## **Blind Channel Estimation and Equalization**

Said Elkassimi<sup>1</sup>, Said Safi<sup>1</sup> and B. Manaut<sup>2</sup>

 <sup>1</sup>Equipe de Traitement de L'information et de Télécommunications, Facultés des Sciences et Techniques, USMS, Béni Mellal, Maroc
 <sup>2</sup>Laboratoire Interdisciplinaire de Recherche en Science et Technique (LIRST), USMS Béni Mellal, Maroc saidelkassimi@gmail.com, safi.said@gmail.com, manaut\_bouzid@yahoo.fr

## Abstract

This paper resolves the problem of channel estimation and identification of a nonminimum phase system using three algorithms. These algorithms play an important role for estimating blindly the parameters of radio mobile channel. Thus studying the blind's problem channel equalization based on the following, Proposed Algorithm, CMA and SKMAA equalizers. The simulation results in the noisy environment and for different SNR values demonstrate that Proposed Algorithm is more performing than the other algorithms. In addition, the Sign Kurtosis Maximization Adaptive Algorithm (SKMAA) is more powerful compared to Constant Modulus Algorithm (CMA), that is to say it gives the right blind channel equalization.

Keywords: Adaptive blind equalization, Blind channel Estimation, Higher Order Cumulants (HOC), CMA, SKMAA, SNR, SER

## 1. Introduction

From the output measurements, the channel system identification is a well defined problem in several science and engineering areas such as speech signal processing, adaptive filtering, spectral estimation, communication[1-3]. Signal processing techniques using Higher-Order Statistics (HOS) or cumulants have attracted a considerable attention in the literature [4]. The information contained in the second-order statistics (autocorrelation functions) would suffice for the complete statistical description of a Gaussian signal. However, there are a practical situation where we have to look beyond the autocorrelation of a signal to extract information regarding deviations from Gaussianity and presence of phase relation. Thus the interest in higher order cumulants (HOC) or higher order statistics (HOS) is permanently growing in the last years [5]. Also the finite impulse response system identification based on HOC of system output has received more attention. Actually the blind equalization of radio mobile channel has become an important topic in digital communications. that why, we try to study the popular adaptive blind equalization Bussgang algorithm (the Godard algorithm [6]) or Constant Modulus Algorithm (CMA) [7], and Sign Kurtosis Maximization Adaptive Algorithm (SKMAA) [8] in the context of non constant modulus data with spatio-temporal diversity. The paper also describes three algorithms, Safi1, Safi2 and Said1, which are used to estimate the parameters of radio mobile channel in noisy and non noisy case. Moreover we attest the blind equalization of channel using the Constant Modulus Algorithm (CMA), Sign Kurtosis Maximization Adaptive Algorithm (SKMAA) and Said1 algorithms.

## 2. Problem Statement

The output of a Finite Impulse Response (FIR) channel, excited by an unobservable input sequences, i.i.d. zero-mean symbols with unit energy, across a selective channel with memory p and additive noise (Figure 1) is given by the following relationship.

$$X(k) = h_p(k)S(k) + V(k$$
(1)

Where  $h_p = [h(1), h(2), ..., h(p)]$  represents the channel parameter, S(k) input system and V(k) is the additive colored Gaussian noise.



Figure 1. Channel Model

## 3. Blind Algorithms

#### 3.1. Safi1 Algorithm[9]

#### Hypothesis:

Let us suppose that:

- The additive noise V(k) is Gaussian, colored or with symmetric distribution, zero mean, with variance  $\sigma^2$ , i.i.d. with the m<sup>th</sup> order cumulants vanishes for m > 2
- The noise V(t) is independent of S(k) and X(k).
- The channel (FIR system) order p is supposed to be known and h(0) = 1.
- The system is causal, i.e., h(i) = 0 if i < 0.
- The m<sup>th</sup> order cumulant of the output signal is given by the following equation

$$C_{my}(t_1, \dots, t_{m-1}) = \gamma_{mx} \sum_{-\infty}^{+\infty} h(i)h(i+t_1) \cdots h(i+t_{m-1})$$
(2)

Where  $\gamma_{mx}$  represents the m<sup>th</sup> order cumulants of the excitation signal (S(k)). Based on equation (2), Safi1 algorithm is developed by the following relationship:

$$\sum_{i=0}^{p} h(i)C_{3y}(t_1 - i, t_2 - i) = \epsilon \sum_{i=0}^{p} h(i)h(i + t_2 - t_1)C_{2y}(t_1 - i)$$
(3)

