Blind Non-Minimum Phase Channel Identification Using $3^{rd}$ and $4^{th}$ Order Cumulants

S. Safi, and A. Zeroual

Abstract—In this paper we propose a family of algorithms based on $3^{rd}$ and $4^{th}$ order cumulants for blind single-input single-output (SISO) Non-Minimum Phase (NMP) Finite Impulse Response (FIR) channel estimation driven by non-Gaussian signal. The input signal represents the signal used in 10GBASE-T (or IEEE 802.3an-2006) as a Tomlinson-Harashima Precoded (THP) version of random Pulse-Amplitude Modulation with 16 discrete levels (PAM-16). The proposed algorithms are tested using three non-minimum phase channel for different Signal-to-Noise Ratios (SNR) and for different data input length. Numerical simulation results are presented to illustrate the performance of the proposed algorithms.

Keywords—Higher Order Cumulants, Channel identification, Ethernet communication.

I. INTRODUCTION

FINITE Impulse Response (FIR) system identification from output measurements only is a well-defined problem in several science and engineering areas such as communications, speech signal processing, adaptive filtering, spectral estimation, radar Doppler, sonar, geophysical, biomedicine, blind equalization, plasma physics, seismic data processing, image reconstruction, harmonic retrieval, time-delay estimation and array processing ([1], [2], [3], [4], [6], [7], [8], [9], [10], [11], [12], [13], [14], [16]). The interest in Higher Order Cumulants (HOC) (or Higher Order Statistics (HOS)) has been permanently growing in the last years. Mainly finite impulse response (FIR) system identification based on HOC of system output has received more attention. Tools that deal with problems related to either non-linearity, non-Gaussianity, or non-minimum phase (NMP) systems are available, because they contain the phase information of the underlying linear system in contrast to second order statistics, and they are of great value in applications, such as radar, sonar, array processing, blind equalization, time daily estimation, data communication, image and speech processing and seismology. Many algorithms have been proposed in the literature for the identification of FIR system using cumulants. These algorithms can be classified into three broad classes of solutions: Closed form solutions [13], [17] Optimization-based solutions [11], [15] and Linear algebra solutions [13], [14], [21]. Recently, the latter have received great attention because they have “simpler” computation and are free of the problems of local extreme values that often occur in the optimization solution. Although the closed-form solutions have similar features, they usually do not smooth out the noises caused from the observation and computation. Therefore, while these solutions are more interesting from the theoretical point of view, they are not recommended for practical applications. In this paper, we propose a family of algorithms based on linear algebra solution, exploit third, and fourth order cumulants. In the part of simulation, we have tested the proposed algorithms for channel identification, principally the Ethernet channel. The Ethernet has evolved into the most widely implemented physical and link layer protocol today. Fast Ethernet increased speed from 10 to 100 megabits per second (Mb/s). Gigabit Ethernet was the next iteration, increasing the speed to 1000Mbit/s. The initial standard for gigabit Ethernet was standardized by the IEEE in June 1998 as IEEE 802.3z. 10 gigabit Ethernet or 10GbE is the most recent (as of 2006) and fastest of the Ethernet standards. It defines a version of Ethernet with a nominal data rate of 10Gbit/s, ten times as fast as gigabit Ethernet. 10GbE over fiber and InfiniBand “like” copper cabling are specified by the IEEE 802.3-2005 standard. 10GbE over twisted pair has been released under the IEEE 802.3an amendment. The 802.3an standard defines the wire-level modulation for 10GBASE-T as a Tomlinson-Harashima Precoded (THP) version of pulse-amplitude modulation with 16 discrete levels (PAM-16), encoded in a two-dimensional checkerboard pattern known as DSQ128. Several proposals were considered for wire-level modulation, including PAM with 12 discrete levels (PAM-12), 10 levels (PAM-10), or 8 levels (PAM-8), both with and without Tomlinson-Harashima Precoding (THP). PAM-5 was used in the older 1000BASE-T gigabit Ethernet standard [22], [23], [24], and [25]. In this paper, we will consider a NMP channel exited by a random PM-16, for different signal to noise ratio (SNR) and for different size data input. The results show the performance of the proposed algorithms for small data input in noisy environment.

II. PROBLEM STATEMENT

A. Channel modeling

Consider the transmission of N i.i.d zero-mean symbols with unit energy, belonging to some alphabet A, across a frequency selective channel with memory p and Additive white Gaussian Noise (AWGN) (Fig. 1).

