOC, Blind identification and equalization, BRAN channel, MC-CDMA systems, Bit error rate, MMSE equalizer*

1. Introduction

The channel identification is of primary importance in digital communication systems, appears as a major concern. In fact several methods have been explored. Nevertheless, the most commonly used are adaptive methods that send occasionally a training sequence known to the transmitter and receiver. The presence the training sequence in this approach reduces the spectral efficiency and hence transmission rate. Looking forward better tradeoffs between the quality of information recovery and suitable bit rates, the use of blind techniques is of great interest.

In this paper, we focus on the problem of blind identification and equalization of the Broadband Radio Access Networks channels, using Higher Order Cumulants (HOC) in MC-CDMA systems. Several works developed in the literature show that the blind identification channels using HOC have attracted considerable attention [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12]. Thus, the first methods utilizing the output of the second order cumulants (autocorrelation function) of the observed sequences for identification of minimum phase channel driven by gaussian distribution input [6, 9, 10]. However, in several applications, the observed signals are non gaussian and the system to be identified has non minimum phase and is contaminated by a gaussian noise. Moreover, the non minimum phase channels cannot be identified correctly using the autocorrelation function sequence [10], because the second order cumulants for a gaussian process are not identically zero. Hence, when the processed signal is non gaussian and the additive noise is gaussian, the noise will vanish in the higher order cumulants (3^{rd} and 4^{rd} cumulants) domain.

In this contribution, we propose two blind algorithms based on fourth order cumulants, this approach allows the resolution of the insoluble problems using the second order statistics. In order

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to test the efficiency of the proposed algorithms we have considered two theoretical channels, and one practical frequency selective fading channel such as BRAN C [14, 15] normalized for MC-CDMA systems, exited by a non gaussian sequences, for different signal to noise ratio (SNR) and important data input.

In this work, we address the application of proposed methods based on HOC in the context of blind equalization of MC-CDMA systems. Indeed the principles of MC-CDMA is that a single data symbol is transmitted at multiple narrow band subcarriers [17]. However, in MC-CDMA systems, spreading codes are applied in the frequency domain and transmitted over independent sub-carriers. The problem encountered in digital communication is the synchronization between the transmitter and the receiver. Nevertheless in most wireless environments, there are many different propagation paths caused by many obstacles in the channels, such as buildings, mountains and walls between the transmitter and receiver. Synchronization errors cause loss of orthogonality among sub-carriers and considerably degrade the performance especially when large number of subcarriers presents [18, 19]. In this paper we are concerned with the problem of the blind identification of the broadband radio access network channel such as BRAN C, after that we use the Minimum Mean Square Error (MMSE) equalizer technique to correct the channel distortion. The simulation results, in noisy environment, are presented to illustrate the performance of the proposed algorithms.

2. Problem statement

2.1. Channel modeling

We consider the single-input single-output (SISO) model of the Finite Impulse Response (FIR) system described by the following figure (Fig. 1):

We assumed that the channel is time invariant and it's impulse response is characterized by P

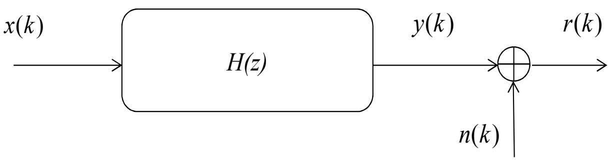

Figure 1. SISO channel model

paths of magnitudes β_p and phases θ_p. The impulse response is given by the following equation:

$$h(\tau) = \sum_{p=0}^{P-1} \beta_p e^{\theta_p} \delta(\tau - \tau_p) \quad (1)$$

The relationship between the emitted signal $x(t)$ and the received signal $r(t)$ is given by:

$$r(t) = h(t) * x(t) + n(t) \quad (2)$$

$$\begin{aligned} r(t) &= \int_{-\infty}^{+\infty} \sum_{p=0}^{P-1} \beta_p e^{\theta_p} \delta(\tau - \tau_p) x(t-\tau) d\tau + n(t) \\ &= \sum_{p=0}^{P-1} \beta_p e^{\theta_p} x(t-\tau_p) + n(t), \end{aligned} \quad (3)$$

where $x(t)$ is the input sequence, $h(t)$ is the impulse response coefficients, p is the order of FIR system, and $n(t)$ is the additive noise sequence.

In order to simplify the construction of the proposed algorithms we assume that:

- The input sequence, $x(k)$, is independent and identically distributed (i.i.d) zero mean, and non gaussian;
- The system is causal and truncated, i.e. $h(k) = 0$ for $k < 0$ and $k > q$, where $h(0) = 1$;
- The system order q is known;
- The measurement noise sequence $n(k)$ is assumed zero mean, i.i.d, gaussian and independent of $x(k)$ with unknown variance.

The problem statement is to identify the parameters of the system $h(k)_{(k=1,..,q)}$ using the HOC of the measured output process $y(k)$.