If we use the property of the ACF of the stationary process, such as  $C_{2y}(t) \neq 0$  only for  $(-p \leq t \leq p)$  and vanishes else were.

$$\sum_{i=0}^{p} h(i)C_{3y}(-p-i,t_2-i) = \epsilon h(0)h(t_2+p)C_{2y}(-p)$$
(4)

Else, if we suppose that  $t_2 = -p$ , Eq. (4) will become

$$C_{3y}(-p,-p) = \epsilon h(0)C_{2y}(-p)$$
(5)

Using Eqs. (4) and (5) we obtain the following relation

(6)

$$\sum_{i=0}^{p} h(i)C_{3y}(-p-i,t_2-i) = h(t_2+p)$$

Else, if we suppose that the system is causal, i.e., h(i) = 0 if i < 0. So, for  $t_2 = -p, \dots, 0$ , the system of Eq. (6) can be written in matrix form as:

$$\begin{pmatrix} C_{3y}(-p-1,-p-1) & \cdots & C_{3y}(-2q,-2q) \\ C_{3y}(-p-1,-p)-\alpha & \cdots & C_{3y}(-2p,-2p+1) \\ \vdots & \ddots & \vdots \\ C_{3y}(-p-1,1) & \cdots & C_{3y}(-2p,-p)-\alpha \end{pmatrix} \begin{pmatrix} h(1) \\ h(2) \\ \vdots \\ h(p) \end{pmatrix}$$

$$= \begin{pmatrix} 0 \\ -C_{3y}(-p,-p+1) \\ \vdots \\ -C_{3y}(-p,0) \end{pmatrix}$$
(7)

Were  $\alpha = C_{3y}(-p, -p)$ . The above Eq. (7) can be written in compact form as

(7) can be written in compact form as

$$Mh_p = d_1 \tag{8}$$

Where *M* is the matrix of size  $(p + 1) \times (p)$  elements  $h_p$  is a column vector constituted by the unknown impulse response parameters h(n): n = 1, ..., p and  $d_1$  is a column vector of size  $(p + 1) \times (1)$  as indicated in the Eq. (7). The least squares solution (LS) of the system of Eq. (8), permits blindly identification of the parameters h(n) and without any "information" of the input selective channel. So, the solution will be written under the following form

$$h_p = (M^T M)^{-1} M^T d_1 (9)$$

#### 3.2. Safi2 Algorithm[9]

From the Eq. (2), the m<sup>th</sup> and n<sup>th</sup> cumulants of the output signal,  $\{y(n)\}$ , and the coefficients  $\{h(i)\}$ , where n > m, are linked by the following relationship:

$$\sum_{j=0}^{i} h(j) C_{ny}(j+t_1, \dots, j+t_{m-1}, t_m, \dots, t_{n-1}) = \frac{\gamma_{ne}}{\gamma_{me}} \sum_{i=0}^{p} h(i) \left[ \prod_{k=m}^{n-1} h(i+t_k) \right] C_{my}(i+t_1, \dots, i+t_{m-1})$$
(10)

If we take n = 4 and m = 3 into Eq. (10), we find the basic relationship developed in [12,13]. If we take n = 3 and m = 2 into Eq. (9), we find the basic relationship of the algorithms developed in [14]. So, the equation proposed in [15] presents the relationship between different n<sup>th</sup> cumulant slices of the output signal  $\{X(n)\}$ , as follows

$$\sum_{j=0}^{p} h(j) \left[ \prod_{k=1}^{r} h(j+t_k) \right] C_{ny}(\beta_1, \dots, \beta_r, j+\alpha_1, \dots, \alpha_{n-r-1})$$
$$= \sum_{i=0}^{p} h(i) \left[ \prod_{k=1}^{r} h(i+\beta_k) \right] C_{ny}(t_1, \dots, t_r, i+\alpha_1, \dots, i+\alpha_{n-r-1})$$
(11)

Where  $1 \le r \le n - 2$ .