The NMP channel output is modeled as the output of a FIR system that is excited by an unobservable input and is
Fig. 1. Discrete time Non-Minimum phase channel.

The input sequence, \( e(n) \), is corrupted at its output by an additive white Gaussian noise. The output time series is described by

\[
y(n) = \sum_{i=0}^{q} h(n)e(n - i)
\]

(1)

Where \( \{ e(n) \} \) is the input sequence, \( \{ h(n) \} \) the impulse response coefficients, is the order of FIR system and \( \{ y(n) \} \) is the non-measurable sequences.

The observed “measurable” output \( \{ r(n) \} \) is given by

\[
r(n) = y(n) + w(n)
\]

(2)

where \( \{ w(n) \} \) is the noise sequence.

In order to simplify the construction of the algorithm we assume that: The input sequence, \( \{ e(n) \} \), is independent and identically distributed (i.i.d) zero mean, and non-Gaussian. The system is causal, i.e. \( h(n) = 0 \) for \( i < 0 \) and \( i \geq q \), where \( h(0) = 1 \) and \( h(q) \neq 0 \). The system order \( q \) is known or may be computed by an a priori knowledge [5], [6]. The measurement noise sequence \( \{ w(n) \} \) is assumed zero mean, i.i.d, Gaussian and independent of \( \{ e(n) \} \) with unknown variance.

### B. Basic Relationships

In this section, we present the general relationships for impulse response coefficients that constitute the basic relations in development of most linear HOC based methods proposed in the literature.

The \( m^{th} \) order cumulants of the \( \{ y(n) \} \) can be expressed as a function of the impulse response coefficients \( \{ h(i) \} \) as follows [20]:

\[
C_{my}(t_1, ..., t_{m-1}) = \gamma_{me} \sum_{i=0}^{q} h(i)h(i+t_1)...h(i+t_{m-1})
\]

(3)

Where \( \gamma_{me} \) is the cumulant at origin of the input sequences. From this relation (3), the methods [8], [1], [9], [11], [10], [13], [14], [21] are derived. The third and fourth order cumulants of \( \{ y(n) \} \), are expressed respectively by

\[
C_{3y}(t_1, t_2) = \gamma_{3e} \sum_{i=0}^{q} h(i)h(i+t_1)h(i+t_2)
\]

(4)

\[
C_{4y}(t_1, t_2, t_3) = \gamma_{4e} \sum_{i=0}^{p} h(i)h(i+t_1)h(i+t_2)h(i+t_3)
\]

(5)

Our interest is to search the relationships between the third and fourth order cumulants. Therefore, the Fourier transform of the third order cumulant (4) is given by

\[
S_{3y}(\omega_1, \omega_2) = \gamma_{3e} H(\omega_1)H(\omega_2)H(-\omega_1 - \omega_2)
\]

(6)

The same, The Fourier transform of fourth order cumulant (5) is given as well by

\[
S_{4y}(\omega_1, \omega_2, \omega_3) = \gamma_{4e} H(\omega_1)H(\omega_2)H(\omega_3)
\]

\[
\times H(-\omega_1 - \omega_2 - \omega_3)
\]

(7)

with \( H(\omega) = \sum_{i=0}^{\infty} h(i) \exp^{-j\omega i} \) \( (j^2 = -1) \)

If we replace \( \omega_2 \) in equation (6) by \( \omega_2 + \omega_3 \), the equation (6) becomes

\[
S_{3y}(\omega_1, \omega_2 + \omega_3) = \gamma_{3e} H(\omega_1)H(\omega_2 + \omega_3)
\]

\[
\times H(-\omega_1 - \omega_2 - \omega_3)
\]

(8)

from the equation (7) and (8) we obtain the following equation

\[
H(\omega_2)H(\omega_3)S_{3y}(\omega_1, \omega_2 + \omega_3) = \epsilon H(\omega_2 + \omega_3)
\]

\[
\times S_{3y}(\omega_1, \omega_2, \omega_3)
\]

(9)

where \( \epsilon = \left( \frac{\gamma_{3e}}{\gamma_{4e}} \right) \). So, if we take the inverse Fourier transform of the equation (9), we obtain the fundamental relationships, which link the third and fourth order cumulants to the system parameters (proof see appendix A)

\[
\sum_{i=0}^{q} h(i)h(i+t_3-t_2)C_{3y}(t_1, t_2-i)
\]

\[
= \sum_{i=0}^{q} \epsilon h(i)C_{4y}(t_1, t_2-i, t_3-i)
\]

(10)

for different values of \( t_1, t_2 \) and \( t_3 \) we can obtain different algorithms.