2.2. Basic Relationships

In this section, we describe the main general relationships between cumulants and impulse response coefficients.
Brillinger and Rosenblatt showed that the m^{th} order cumulants of $y(k)$ can be expressed as a function of impulse response coefficients $h(i)$ as follows [20]:

$$C_{m,y}(t_1, t_2, ..., t_{m-1}) = \xi_{m,x} \sum_{i=0}^{q} h(i)h(i+t_1)...h(i+t_{m-1}), \tag{4}$$

where $\xi_{m,x}$ represents the m^{th} order cumulants of the excitation signal $x(i)$ at origin.
If $m = 2$ into Eq. (4) we obtain the second order cumulant (Autocorrelation function):

$$C_{2,y}(t_1) = \xi_{2,x} \sum_{i=0}^{q} h(i)h(i+t_1) \tag{5}$$

The same, if $m = 4$, Eq. (4) yield to:

$$C_{4,y}(t_1, t_2, t_3) = \xi_{4,x} \sum_{i=0}^{q} h(i)h(i+t_1)h(i+t_2)h(i+t_3) \tag{6}$$

Peyre, $et\ al.$, presents the relationship between different m and n cumulants of the output signal, $y(k)$, and the coeffecients $h(i)$, where $n > m$ and $(n, m) \in N^* - \{1\}$, are linked by the following relationship [13]:

$$\begin{aligned} &\sum_{j=0}^{q} h(j)C_{n,y}(j+\tau_1, j+\tau_2, ..., j+\tau_{m-1}, \tau_m, ..., \tau_{n-1}) \\ = \quad &\mu \sum_{i=0}^{q} h(i)\Big[\prod_{k=m}^{n-1} h(i+\tau_k)\Big]C_{m,y}(i+\tau_1, i+\tau_2, ..., i+\tau_{m-1}), \end{aligned} \tag{7}$$

where $\mu = \frac{\xi_{n,x}}{\xi_{m,x}}$

Proof:

Let:

$$P_{mn} = \sum_{ij} h(i)h(j)\Big[\prod_{k=1}^{m-1} h(i+j+\tau_k)\Big]\Big[\prod_{k=m}^{n-1} h(i+\tau_k)\Big] \tag{8}$$

Firstly, if we sum on i afterwards on j in (8), we will find:

$$P_{mn} = \sum_j h(j) \sum_i h(i) \Big[\prod_{k=1}^{m-1} h(i+j+\tau_k) \Big] \Big[\prod_{k=m}^{n-1} h(i+\tau_k) \Big] \quad (9)$$

If we multiply (9) by $\xi_{n,x}$ and take the Brillinger and Rosenblatt formula (4) into account, we will obtain:

$$\xi_{n,x} P_{mn} = \sum_j h(j) C_{n,y}(j+\tau_1, j+\tau_2, ..., j+\tau_{m-1}, ..., \tau_m, ..., \tau_{n-1}) \quad (10)$$

Changing the order of summation in (8) yields:

$$P_{mn} = \sum_i h(i) \Big[\prod_{k=m}^{n-1} h(i+\tau_k) \Big] \sum_j h(j) \Big[\prod_{k=1}^{m-1} h(i+j+\tau_k) \Big] \quad (11)$$

If we multiply the right and left sides of (11) by $\xi_{m,x}$ and take the relation (4) into account, we will obtain:

$$\xi_{m,x} P_{mn} = \sum_i h(i) \Big[\prod_{k=m}^{n-1} h(i+\tau_k) \Big] C_{m,y}(i+\tau_1, i+\tau_2, ..., i+\tau_{m-1}) \quad (12)$$

From (10) and (12), we obtain the relation of the Peyre, $et\ al$.

3. Proposed algorithms

3.1. First Algorithm: Algo1

If we take $n = 4$ and $m = 2$ into Eq. (7) we obtain the following equation:

$$\sum_{j=0}^{q} h(j) C_{4,y}(j+\tau_1, \tau_2, \tau_3) = \mu \sum_{i=0}^{q} h(i) \Big[\prod_{k=2}^{3} h(i+\tau_k) \Big] C_{2,y}(i+\tau_1) \quad (13)$$

$$\sum_{j=0}^{q} h(j) C_{4,y}(j+\tau_1, \tau_2, \tau_3) = \mu \sum_{i=0}^{q} h(i) h(i+\tau_2) h(i+\tau_3) C_{2,y}(i+\tau_1), \quad (14)$$

the autocorrelation function of the FIR systems vanishes for all values of $|t| > q$, equivalently:

$$C_{2,y}(t) = \begin{cases} \neq 0, & |t| \leq q; \\ 0 & \text{otherwise.} \end{cases}$$

If we suppose that $\tau_1 = q$ the Eq. (14) becomes:

$$\sum_{j=0}^{q} h(j) C_{4,y}(j+q, \tau_2, \tau_3) = \mu h(0) h(\tau_2) h(\tau_3) C_{2,y}(q), \quad (15)$$

if we fixe that $\tau_3 = 0$ the Eq. (15) becomes:

$$\sum_{j=0}^{q} h(j) C_{4,y}(j+q, \tau_2, 0) = \mu h^2(0) h(\tau_2) C_{2,y}(q) \quad (16)$$

The considered system is causal. Thus, the interval of the τ_2 is $\tau_2 = 0, ..., q$.
Else if we suppose that $\tau_2 = 0$, and using the cumulants properties $C_{m,y}(\tau_1, \tau_2, ..., \tau_{m-1}) = 0$, if one of the variables $\tau_k > q$, where $k = 1, ..., m-1$; the Eq. (16) becomes:

$$C_{4,y}(q, 0, 0) = \mu h^3(0) C_{2,y}(q) \quad (17)$$

Thus, we based on Eq. (17) for eliminating $C_{2,y}(q)$ in Eq. (16), we obtain the equation constituted of only the fourth order cumulants:

$$\sum_{j=0}^{q} h(j) C_{4,y}(j+q, \tau_2, 0) = h(\tau_2) C_{4,y}(q, 0, 0) \quad (18)$$