If we take n=3 we obtain that r=1, so the Eq. (10) will be  

$$\sum_{j=0}^{p} h(j)h(j+t_1)C_{3y}(\beta_1, j+\alpha_1) = \sum_{i=0}^{p} h(i)h(i+\beta_1)C_{3y}(t_1, i+\alpha_1)$$
(12)

In the following, we develop an algorithm based only on  $4^{\text{th}}$  order cumulants. If we take n = 4 into Eq. (11) we obtain the following equation:

$$\sum_{i=0}^{j} h(i)h(i+t_1)h(i+t_2) C_{4y}(\beta_1,\beta_1,i+\alpha_1) = \sum_{j=0}^{p} h(j)h(j+\beta_1)h(j+\beta_2)C_{4y}(t_1,t_2,+\alpha_1)$$
(13)

If  $t_1 = t_2 = p$  and  $\beta_1 = \beta_2 = 0$ , Eq. (13) takes the form:

$$h(0)h^{2}(p)C_{4y}(0,0,i+\alpha_{1}) = \sum_{j=0}^{i} h^{3}(j)C_{4y}(p,p,j+\alpha_{1})$$
(14)

As the system is a FIR, and is supposed causal with an order p, so, the  $j + \alpha_1$  will be necessarily into the interval [0, p], this implies that the determination of the range of the parameter  $\alpha_1$  is obtained as follows:  $0 \le j + \alpha_1 \le p \Rightarrow -j \le \alpha_1 \le q - j$ , and we have  $0 \le j \le p$ . From these two inequations, we obtain:

$$-p \le \alpha_1 \le p. \tag{15}$$

Then, from the Eqs. (13) and (14) we obtain the following system of equations:

$$\begin{pmatrix} C_{4y}(p,p,-p) & \dots & C_{4y}(p,p,0) \\ \vdots & \ddots & \vdots \\ C_{4y}(p,p,0) & \dots & C_{4y}(p,p,p) \\ \vdots & \ddots & \vdots \\ C_{4y}(p,p,p) & \dots & C_{4y}(p,p,2p) \end{pmatrix} \begin{pmatrix} h^{3}(0) \\ \vdots \\ h^{3}(i) \\ \vdots \\ h^{3}(p) \end{pmatrix} = h(0)h^{2}(p) \begin{pmatrix} C_{4y}(0,0,-p) \\ \vdots \\ C_{4y}(0,0,0) \\ \vdots \\ C_{4y}(0,0,p) \end{pmatrix}$$
(16)

and as we have assumed that h(0) = 1, if, we consider that  $h(p) \neq 0$  and the cumulant  $C_{my}(t_1, \ldots, t_{m-1}) = 0$ , if one of the variables  $t_k > p$ , where  $k = 1, \ldots, m-1$ , the system of Eq. (16) will be written as follows:

$$\begin{pmatrix} 0 & \cdots & 0 & C_{4y}(p, p, 0) \\ \vdots & \ddots & \vdots \\ 0 & & & \\ C_{4y}(p, p, 0) & \cdots & & C_{4y}(p, p, p) \\ \vdots & & \ddots & 0 \\ C_{4y}(p, p, p) & 0 & \cdots & & 0 \end{pmatrix} \begin{pmatrix} \frac{1}{h^{2}(p)} \\ \vdots \\ \frac{h^{3}(i)}{h^{2}(p)} \\ \vdots \\ \frac{h^{3}(p)}{h^{2}(p)} \end{pmatrix} = \begin{pmatrix} C_{4y}(0, 0, -p) \\ \vdots \\ C_{4y}(0, 0, 0) \\ \vdots \\ C_{4y}(0, 0, p) \end{pmatrix}$$
(17)

In more compact form, the system of Eq. (17) can be written in the following form:

$$Mb_p = d_2 \tag{18}$$

where M,  $b_p$  and  $d_2$  are defined in the system of Eq. (17). The least squares solution of the system of Eq. (18) is given by:

$$\hat{b}_p = (M^T M)^{-1} M^T d_2 \tag{19}$$

This solution give us an estimation of the quotient of the parameters  $h^3(i)$  and  $h^3(p)$ , with  $b_p(i) = \left(\frac{\hat{h}^3(i)}{h^2(p)}\right), i = 1, ..., p$ 

So, in order to obtain an estimation of the parameters  $\hat{h}(i), i = 1, ..., p$  we proceed as follows:

• The parameters h(i) for i = 1, ..., p-1 are estimated from the estimated values  $b_p(i)$  using the following equation:

$$\hat{h}(i) = sign \left[ \hat{b}_{p}(i) (\hat{b}_{p}(p))^{2} \right] \left\{ abs \left( \hat{b}_{p}(i) \right) (\hat{b}_{p}(p))^{2} \right\}^{\frac{1}{3}}$$
(20)

where  $sign(x) = \begin{cases} 1, & if \quad x > 0; \\ 0, & if \quad x = 0; \\ -1 & if \quad x < 0. \end{cases}$ 

and abs(x) = |x| indicates the absolute value of x

• The  $\hat{h}(p)$  parameters is estimated as follows :

$$\hat{h}(p) = \frac{1}{2} sign\left[\hat{b}_{p}(p)\right] \left\{ abs\left(\hat{b}_{p}(p)\right) + \left(\frac{1}{\hat{b}_{p}(1)}\right)^{1/2} \right\}$$
(21)

#### 3.3 Proposed algorithm Said1

The general problem of interest here may be characterized using the following model:



Figure 2. System Model

The convolution model is represented by:

$$X_{n} = \sum_{l=0}^{L} h_{l} S_{n-l} + V_{n}$$
(22)

 $h_l$  represents the channel parameter,  $S_{n-l}$  input system,  $X_n$  output system and  $V_n$  is the additive colored Gaussian noise.

Or model vector of equation (22) is:

$$X_{n} = [h_{0} \dots h_{l}] \begin{bmatrix} S_{n} \\ \vdots \\ S_{n-l} \end{bmatrix} + V_{n}$$

$$X_{n} = h^{T} S_{n} + V_{n}$$
(23)

The matrix system will be written as follows:

$$\begin{bmatrix} X_n \\ \vdots \\ X_{n-N} \end{bmatrix} = \begin{bmatrix} h_0 & \dots & h_l & 0 & 0 \\ 0 & \ddots & \ddots & \ddots & 0 \\ 0 & 0 & h_0 & \ddots & h_l \end{bmatrix} \begin{bmatrix} S_n \\ \vdots \\ S_{n-N-l} \end{bmatrix}$$
(24)

Or

$$X(n) = h(n).S(n) + V(n)$$
 (25)

With X(n) of size  $(N + 1) \times 1$ , h(n) is of size  $(N + 1) \times (N + L + 1)$  and S(n) of size  $(N + L + 1) \times 1$ . The Said1 algorithm is a general method for blind solving estimation problems of channel parameters. The considerations leading to the Said1 algorithm is given below.

• Let  $S_0, \dots, S_M$  be known Let N=L, Then:

$$E[X(n)S_{n-L}^*] = \begin{bmatrix} h_0 \\ \vdots \\ h_L \end{bmatrix}$$
(26)

Where in practice,

$$E[X(n)S_{n-L}^*] = \frac{1}{M-L+1} \left( \sum_{n=L}^M X(n)S_{n-L}^* \right)$$
(27)

• Calculate mean square error of channel estimation: From equation (26), we have estimation:

$$\hat{h} = \begin{bmatrix} h_0 \\ \vdots \\ h_L \end{bmatrix}$$
(28)

Normalization of *h* and  $\hat{h}$  is given by:

$$h = \frac{h}{\|h\|}, \qquad \hat{h} = \frac{\hat{h}}{\|\hat{h}\|}$$

So, MSE is calculated by the following equation:

$$MSE = \left\| h - \hat{h} \right\| \tag{29}$$

The principle of this algorithm is given by the following diagram:



Figure 3. Diagram of Proposed Algorithm (Said1)

## 4. Said1Equalization

#### 4.1. ZF Equalization

In order to compensate the effect of power line communication (PLC) channel, we consider the ZF equalizer, wich satisfies the condition shown below.

$$f_{ZF}H = I \tag{30}$$

Where  $f_{ZF} = (H^H H)^{-1} H^H$  is the ZF decoding matrix, (.)<sup>H</sup> denotes Hermitian transpose, H is the channel matrix and I is the identity matrix. Given the received signal X, the receiver can obtain the estimated signal by using the ZF equalization, which is given by:

$$\hat{S}(n) = f_{ZF} X(n)$$

$$\hat{S}(n) = f_{ZF} H S(n) + f_{ZF} V(n)$$

$$\hat{S}(n) = I S(n) + f_{ZF} V(n)$$
(31)

Where  $\hat{S}$  is an estimate matrix of the transmitted signal. If the determinant of *H* is not zero so that there exists the inverse matrix of *H* the decoding matrix can be expressed as

$$f_{ZF} = H^{-1}$$
 (32)

The ZF equalization is ideal when the channel is noiseless. However, when the channel is noisy, the ZF equalization plays an important role to cancel the additive colored Gaussian noise.