### C. Proposed algorithms

In order to identify the parameter \( \{ h(i) \} : i = 1, ..., q \), of the communication channel impulse response, we use a Least Squares (LS) solution of the system of equation (10) as follow:

If we take \( t_1 = \lambda \) and \( t = t_2 = t_3 \) in equation (10), for each \( \lambda \) we can estimate the parameters \( h(i) \) by a Least Squares (LS) solution of the following systems

\[
\sum_{i=0}^{q} h(i)C_{4y}(\lambda, t-i, t-i) = \sum_{i=0}^{q} h^2(i)C_{3y}(\lambda, t-i)
\]

(11)

the equation (11) can be written into the following system

\[
\left( \sum_{i=0}^{q} h(i)C_{4y}(\lambda, t-i, t-i) - \sum_{i=1}^{q} h^2(i)C_{3y}(\lambda, t-i) \right) = C_{3y}(\lambda, t)
\]

(12)

else if we suppose that the system is causal, i.e. that \( h(i) = 0 \) if \( i < 0 \). So, for \( t = -q, ..., 0, ..., q \) the system of equations (12) can be written in matrix form as follow
The Least Squares solution of the system provides an estimation of the parameters of the communication channel impulse response are given by

\[ h_{\lambda=q+1}(i) = \frac{1}{2} \left( \frac{\hat{e}(i)}{\epsilon} + \text{sign}(\frac{\hat{e}(i)}{\epsilon})(\hat{h}^2(i))^{1/2} \right) \]  

(17)

3) Third algorithm ALG3: if we take \( \lambda=0 \) and for \( t = -q, ..., q \) into the equation (13), we obtain the third LS algorithm (ALG3) and the parameters of the communication channel impulse response are given by

\[ h_{\lambda=0}(i) = \frac{1}{2} \left( \frac{\epsilon h(1)}{\epsilon} + \text{sign}(\frac{\epsilon h(1)}{\epsilon})(\hat{h}^2(i))^{1/2} \right) \]  

(18)

4) Fourth algorithm (ALG4): if we take \( \lambda = q - 1 \) and for \( t = -q, ..., q \) into the equation (13), we obtain the fourth LS algorithm (ALG4) and the in the same way the parameters of the communication channel impulse response are given by

\[ h_{\lambda=q-1}(i) = \frac{1}{2} \left( \frac{\epsilon h(1)}{\epsilon} + \text{sign}(\frac{\epsilon h(1)}{\epsilon})(\hat{h}^2(i))^{1/2} \right) \]  

(19)

5) Fifth algorithm (ALG5): if we take \( \lambda = q \) and for \( t = -q, ..., q \) into the equation (13), we obtain the fifth LS algorithm (ALG5) and in the same manner the parameters of the communication channel impulse response are given by

\[ h_{\lambda=q}(i) = \frac{1}{2} \left( \frac{\epsilon h(1)}{\epsilon} + \text{sign}(\frac{\epsilon h(1)}{\epsilon})(\hat{h}^2(i))^{1/2} \right) \]  

(20)

6) Mean algorithm ALGm: so, in general, if the system order is \( q \) we can construct \( 2q + 1 \) algorithms for each \( \lambda \in [-q, q] \), from this algorithms we can obtain the means of the estimated parameters as follow

\[ h_{\text{mean}}(i) = \frac{1}{2q+1} \sum_{\lambda=-q}^{q} h_{\lambda}(i) \]  

(21)

III. SIMULATIONS AND DISCUSSIONS

In order to evaluate the performance of the proposed algorithms, we consider a non-minimum phase channel in which the order is known. The channel output was corrupted by an Additive White Gaussian Noise (AWGN) for different sample sizes and for 100 Monte Carlo runs.

A. First channel

We consider the channel described by the model FIR-NMP (2) with the zeros located at 0.75 and 1.333, given by the following equations

\[ y(n) = e(n) - 2.083e(n-1) + 1.0e(n-2), \]  

in noise free case. 

\[ S(n) = y(n) + w(n), \] in presence of Gaussian noise.