The system of Eq. (18) can be written in matrix form as:

$$\begin{pmatrix} C_{4,y}(q+1,0,0) & ... & C_{4,y}(2q,0,0) \\ C_{4,y}(q+1,1,)-\alpha & ... & C_{4,y}(2q,1,0) \\ . & . & . \\ . & . & . \\ . & . & . \\ C_{4,y}(q+1,q,0) & ... & C_{4,y}(2q,q,0)-\alpha \end{pmatrix} \times \begin{pmatrix} h(1) \\ . \\ . \\ h(i) \\ . \\ . \\ h(q) \end{pmatrix} = \begin{pmatrix} 0 \\ -C_{4,y}(q,1,0) \\ . \\ . \\ . \\ -C_{4,y}(q,q,0) \end{pmatrix}, \tag{19}$$

where $\alpha = C_{4,y}(q,0,0)$.
Or in more compact form, the Eq. (19) can be written as follows:

$$Mh_{e1} = d, \tag{20}$$

where M is the matrix of size $(q+1) \times (q)$ elements, h_{e1} is a column vector constituted by the unknown impulse response parameters $h(i)_{i=1,...,q}$ and d is a column vector of size $(q+1)$ as indicated in the Eq. (19). The least squares solution of the system of Eq. (20), permits blindly identification of the parameters $h(i)$ and without any information of the input selective channel. Thus, the solution will be written under the following form:

$$\widehat{h}_{e1} = (M^T M)^{-1} M^T d \tag{21}$$

3.2. Second algorithm: Algo2

The Z-transform of the second order cumulant is straightforward and gives the following equation:

$$S_{2,y}(z) = \xi_{2,x} H(z) H(z^{-1}) \tag{22}$$

The Z-transform of equation (6) is equation (23):

$$S_{4,y}(z_1,z_2,z_3) = \xi_{4,x} H(z_1) H(z_2) H(z_3) H(z_1^{-1} \times z_2^{-1} \times z_3^{-1}) \tag{23}$$

If we suppose that $z = z_1 \times z_2 \times z_3$ Eq. (22) becomes:

$$S_{2,y}(z_1 \times z_2 \times z_3) = \xi_{2,x} H(z_1 \times z_2 \times z_3) H(z_1^{-1} \times z_2^{-1} \times z_3^{-1}) \tag{24}$$

Then, from Eqs. (23) and (24) we obtain the following equation:

$$H(z_1 \times z_2 \times z_3) S_{4,y}(z_1,z_2,z_3) = \mu H(z_1) H(z_2) H(z_3) S_{2,y}(z_1 \times z_2 \times z_3), \tag{25}$$

with $\mu = \frac{\xi_{4,x}}{\xi_{2,x}}$
The inverse Z-transform of Eq. (25) demonstrates that the 4^{th} order cumulants, the autocorrelation function and the impulse response channel parameters are combined by the following equation:

$$\sum_{i=0}^{q} C_{4,y}(t_1 - i, t_2 - i, t_3 - i) h(i) = \mu \sum_{i=0}^{q} h(i) h(t_2 - t_1 + i) h(t_3 - t_1 + i) C_{2,y}(t_1 - i) \tag{26}$$

If we use the autocorrelation function property of the stationary process such as $C_{2,y}(t) \neq 0$ only for $-q \leq t \leq q$ and vanishes elsewhere. If we suppose that $t_1 = 2q$ the Eq. (26) becomes:

$$\sum_{i=0}^{q} C_{4,y}(2q - i, t_2 - i, t_3 - i) h(i) = \mu h(q) h(t_2 - q) h(t_3 - q) C_{2,y}(q), \tag{27}$$

else if we suppose that $t_2 = q$ the Eq. (27) becomes:

$$\sum_{i=0}^{q} C_{4,y}(2q - i, q - i, t_3 - i) h(i) = \mu h(q) h(0) h(t_3 - q) C_{2,y}(q) \tag{28}$$

For eliminating $h(q)$ in (28), we consider the relation of Brillinger and Rosenblatt describe with following equation for $m = 4$:

$$C_{4,y}(t_1, t_2, t_3) = \xi_{4,x} \sum_{i=0}^{q} h(i)h(i + t_1)h(i + t_2)h(i + t_3) \tag{29}$$

If $t_1 = t_2 = t_3 = q$ Eq. (29) becomes:

$$C_{4,y}(q, q, q) = \xi_{4,x} h^3(q), \tag{30}$$

else if $t_1 = t_2 = q$ and $t_3 = 0$ (29) reduces:

$$C_{4,y}(q, q, 0) = \xi_{4,x} h^2(q) \tag{31}$$

From (30), (31) we obtain:

$$h(q) = \frac{C_{4,y}(q, q, q)}{C_{4,y}(q, q, 0)} \tag{32}$$

Thus, we based on (32) for eliminating $h(q)$ in (28), we obtain the following equation:

$$\sum_{i=0}^{q} C_{4,y}(2q - i, q - i, t_3 - i)h(i) = \mu \frac{C_{4,y}(q, q, q)}{C_{4,y}(q, q, 0)} h(t_3 - q)C_{2,y}(q) \tag{33}$$