#### 4.2 MMSE equalization

In order to minimize the power of the noise component, we employ the MMSE equalization, which is given by:

$$f_{MMSE} = \min_{f_{MMSE}} E \left\| \left\| S_{n-d} - f_{MMSE}^{H} X(n) \right\|^{2} \right\|$$
(33)

Where  $f_{MMSE}$  is the MMSE decoding matrix and  $\|.\|$  the norm of  $S_{n-d} - f_{MMSE}^H X(n)$ . Or:

$$f_{MMSE} = R_X \hat{h}_d \tag{34}$$

Where  $R_X = E[X(n)X^H(n)]$  and  $\hat{h}_d = E[X(n)S^*_{n-d}]$ . In practice the expression of  $R_X$  and  $\hat{h}_d$  is:

$$R_{X} = \frac{1}{k} \sum_{n=1}^{k} X(n) X^{H}(n)$$

$$\hat{h}_{d} = \frac{1}{M} \sum_{n=1}^{M} X(n) S_{n-d}^{*}$$
(35)
(36)

The MMSE equalization can be used to estimate the channel effect with varying the decoding matrix in accordance with SNR. Besides, it prevents the noise component from being amplified.

So, equalization said algorithm is defined by the steps following:

- Transmit k symbols, the first M is assured known,
- Obtain received samples  $X_n$ ,
- Construct sample vectors *X*(*n*),
- Calculate  $R_X$  and  $\hat{h}_d$ ,
- Calculate  $f_{MMSE} = R_X^{-1} \hat{h}_d$ ,
- Calculate symbol error rate (SER):
  - ✓ Use  $f^H X(n)$  to estimate symbol  $\hat{S}_{n-d}$ .
  - ✓ Compare  $\hat{S}_{n-d}$  with  $S_{n-d}$ .

## 5. Adaptive Equalization

One approach to removing inter-symbol interference in a communications channels is to employ adaptive blind equalization to reduce the Symbol Error Rate (SER). The most popular class of algorithms used for blind equalization are those that minimize the Godard (or constant modulus) criteria [6,16]. In this paper we study the performance of the Constant Modulus Algorithm (CMA).

#### 5.1. The Constant Modulus Algorithm (CMA)

The problem with blind adaptation techniques is their poor convergence property compared to traditional techniques using training sequences. Generally a gradient descent based algorithm is used with the blind adaptation schemes. The most commonly used gradient descent based blind adaptation algorithm is the Constant Modulus Algorithm (CMA). The Constant Modulus Algorithm (CMA) [16,17] has gained widespread practical use as a blind adaptive equalization algorithm for digital communications systems operating over inter-symbol interference channels.

The constant modulus (CM) criterion can be expressed by the cost function  $J_{CM} = \frac{1}{4}E\{(|X_n|^2 - \gamma)^2\}$ , where  $\gamma$  is a positive constant known as the Godard radius [6]. The equalizer update algorithm leading to a stochastic gradient descent of  $J_{CM}$  is known as the Constant Modulus Algorithm (CMA) and is specified by:

$$f(n+1) = f(n) + \mu S^{*}(n) \underbrace{X_{n}(\gamma - |X_{n}|^{2})}_{\triangleq \psi(X(n))}$$
(37)

Where  $\mu$  is a step-size and  $S^*(n)$  is the equalizer input vector at time index n. the asterisk denotes conjugation. The function  $\psi(.)$  identified in (37) is referred to as the CMA error function.

#### 5.2. KMAA Algorithm

Sign Kurtosis Maximization Adaptive Algorithm (SKMAA) is used to blind channel equalization, that is to say SKMAA is developed based on kurtosis of stochastic signals, the stochastic ascend approach, and sign algorithm for restoring the blind equalizer weight vectors [8]. Furthermore it is also necessary to calculate the output sample y(n) of the equalizer filter once per algorithm update. The general idea is to maximize the chosen cost function. To assure that the SKMAA algorithm ascends for each time step n the following requirement is made

$$J(f(n+1)) > J(f(n))$$
(38)