Where the signal to noise ratio (SNR) is defined [14] by

\[ SNR = 10 \log \left( \frac{E(y^2(n))}{E(w^2(n))} \right) \]  

(22)

To measure the accuracy of parameter estimation with respect to the real values, we define the mean square error (MSE) for each run as

\[ MSE = \frac{1}{q} \sum_{i=0}^{q} \left( \frac{h(i) - \hat{h}(i)}{h(i)} \right)^2 \]  

where, \( h(i) \) , \( \hat{h}(i) \) for \( i = 0, ..., q \), represent the true and estimated parameters respectively. In the following figure (Fig. 2) we have represented the magnitude, phase and zeros of the impulse response of the first channel. The magnitude response is more flat and the phase response is linear.
observation concerns principally the gap between the estimated phases and the true ones. This estimation of the phase response, we have observed a constant estimated magnitude response, using all the proposed algorithms, for the input data length. In the figure (Fig. 3) we remark that the first channel impulse response in noise free case and for 1024

\(N = 1024\). This is a test of the influence of the noise on the estimation.

In the case of an \(SNR = 8dB\) and for a data length \(N = 1024\), we remark from the figure (Fig. 4) that the presence of noise has “nearly” no influence on the estimation of the magnitude and phase response using all the proposed algorithms.

From the Tables (TABLE II and III), we notice that the estimated parameters are slowly affected by the noise presence, this is more apparent if we observe the variance of the noise on the estimation.

![Fig. 2. First channel impulse response characteristics.](image)

![Fig. 3. Estimated magnitude and phase of the channel 1 impulse response, in noise free case, using the proposed algorithms, when the data input is \(N = 1024\).](image)

![Fig. 4. Estimated magnitude and phase of the channel 1 impulse response, using the proposed algorithms, when the data input is \(N = 1024\) and \(SNR = 8dB\).](image)

### TABLE I
**TRUE AND ESTIMATED PARAMETERS OF THE FIRST CHANNEL EXCITED BY A PAM(16) INPUT SEQUENCE OF 1024 SAMPLES (100 ITERATIONS)**

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>(h(1) \pm \sigma)</th>
<th>(h(2) \pm \sigma)</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALG1</td>
<td>(-1.729 \pm 1.158)</td>
<td>(1.221 \pm 0.811)</td>
<td>0.077</td>
</tr>
<tr>
<td>ALG2</td>
<td>(-1.736 \pm 0.748)</td>
<td>(1.249 \pm 0.791)</td>
<td>0.089</td>
</tr>
<tr>
<td>ALG3</td>
<td>(-1.511 \pm 0.791)</td>
<td>(1.036 \pm 0.724)</td>
<td>0.076</td>
</tr>
<tr>
<td>ALG4</td>
<td>(-1.669 \pm 0.989)</td>
<td>(0.984 \pm 0.797)</td>
<td>0.039</td>
</tr>
<tr>
<td>ALG5</td>
<td>(-1.344 \pm 0.698)</td>
<td>(0.980 \pm 0.534)</td>
<td>0.126</td>
</tr>
<tr>
<td>ALGm</td>
<td>(-1.764 \pm 0.721)</td>
<td>(1.257 \pm 0.763)</td>
<td>0.094</td>
</tr>
</tbody>
</table>

1) **performance in noise free case**: In the following Table (I) we have summarized the simulation results when the length data input is 1024.

From the Table (TABLE I) we can conclude that:

- All proposed algorithms gives approximately the same results on the estimation of the impulse response. These estimations are closed to the true ones.
- The variances of the estimated parameters are acceptable.
- The mean squares error is small for all algorithms, which demonstrates that the estimated channel impulse response parameters are more closed to the true ones.

A above results -TABLE I- are obtained in noise free case, but in the following Tables TABLE II and III we estimate the non-minimum phase channel impulse response parameters described by the system 1 for a very low \(SNR (8dB\) and 0dB) and for the input data length \(N = 1024\). In the following figure (Fig. 3) we represent the estimated magnitude and phase of the first channel impulse response in noise free case and for 1024 input data length. In the figure (Fig. 3) we remark that the estimated magnitude response, using all proposed algorithms, are not very different from the true ones. Concerning the estimation of the phase response, we observe a constant gap between the estimated phases and the true ones. This observation concerns principally the ALG1, ALG2, ALG3 and ALGm algorithms. But the estimated phase response using the ALG4 and ALG5 have approximately the same phase in comparison with the true ones.