The considered system is causal. Thus, the interval of the t_3 is $t_3 = q, ..., 2q$
The system of Eq. (33) can be written in matrix form as:

$$\begin{pmatrix} C_{4,y}(2q-1, q-1, q-1) & ... & C_{4,y}(q, 0, 0) \\ C_{4,y}(2q-1, q-1, q) - \theta & ... & C_{4,y}(q, 0, 1) \\ . & . & . \\ . & . & . \\ . & . & . \\ C_{4,y}(2q-1, q-1, 2q-1) & ... & C_{4,y}(q, 0, q) - \theta \end{pmatrix} \times \begin{pmatrix} h(1) \\ . \\ . \\ h(i) \\ . \\ . \\ h(q) \end{pmatrix} = \begin{pmatrix} \theta - C_{4,y}(2q, q, q) \\ -C_{4,y}(2q, q, q+1) \\ . \\ . \\ . \\ -C_{4,y}(2q, q, 2q) \end{pmatrix}, \tag{34}$$

where $\theta = \mu \frac{C_{4,y}(q,q,q)}{C_{4,y}(q,q,0)} C_{2,y}(q)$.
The least squares solution of the system of Eq. (34), permits blindly identification of the parameters $h(i)$ and without any information of the input selective channel. Thus, the solution will be written under the following form:

$$\widehat{h}_{e2} = (M^T M)^{-1} M^T d \tag{35}$$

4. Application of MC-CDMA systems

The multicarrier code division multiple access (MC-CDMA) systems is based on the combination of code division multiple access (CDMA) and orthogonal frequency division multiplexing (OFDM) which is potentially robust to channel frequency selectivity.

4.1. MC-CDMA Transmitter

Fig. 2 explains the principle of the transmitter for downlink MC-CDMA systems. The MC-CDMA signal is given by

$$x(t) = \frac{a_i}{\sqrt{N_p}} \sum_{k=0}^{N_p - 1} c_{i,k} e^{2jf_k t}, \tag{36}$$

where $f_k = f_0 + \frac{k}{T_c}$, N_u is the user number and N_p is the number of subcarriers, and we consider L_c=N_p.

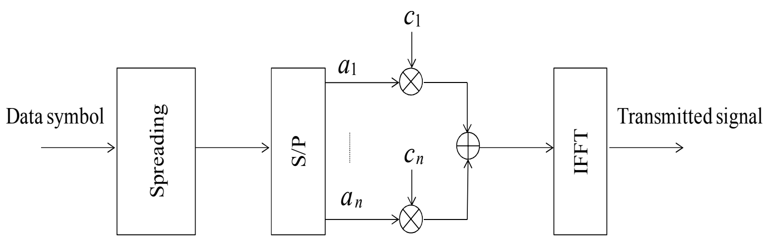

Figure 2. The transmitter for downlink MC-CDMA systems

4.2. MC-CDMA Receiver

The downlink received MC-CDMA signal at the input receiver is given by the following equation:

$$r(t) = \frac{1}{\sqrt{N_p}} \sum_{p=0}^{P-1} \sum_{k=0}^{N_p-1} \sum_{i=0}^{N_u-1} \Re\{\beta_p e^{j\theta_p} a_i c_{i,k} e^{2j\pi(f_0+k/T_c)(t-\tau_p)}\} + n(t) \tag{37}$$

In Fig. 3 we represent the receiver for downlink MC-CDMA systems.
At the reception, we demodulate the signal according the N_p subcarriers, and then we multiply

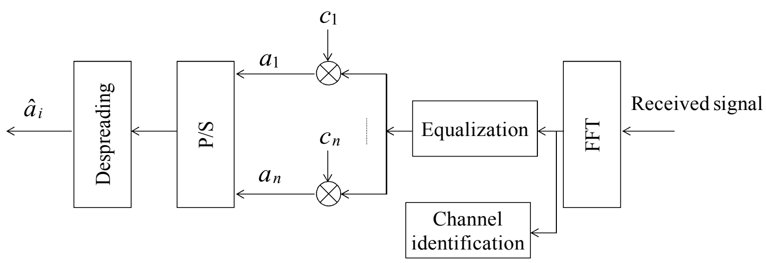

Figure 3. The receiver for downlink MC-CDMA systems

the received sequence by the code of the user. After the equalization and the despreading operation, the estimation $\widehat{a_i}$ of the emitted user symbol a_i, of the i^{th} user can be written by the following equation:

$$\begin{aligned} \widehat{a_i} &= \sum_{q=0}^{N_u-1} \sum_{k=0}^{N_p-1} c_{i,k} g_k h_k c_{q,k} a_q + g_k n_k \\ &= \underbrace{\sum_{k=0}^{N_p-1} c_{i,k}^2 g_k h_k a_i}_{I \quad (i=q)} + \underbrace{\sum_{q=0}^{N_u-1} \sum_{k=0}^{N_p-1} c_{i,k} c_{q,k} g_k h_k a_q}_{II \quad (i \neq q)} + \underbrace{\sum_{k=0}^{N_p-1} c_{i,k} g_k n_k}_{III}, \end{aligned} \tag{38}$$

where the term I, II and III of Eq. (38) are, respectively, the signal of the considered user, a signals of the others users (multiple access interferences) and the noise pondered by the equalization coefficient and by spreading code of the chip.