Or the cost function is given by

$$J_{KMA}(f) = \frac{|Kurtosis[y(n)]|}{E^2|y(n)|^2}$$
(39)

where y(n) is the equalizer output and *Kurtosis*[y(n)] is defined by:

$$Kurtosis[y(n)] = E\{y^4(n)\} - 3E^2\{y^2(n)\}$$
(40)

The update is then given by

$$f(n + 1) = f(n) + \mu \Delta f J_{KMA}(f)$$
  
= f(n) + \mu F(y)[S(n) \* h(n)]  
= f(n) + \mu F(y)X(n) (41)

or

$$\Delta f J_{KMA}(f) = F(y)X(n) \tag{42}$$

where *F* is the feedback function defined by:

$$F(y) = \frac{4(E[y^2]y^2 - E[y^4])y}{E^3[y^2]}$$
(43)

a Sign Algorithm is introduced into KMAA. So the SKMAA is written by:

$$f(n+1) = f(n) + \alpha Sign[F(y)] \cdot [X(n)]$$
(44)

where Sign[.] is a simple sign function, and  $\alpha$  is a forgetting factor which is used to replace the ensemble averages by empirical averages which are then adaptively updated  $(0 < \alpha < 1)[8]$ .

## 6. Simulation Results

#### 6.1. Performance of Safi1, Safi2 and Said1 algorithms in the without Noise Case

In this part, we will test the performance of the presented algorithms (Safi1, Safi2 and Said1) in order to estimate the channel's parameters. Table1 represents the obtained results using different data length and the Real parameters of Proakis (B) channel [18], by applying the modulation QPSK or 4 QAM symbol sequence channel without noisy case. In the simulation we utilized the relations (9), (20) and (26) with the matlab logiciel.

N	Algorithms	h(1)	h(2)	h(3)	MSE
512	Safi 1	-0.1852	0.3324	0.1456	1.6804
	Safi2	0.669	0.8962	0.7719	1.2283
	Said1	0.3426	0.7944	0.4622	0.1140
	Safi1	-0.2575	0.5186	0.2792	1.3604
1024	Safi2	0.6464	0.9017	0.7657	1.1343
	Said1	0.3997	0.8082	0.4286	0.0630
	Safi1	0.0944	0.1009	0.1135	1.2774
2048	Safi2	0.5692	0.8614	0.6953	0.7639
	Said1	0.0553	0.8136	0.4065	0.0553
4096	Safi 1	0.1204	0.4851	0.1675	0.7387
	Safi2	0.5004	0.8067	0.6329	0.5609
	Said1	0.4135	0.8131	0.4096	0.0140
	Real Parameters	0.407	0.815	0.407	

## Table 1. Coefficients of Proakis (B) channel using the Three Algorithms



Figure 4. The Variation of the MSE using Safi1, Safi2 and Said1 Algorithms with Different Numbers of Samples N

From Table 1 we can conclude that for all numbers of samples (N = 512, 1024, 2048 and 4096), Said1algorithm gives satisfactory results so as to estimate the parameters of Proakis (B) channel if MSE value is very low, that is to say, Said1 has a good performance regarding to Safi1 and Safi2 algorithms.

#### 6.2. Performance of Safi1, Safi2 and Said1 Algorithms in the Noise Case

From the previous section, we will compare the performance of the three presented algorithms (Safi1, Safi2 and Said1), with the Additive Gaussian Noise (AWGN). For this reason we select two values of Signal Noise Ratio (SNR=0 dB and SNR=16 dB).

SNR	Algorithms	<i>h</i> (1)	h(2)	h(3)	MSE
0 dB	Safi1	-0.1816	0.1849	0.2043	2.9375
	Safi2	0.4383	0.6983	0.6086	0.2717
	Said1	0.4306	0.8051	0.4013	0.0783
16dB	Safi1	-0.15650	0.2930	0.2445	2.4863
	Safi2	0.4723	0.6833	0.4295	0.1922
	Said1	0.4040	0.8226	0.4001	0.0142
	Real Parameters	0.407	0.815	0.407	

## Table 2. Parameters of Proakis (B) Channel in the Noisy case using theThree Algorithms with Number of Sample N = 1024

In the similar way, we conclude that the third algorithm (Said1) gives a good estimation to channel's parameters which are very close to the real values, so Said1 algorithm is shown an outperformance than Safi1 and Safi2 algorithms.