In the figure (Fig. 4) we have plotted the estimation of the magnitude and phase of first, the case of the \(SNR = 8dB\) and for data length of \(N = 1024\). This is a test of the influence of the noise on the estimation.

![Fig. 5. True and estimated parameters of the first channel excited by a PAM(16) input sequence of 1024 samples (100 iterations).](image)
of the estimated parameters. The $MSE$ is not very different from the noiseless case (TABLE I).

Now what will happen if the variance of noise is equal to the output channel variance (i.e. $SNR = 0dB$). The following figure (Fig. 5) will explain this situation. If the noise variance is equal to the output channel variance (i.e. $SNR = 0dB$) and for the same data length, we conclude that all algorithms give the “same” estimations of the phase which have a constant difference comparing to the true ones. The estimated magnitude response using the proposed algorithms are not different from the original ones excepted those parts of magnitude $\leq 0dB$.

As a result, we can say that:

- The proposed algorithms yield approximately the same estimation of system parameters.
- We observe some increases of the variance estimations, this is due to the presence of noise and short data input (due to a bias estimation of the cumulants).
- If $\lambda$ approaches zero, i.e $\lambda = -1, 0$ and 1, the algorithms ( ALG2, ALG3 and ALG4) give good estimation for all $SNR$ and for different input data length (low $MSE$ (Fig. 6), because in this case we use more cumulants information if the lags are centered round to zero.

In Tables IV and V we increase the sample data to 2048 and for two $SNR$ (0 and 16 dB). From the results shown in the TABLE IV and V, we can deduce that the estimated parameters are not very different from those shown in TABLE II. This is implies that the data length does not influence the estimation of third fourth order cumulants. The $MSE$ are approximately of the same values.

![Image](image.jpg)

**Fig. 5.** Estimated magnitude and phase of the first channel impulse response, using the proposed algorithms, when the data input is $N = 1024$ and $SNR = 0dB$.

**Fig. 6.** $MSE$ (first channel) for each algorithm and for different $SNR$ and for a data length $N = 1024$. 

**Table III**

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>$h(1) \pm \sigma$</th>
<th>$h(2) \pm \sigma$</th>
<th>$MSE$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALG1</td>
<td>$-1.556 \pm 1.035$</td>
<td>$1.611 \pm 1.174$</td>
<td>0.436</td>
</tr>
<tr>
<td>ALG2</td>
<td>$-1.922 \pm 1.171$</td>
<td>$1.403 \pm 0.839$</td>
<td>0.168</td>
</tr>
<tr>
<td>ALG3</td>
<td>$-1.586 \pm 0.427$</td>
<td>$1.386 \pm 0.827$</td>
<td>0.205</td>
</tr>
<tr>
<td>ALG4</td>
<td>$-1.903 \pm 0.656$</td>
<td>$1.457 \pm 0.578$</td>
<td>0.216</td>
</tr>
<tr>
<td>ALG5</td>
<td>$-2.036 \pm 1.027$</td>
<td>$1.577 \pm 0.827$</td>
<td>0.333</td>
</tr>
<tr>
<td>ALGm</td>
<td>$-1.801 \pm 0.756$</td>
<td>$1.486 \pm 0.865$</td>
<td>0.271</td>
</tr>
</tbody>
</table>

**Table IV**

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>$h(1) \pm \sigma$</th>
<th>$h(2) \pm \sigma$</th>
<th>$MSE$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALG1</td>
<td>$-1.329 \pm 0.178$</td>
<td>$1.288 \pm 0.824$</td>
<td>0.174</td>
</tr>
<tr>
<td>ALG2</td>
<td>$-1.725 \pm 1.109$</td>
<td>$1.342 \pm 0.852$</td>
<td>0.146</td>
</tr>
<tr>
<td>ALG3</td>
<td>$-1.330 \pm 0.676$</td>
<td>$1.142 \pm 0.898$</td>
<td>0.150</td>
</tr>
<tr>
<td>ALG4</td>
<td>$-1.355 \pm 1.152$</td>
<td>$0.733 \pm 0.687$</td>
<td>0.193</td>
</tr>
<tr>
<td>ALG5</td>
<td>$-1.279 \pm 1.132$</td>
<td>$1.039 \pm 1.051$</td>
<td>0.150</td>
</tr>
<tr>
<td>ALGm</td>
<td>$-1.404 \pm 0.992$</td>
<td>$1.093 \pm 0.932$</td>
<td>0.162</td>
</tr>
</tbody>
</table>