4.3. Minimum Mean Square Error (MMSE) equalizer for MC-CDMA

The MMSE technique minimize the mean square error for each subcarrier k between the transmitted signal x_k and the output detection:

$$E[|\varepsilon|^2] = E[|x_k - g_k r_k|^2] \tag{39}$$

The minimization of the function $E[|\varepsilon|^2]$, gives us the optimal equalizer coefficient, under the minimization of the mean square error criterion, of each subcarrier as:

$$g_k = \frac{h_k^*}{|h_k|^2 + \frac{1}{\zeta_k}}, \tag{40}$$

where $\zeta_k = \frac{E[|x_k h_k|^2]}{E[|n_k|^2]}$.
The estimated received symbol, $\widehat{a_i}$ of symbol a_i of the user i is described by:

$$\widehat{a_i} = \underbrace{\sum_{k=0}^{N_p-1} c_{i,k}^2 \frac{|h_k|^2}{|h_k|^2 + \frac{1}{\zeta_k}} a_i}_{I \quad (i=q)} + \underbrace{\sum_{q=0}^{N_u-1} \sum_{k=0}^{N_p-1} c_{i,k} c_{q,k} \frac{|h_k|^2}{|h_k|^2 + \frac{1}{\zeta_k}} a_q}_{II \quad (i \neq q)} + \underbrace{\sum_{k=0}^{N_p-1} c_{i,k} \frac{h_k^*}{|h_k|^2 + \frac{1}{\zeta_k}} n_k}_{III} \tag{41}$$

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

$$\sum_{k=0}^{N_p-1} c_{i,k} c_{q,k} = 0 \qquad \forall i \neq q \tag{42}$$

Eq.(41) will become:

$$\widehat{a_i} = \sum_{k=0}^{N_p-1} c_{i,k}^2 \frac{|h_k|^2}{|h_k|^2 + \frac{1}{\zeta_k}} a_i + \sum_{k=0}^{N_p-1} c_{i,k} \frac{h_k^*}{|h_k|^2 + \frac{1}{\zeta_k}} n_k \tag{43}$$

5. Simulation results

5.1. Algorithms test

In this subsection we test the performance of the proposed algorithms, for that we have considered two theoretical channels. The channel output was corrupted by an additive gaussian noise for different signal to noise ratio and for 50 Monte Carlo runs.
Where the signal to noise ratio (SNR) is defined by:

$$SNR = 10log\Big[\frac{\sigma_y^2(k)}{\sigma_n^2(k)}\Big] \tag{44}$$

To measure the accuracy of parameter estimation with respect to the real values, we define the Mean Square Error (MSE) for each run as:

$$MSE = \frac{1}{q}\sum_{i=0}^{q}\Big[\frac{h(i) - \widehat{h}(i)}{h(i)}\Big]^2, \tag{45}$$

where $\widehat{h}(i)$, $i = 1, ..., q$ are the estimated parameters in each run, and $h(i)$ are the real parameters in the model.

5.1.1. First channel

In this example, we consider a non minimum phase impulse response channel, given by the following equation:

$$\begin{cases} y(k) = x(k) + 0.327x(k-1) - 0.815x(k-2) + 0.470x(k-3) \\ \text{zeros: } z_1 = -1.2650; z_2 = 0.4690 + 0.3893j; z_3 = 0.4690 - 0.3893j. \end{cases} \tag{46}$$

In the Table 1 we represent the estimated impulse response parameters using proposed algorithms.

Table 1. Estimated parameters of the first channel for different SNR and excited by sample sizes $N = 2048$.

SNR	$\widehat{h}(i)\pm\sigma$	$Algo1$	$Algo2$
0 dB	$\widehat{h}(1)\pm\sigma$	0.4867 ± 0.2360	0.3144 ± 0.1033
	$\widehat{h}(2)\pm\sigma$	-0.8575 ± 0.1798	-0.7385 ± 0.1227
	$\widehat{h}(3)\pm\sigma$	0.3081 ± 0.1821	0.0980 ± 0.0583
	MSE	0.0900	0.1592
4 dB	$\widehat{h}(1)\pm\sigma$	0.4735 ± 0.1621	0.4344 ± 0.1223
	$\widehat{h}(2)\pm\sigma$	-0.9292 ± 0.1757	-0.8076 ± 0.0848
	$\widehat{h}(3)\pm\sigma$	0.4937 ± 0.2102	0.1731 ± 0.0658
	MSE	0.0557	0.1267
12 dB	$\widehat{h}(1)\pm\sigma$	0.3648 ± 0.0907	0.4681 ± 0.1104
	$\widehat{h}(2)\pm\sigma$	-0.8036 ± 0.0947	-0.8522 ± 0.1205
	$\widehat{h}(3)\pm\sigma$	0.3357 ± 0.1479	0.2839 ± 0.0993
	MSE	0.0238	0.0863