## 6.3. Blind Identification Channel (Bran A)

In this section we are going to identify the amplitude and the phase of BRAN A channel [19], [20] using the number of samples N = 2048 and the SNR= 16 dB, to attest the performance of the Safi1, Safi2 and Said1 algorithms.



# Figure 5. Identification of the Amplitude and the Phase BRAN A Channel's, using the Three Algorithms

The simulation result obtained (Figure 5) shows that both algorithms have very satisfactory results in terms of the amplitude of the impulse response compared to the real measure. Concerning the phase of impulse response is different from the real measure of Safi1, but is the same for Said1 and Safi2 algorithms, so Said1 algorithm gives a good identification to BRAN A channel.

## 6.4. Equalization of Channel by Said1, CMA and SKMAA Algorithms

In this part we attest the performance of Said1, CMA and SKMAA algorithms to equalize the output of channel, Using the different SNR values, the total number of data is T=1024 and the modulation QPSK or 4 QAM symbol sequence.



Figure 6. Channel Equalization by Said1 Algorithm, with the SNR=25 dB



Figure 7. Channel Equalization by CMA Algorithm, with the SNR=25 dB



Figure 8. Channel Equalization by SKMAA Algorithm, with the SNR=25 dB



Figure 9. SER in Function the SNR Values using Said1, CMA and SKMAA Algorithms



Figure 10. SER in Function the Number Total of Symbols M using Said1, CMA and SKMAA algorithms with SNR=6 dB

From the results of simulation obtained, we notice that the Said1 algorithm gives the good equalization of channel regarding to CMA and SKMAA algorithms. In addition, the SER is decreasing according to SNR values (Figure 9) and is increasing according to number total of symbols M (Figure 10) for the three algorithms (Said1, CMA and SKMAA).

## 7. Conclusion

This paper has presented three algorithms: Safi1, Safi2 and Said1 which are essential to estimate the channel's parameters (Prokis B) and to identify the radio mobile channels (Bran A). Furthmore this work investigated the problem of blind channel equalization by the following algorithms; Said1, the Constant Modulus Algorithm (CMA) and Sign Kurtosis Maximization Adaptive Algorithm (SKMAA). Simulation results show that the Proposed Algorithm (Said1) gives a good estimation to the parameters of channel in the noisy environment (SNR = 0dB), regarding to Safi1 and Safi2 algorithms. Concerning SKMAA algorithm performance is more higher compared to CMA algorithm, but Said1 stays the most potential algorithm in relation to other equalizers (CMA, SKMAA) for blind channel equalization.