**Table V**

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>$h(1) \pm \sigma$</th>
<th>$h(2) \pm \sigma$</th>
<th>$MSE$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALG1</td>
<td>$-1.613 \pm 0.719$</td>
<td>$1.296 \pm 0.807$</td>
<td>0.137</td>
</tr>
<tr>
<td>ALG2</td>
<td>$-2.093 \pm 1.214$</td>
<td>$1.362 \pm 1.013$</td>
<td>0.131</td>
</tr>
<tr>
<td>ALG3</td>
<td>$-1.474 \pm 0.851$</td>
<td>$1.066 \pm 0.801$</td>
<td>0.089</td>
</tr>
<tr>
<td>ALG4</td>
<td>$-1.461 \pm 0.692$</td>
<td>$0.783 \pm 0.569$</td>
<td>0.136</td>
</tr>
<tr>
<td>ALG5</td>
<td>$-1.384 \pm 0.556$</td>
<td>$0.857 \pm 0.499$</td>
<td>0.133</td>
</tr>
<tr>
<td>ALGm</td>
<td>$-1.606 \pm 0.726$</td>
<td>$1.073 \pm 0.659$</td>
<td>0.125</td>
</tr>
</tbody>
</table>

We remark from the above results that the noise have a small influence on the magnitude and phase estimation, but now we will know the influence of the data length on the estimation of the impulse response estimation. In the Fig.5 we have represent the results for an $SNR = 16dB$ and the data length is $N = 2048$.

In Fig.7 we have increased the data length to have $N = 2048$ and the $SNR = 16dB$, we remark that the estimated magnitude of the first channel impulse response are not very different from the true ones excepted those with a magnitude $\leq 0dB$. The estimated phase response using the algorithms $ALG1$, $ALG2$ and $ALG3$ have approximately the same allure.
comparing the true ones; but the algorithms ALG4, ALG5 and ALGm give a constant gap comparing to the true ones.

B. Second channel

In this section, we increase the channel order (in order to know the influence of the increasing system order on the parameters estimation). Let us consider the channel impulse response described by the system FIR-NMP(3), with the zeros that are located at -0.955, 0.812 and 1.226 given by the equation:
\[ y(n) = e(n) - 1.083e(n-1) - 0.95e(n-2) + 0.95e(n-3), \]
in noise free case.
\[ r(n) = y(n) + w(n), \]
in presence of an AWGN.

In the following figure (Fig. 8) we represent the magnitude, phase and zeros of the impulse response of second channel. The magnitude response represents more selectivity in frequency and the phase response is not linear.

![Second channel impulse response characteristics](image)

In the following Table (TABLE VI) we represent the simulation results where the data input is \( N = 1024 \) and for an \( SNR = 16dB \). From the Table VI we can conclude that:

- The estimated parameters are good for all algorithms.
- The ALG1 gives a better estimation compared to the other algorithms, if we observe the values of variance \( \sigma \) and \( MSE \).
- The ALG4 and ALG5 are not very efficient compared to other algorithms, because they have the greatest \( MSE \) compared to the rest of algorithms.

In the following figure (Fig. 9) we represent the \( MSE \) for the proposed algorithms, when the length of the data input is \( N = 1024 \) and the \( SNR = 16dB \). The results in TABLE VI shows that the noise presence has a small influence on the parameters estimation (overestimation of the parameter \( h(3) \) ), but not a great influence on the parameters estimation using all algorithms. This can be observed in the values of the \( MSE \). From Fig. 9 we can observe the robustness of the ALG1 compared to the other algorithms. The imprecision of the algorithms ALG4 and ALG5 is minimized by using the mean algorithm ALGm.