From the Table 1 we can conclude that: The MSE values, obtained using the first algorithm $(Algo1)$ are small for all SNR than those given by the second algorithm $(Algo2)$, this imply, that the estimated parameters are very close to the original ones if we use the first algorithm $(Algo1)$. Using the two methods the variances of the estimated parameters are acceptable.
In the following, Fig. 4, we represent the estimation of the magnitude and phase of the channel impulse response for a data input $N = 2048$ and for $SNR = 0\ dB$.
The Fig. 4 proof that the proposed algorithms gives a very good estimation for phase response,

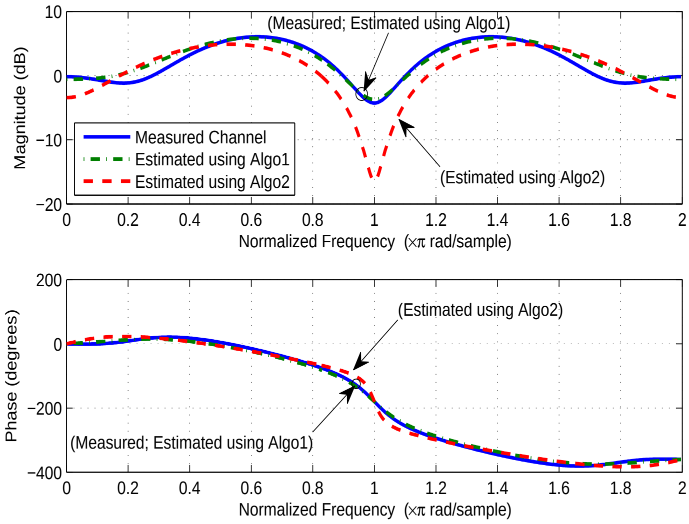

Figure 4. Estimated magnitude and phase of the first channel impulse response, using the proposed algorithms, when the data input is $N = 2048$ and an $SNR = 0\ dB$

the estimated phase are closed to the true ones, and an important estimation on the magnitude using first algorithm $(Algo1)$, but using the second algorithm $(Algo2)$ we have more difference between measured and estimated magnitude.

5.1.2. Second channel: Macchi channel

The Macchi channel is defined by the following equation:

$$\begin{cases} y(k) = 0.8264x(k) - 0.1653x(k-1) + 0.8512x(k-2) + 0.1636x(k-3) + 0.8100x(k-4), \\ \text{zeros: } z_1{=}0.5500 + 0.9526j; z_2{=}0.5500 - 0.9526j; z_3{=}-0.4500 + 0.7794j; z_4{=}-0.4500 - 0.7794j. \end{cases} \quad (47)$$

The Macchi channel is a non minimum phase because two of its zeros are outside of the unit circle.

In the Table 2 we have summarized the simulation results, using proposed algorithms, when the length data input is $N = 2048$.

From the Table 2 we observe that the parameters estimation of the Macchi channel impulse

Table 2. True and estimated parameters of macchi channel excited by input sequence of $N = 2048$ samples and for different SNR

SNR	$\widehat{h}(i)\pm\sigma$	$Algo1$	$Algo2$
0 dB	$\widehat{h}(1)\pm\sigma$	0.8080 ± 0.2683	0.6118 ± 0.1812
	$\widehat{h}(2)\pm\sigma$	-0.1128 ± 0.2446	-0.0502 ± 0.2504
	$\widehat{h}(3)\pm\sigma$	0.6271 ± 0.1363	0.5062 ± 0.1376
	$\widehat{h}(4)\pm\sigma$	0.2035 ± 0.1468	0.2007 ± 0.1320
	$\widehat{h}(5)\pm\sigma$	0.5041 ± 0.1776	0.0864 ± 0.0397
	MSE	0.0621	0.2610
4 dB	$\widehat{h}(1)\pm\sigma$	0.9593 ± 0.6516	0.7412 ± 0.3183
	$\widehat{h}(2)\pm\sigma$	-0.2370 ± 0.5398	-0.0908 ± 0.2261
	$\widehat{h}(3)\pm\sigma$	0.8363 ± 0.3581	0.7028 ± 0.2154
	$\widehat{h}(4)\pm\sigma$	0.1924 ± 0.1009	0.1853 ± 0.0860
	$\widehat{h}(5)\pm\sigma$	0.8470 ± 0.3873	0.3811 ± 0.3359
	MSE	0.0412	0.0904
12 dB	$\widehat{h}(1)\pm\sigma$	0.8336 ± 0.2350	0.7935 ± 0.2648
	$\widehat{h}(2)\pm\sigma$	-0.1777 ± 0.2687	-0.2475 ± 0.2782
	$\widehat{h}(3)\pm\sigma$	0.8711 ± 0.2001	0.8297 ± 0.2536
	$\widehat{h}(4)\pm\sigma$	0.1416 ± 0.1433	0.1110 ± 0.1329
	$\widehat{h}(5)\pm\sigma$	0.8762 ± 0.1695	0.6047 ± 0.2900
	MSE	0.0052	0.0695

response, using the first algorithm ($Algo1$), are not different to the true ones compared with the results obtained with second algorithm ($Algo2$). The MSE give us a good idea about the precision of these algorithms.

In the Fig. 5 we have plotted the estimation of the magnitude and phase of Macchi channel, the case of the $SNR = 4\ dB$ and for data length of $N = 2048$.