## References

- [1] M. Boulouird, M. M. Hassani and A. Zeroual, "Blind channel identification using higher-order statistics", vol. 78, no.4, (2008), pp. 325-338.
- [2] S. Safi and A. Zeroual, "MA system identification using higher order cumulants: application to modeling solar radiation", J. Stat. Comp. Simul., Taylor & Francis, vol. 72, no. 7, (2002), pp. 533-548.
- [3] D. N. Godard, "Self-recovering equalization and carrier tracking in two-dimensional data communication systems", IEEE Trans. on Communications, vol. 28, no. 11, (1980), pp. 1867-1875.
- [4] Y. Xiao, M. Shadeyda, and Y. Tadokoro, "Over-determined C(k,q) formula using third and fourth order cumulants", Eletron. Lett., vol. 32, (**1996**), pp. 601-603.
- [5] L. Srinivas and K. V. S. Hari, "FIR system identification using higher order cumulants: a generalized approach", IEEE Trans. Sig. Proces., vol. 43, no. 12, (**1995**), pp. 3061-3065.
- [6] J.-N. Lin and R. Unbehauen, "Bias-remedy least mean square equation error algorithm for IIR parameter recursive estimation", IEEE Trans. Signal Processing, vol. 40, (**1992**), pp. 62-69.
- [7] J. R. Treichler and B. G. Agee, "A new approach to multipath correction of constant modulus signals," IEEE Trans. Acoust., Speech, Signal Processing, vol. 31, (1983), pp. 459-472.
- [8] B. S. K. Reddy and B. Lakshmi, "Minimizing PAPR and Synchronization Errors in OFDM for WiMAX Using Software Defined Radio", Journal of Circuits, Systems and Computers (World Scientific), vol. 24, no. 4, (2015), pp. 1-23.
- [9] S. Safi, M. Frikel, A. Zeroual and M. M'Saad, "Higher Order Cumulants for Identification and Equalization of Multicarrier Spreading Spectrum Systems", journal of telecommunications and information technology, (2011), pp. 74-84.
- [10] S. Safi, A. Zeroual, and M. M. Hassani, "Parametric identification of non-Gaussian signals using diagonal slice cumulants, application to modeling solar process", in Proc. Microwave Symp. MS'2000, Tetouan, Morocco, (2000), pp. 345-350.
- [11] L. Nikias and J. M. Mendel, "Signal processing with higher order spectra", IEEE Sig. Proces. Mag., vol. 10, (**1993**), pp. 10-37.
- [12] Y. Xiao, M. Shadeyda, and Y. Tadokoro, "Over-determined C(k,q)formula using third and fourth order cumulants", Eletron. Lett., vol. 32, (1996), pp. 601-603.
- [13] X. D. Zhang and Y. S. Zhang, "Singular value decomposition based MA order determination of non-Gaussian ARMA models", IEEE Trans. Sig. Proces., vol. 41, (1993), pp. 2657-2664.
- [14] S. Safi and A. Zeroual, "Blind identification in noisy environment of non-minimum phase Finite Impulse Response (FIR) using higher order statistics", Int. J. Sys. Anal. Modell. Simul., Taylor & Francis, vol. 43, no. 5, (2003), pp. 671-681.
- [15] S. Safi, "Identification aveugle des canaux à phase non minimale en utilisant les statistiques d'ordre supérieur: application aux réseaux mobiles", Thèse d'Habilité, Cadi Ayyad University, Marrakesh, Morocco, (2008).
- [16] C. R. Johnson, "Blind equalization using the constant modulus criterion: a review", Submitted to Proceedings of the IEEE, (1997).
- [17] J. R. Treichler and B. G. Agee, "A new approach to multipath correction of constant modulus signals," IEEE Trans. Acoust. Speech Signal Proc., vol. 31, no. 2, (1983).
- [18] S. Safi and A. Zeroual," Blind Non-Minimum Phase Channel Identification Using 3rd and 4th Order Cumulants", International Journal of Mathematical, Computational, Physical, Electrical and Computer Engineering, vol. 2, no. 11, (2008), pp. 849-858.
- [19] ETSI TS 101 475 V1.3.1, "Broadband Radio Access Networks (BRAN), HIPERLAN Type 2, Physical (PHY) layer", (2001).
- [20] TSI TR 101 031 V2.2.1, "Broadband Radio Access Networks (BRAN), (HIPERLAN) Type 2", Requirements and architectures for wireless broadband access, (1999).

#### Authors



**Said Elkassimi** obtained the B.Sc. degree in Physics and M.Sc. degree in computer science from polydisciplinary faculty, in 2009 and from Faculty of Science and Technics Beni Mellal, Morocco, in 2012, respectively. Now he is Ph.D student and his research interests include communications, wide-band wireless communication systems, signal processing and system identification.



Said Safi received the B.Sc.degree in Physics (option Electronics) from Cadi Ayyad University, Marrakech, Morocco in 1995, M.Sc. and Doctorate degrees from Chouaib Doukkali University and Cadi Ayyad University, in 1997 and 2002, respectively. He has been a Professor of information theory and telecommunication systems at the National School for applied Sciences, Tangier, Morocco, from 2003 to 2005. Since 2006, he is a Professor of applied mathematics and programming at the Faculty of Science and Technics, Beni Mellal, Morocco. In 2008 he received the Ph.D. degree in Telecommunication and Informatics from the Cadi Ayyad University. His general interests span the areas of communications and signal processing, estimation, time-series analysis, and system identification subjects on which he has published 14 journal papers and more than 60 conference papers. Current research topics focus on transmitter and receiver diversity techniques for single- and multi-user fading communication channels, and wide-band wireless communication systems.



**Bouzid Manaut** received the B.Sc.degree in Physics (Theoritical Physics) from Cadi Ayyad University, Marrakech, Morocco in 1999, M.Sc. and Doctorate degrees from Cadi Ayyad University and Moulay Ismail University, in 2002 and 2005, respectively. Professor of theoretical Physics from 2006 to now at the Polydisciplinary Faculty, Beni Mellal, Morocco. Ph.D. degree in Theoritical Physics, in 2011, from the Faculty of Science and Technics, USMS, Beni Mellal, Morocco. Current research topics focus on Theoritical Physics.