In the Fig. 5 we remark that the estimated magnitude and phase response using the first algorithm ($Algo1$) have the same allure in comparison with the true ones. Concerning the second algorithm ($Algo2$) we have more difference between the estimated, magnitude and phase, and the true ones.

To conclude, the first algorithm ($Algo1$) is able to estimate the phase and magnitude of the non minimum phase channel impulse response in very noisy environments with very good precision.

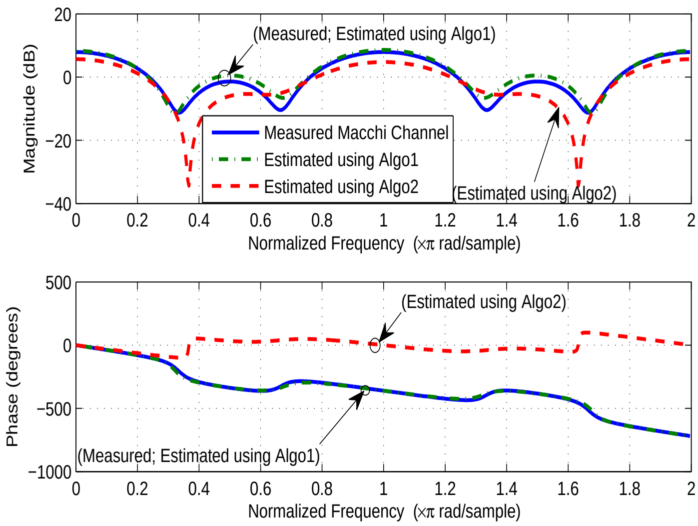

Figure 5. Estimated magnitude and phase of the Macchi channel impulse response, using the proposed algorithms, when the data input is $N = 2048$ and $SNR = 4\ dB$

5.2. Identification of Broadband Radio Access Network: Case of BRAN C channel

In Table 3 we have represented the values corresponding to the BRAN C radio channel impulse response. The Eq. (48) describes the impulse response of BRAN C radio channel.

$$h(\tau) = \sum_{i=1}^{N_T} A_i \delta(\tau - \tau_i) \quad (48)$$

In Figures (6 and 7) we represent, respectively, the estimation of the impulse response of BRAN

Table 3. Delay and magnitudes of 18 targets of BRAN C channel

Delay $\tau_i[ns]$	Mag.$A_i[dB]$	Delay $\tau_i[ns]$	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

C channel using the proposed algorithms in the case of $SNR = 12\ dB$ and $SNR = 20\ dB$ for data length $N = 5400$. From Fig. 6 and Fig. 7, we can conclude that the first algorithm $(Algo1)$ gives good estimation for all target of BRAN C radio channel impulse response for data length $N = 5400$ and different SNR. The 12^{th} first target given by the second algorithm $(Algo2)$ have the same form comparing to those measured, with a difference. If we observe the estimated last sixth values of BRAN C impulse response, using the algorithm $(Algo2)$ we remark, approximately, the same results given by the first algorithm $(Algo1)$.

In the Fig. 8 we have represented the estimated magnitude and phase of the impulse response

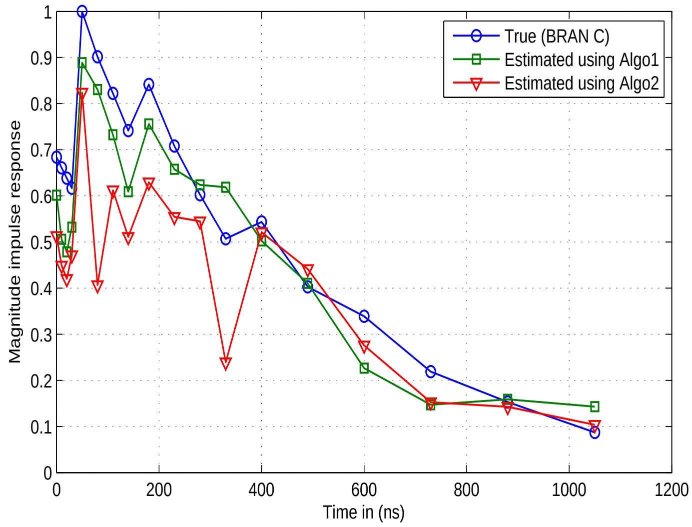

Figure 6. Estimated of the BRAN C channel impulse response, for an $SNR = 12\ dB$ and a data length $N = 5400$

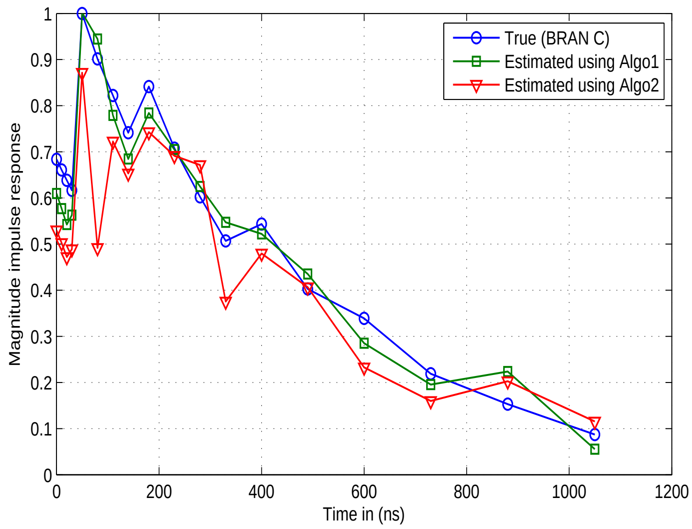

Figure 7. Estimated of the BRAN C channel impulse response, for an $SNR = 20\ dB$ and a data length $N = 5400$

BRAN C using all target, for an data length $N = 5400$ and $SNR = 20\ dB$, obtained using proposed methods.

From the Fig. 8 we observe that the estimated magnitude will be more closed to the true ones using two algorithms. Now we have estimated the phase of BRAN C channel impulse response, we remark an apparent progress of the phase estimation, more closed to the true ones, using the first algorithm $(Algo1)$, but using the second algorithm $(Algo2)$ we remark a more difference between the estimated phase and the measured ones. In conclusion if the SNR is superior to $16\ dB$ ($SNR = 20\ dB$ for example) we remark that the noise is approximately without influence on the phase of BRAN C radio channel impulse response estimation principally if we use the first

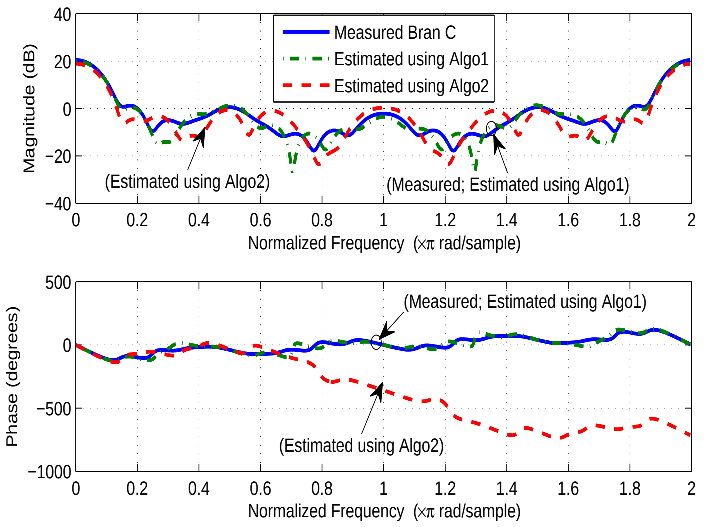

Figure 8. Estimated magnitude and phase of the BRAN C channel using all target, for an $SNR = 20\ dB$ and a data length $N = 5400$

algorithm $(Algo1)$.

6. Equalization of MC-CDMA system

In this section we used the Minimum Mean Square Error (MMSE) equalizer for MC-CDMA system.

We represent in the Fig. 9, the simulation results of Bit Error Rate (BER) estimation, for different SNR, using the proposed algorithms of the BRAN C channel impulse response.

From Fig. 9, we can conclude that the BER simulation for different SNR, demonstrates that

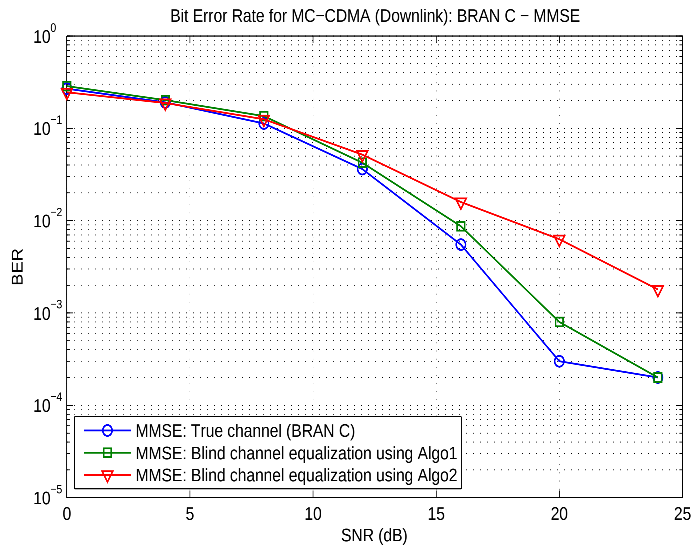

Figure 9. BER of the estimated and measured BRAN C channel using the MMSE equalizer

the estimated values by the first algorithm $(Algo1)$ are more close to the measured values, than those estimated by second algorithm $(Algo2)$. Indeed if the SNR superior to $20\ dB$ we have 1 bit error occurred when we receive 10^3 bit using second algorithm $(Algo2)$, but using first algorithm $(Algo1)$ we obtain only one bit error for 10^4 bit received if we use the MMSE equalizer.

7. Conclusion

In this paper we have proposed two blind algorithms based on higher order cumulants to identify the parameters of the impulse response of the broadband radio access network channel such as, BRAN C. The simulation results show the efficiency of the first algorithm $(Algo1)$ than those obtained using second algorithm $(Algo2)$. The phase and magnitude of the impulse response is estimated with very good precision in noisy environment principally if we use the first algorithm $(Algo1)$. The MMSE equalization technique was used after the channel identification to correct the channel's distortion. It is demonstrated that the performance of the equalization of the downlink MC-CDMA systems, using the first algorithm $(Algo1)$ is more accurate compared with the results obtained with the second algorithm $(Algo2)$ algorithm.

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