![MSE for each algorithm and for different SNR](image)

**TABLE VI**

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>( h(1) \pm \sigma )</th>
<th>( h(2) \pm \sigma )</th>
<th>( h(3) \pm \sigma )</th>
<th>( MSE )</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALG1</td>
<td>-0.956±</td>
<td>-1.027±</td>
<td>1.075±</td>
<td>0.037</td>
</tr>
<tr>
<td>ALG2</td>
<td>-1.207±</td>
<td>-1.081±</td>
<td>1.276±</td>
<td>0.149</td>
</tr>
<tr>
<td>ALG3</td>
<td>-0.996±</td>
<td>-1.083±</td>
<td>1.243±</td>
<td>0.121</td>
</tr>
<tr>
<td>ALG4</td>
<td>-1.351±</td>
<td>-0.940±</td>
<td>1.415±</td>
<td>0.301</td>
</tr>
<tr>
<td>ALG5</td>
<td>-1.147±</td>
<td>-1.330±</td>
<td>1.383±</td>
<td>0.371</td>
</tr>
<tr>
<td>ALGm</td>
<td>-1.131±</td>
<td>-1.092±</td>
<td>1.278±</td>
<td>0.144</td>
</tr>
</tbody>
</table>

From the Table VI we can conclude that:

- The estimated parameters are good for all algorithms.
- The ALG1 gives a better estimation compared to the other algorithms, if we observe the values of variance \( \sigma \) and \( MSE \).
- The ALG4 and ALG5 are not very efficient compared to other algorithms, because they have the greatest \( MSE \) compared to the rest of algorithms.

In the following figure (Fig. 9) we represent the \( MSE \) for the proposed algorithms, when the length of the data input is \( N = 1024 \) and the \( SNR = 16dB \). The results in TABLE VI shows that the noise presence has a small influence on the parameters estimation (overestimation of the parameter \( h(3) \) ), but not a great influence on the parameters estimation using all algorithms. This can be observed in the values of the \( MSE \). From Fig. 9 we can observe the robustness of the ALG1 compared to the other algorithms. The imprecision of the algorithms ALG4 and ALG5 is minimized by using the mean algorithm ALGm.

In the figure (Fig. 10) we represent the estimated magnitude and phase response of the second channel using the proposed algorithms, when the \( SNR = 16 \) and the data length \( N = 1024 \). The estimations of magnitude impulse response of the second channel, using all proposed algorithms, are not more close to the real ones when the data length \( N = 1024 \) and the \( SNR = 16dB \) (Fig. 10), but the phase estimations are different from the true ones by “constant” value.
In the following Table (Table VII) we represent the parameters estimation in the case of a small data input \((N=512)\) and for a very noisy environment \((SNR=0dB)\), in order to test the robustness of the proposed algorithms to noise and small data input.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>(h(1) \pm \sigma)</th>
<th>(h(2) \pm \sigma)</th>
<th>(h(3) \pm \sigma)</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALG1</td>
<td>1.260±</td>
<td>1.271±</td>
<td>1.245±</td>
<td>0.352</td>
</tr>
<tr>
<td>ALG2</td>
<td>1.001±</td>
<td>1.076±</td>
<td>1.568±</td>
<td>0.447</td>
</tr>
<tr>
<td>ALG3</td>
<td>1.968±</td>
<td>1.363±</td>
<td>1.344±</td>
<td>0.372</td>
</tr>
<tr>
<td>ALG4</td>
<td>1.130±</td>
<td>1.425±</td>
<td>1.552±</td>
<td>0.654</td>
</tr>
<tr>
<td>ALG5</td>
<td>0.560</td>
<td>0.943</td>
<td>0.871</td>
<td>0.711</td>
</tr>
<tr>
<td>ALGm</td>
<td>1.081±</td>
<td>1.335±</td>
<td>1.652±</td>
<td>0.468</td>
</tr>
</tbody>
</table>

The results shown in the Table VII demonstrate that:
- There is a little influence of short data input, because the proposed algorithms are based on cumulants of order greater than 2 (3rd and 4th order cumulants)
- There is some influence of short data input \((N=512)\), this implies a bias of the cumulants estimation.
- In conclusion, if we use high data length we will minimize the influence of the bias caused when we estimate the cumulants. In addition we can minimize this influence by dividing the input data \((N)\) into \(M\) interval in which we estimate the cumulants and then we take its means.

In the following figure (Fig. 11) we have considered the bad situation, i.e small data length \((N=512)\) and for a high noise variance \((SNR=0dB)\), of the impulse response estimation using the proposed algorithms. When the output channel is more affected by the noise, i.e. \(SNR=0\), we estimate the magnitude impulse response (using all algorithms) with more precision so that the data length is only \(N=512\) (Fig. 11). But, the estimation phases impulse response have the same constant gap comparing to the true ones.

### C. Third channel

In this example, we consider a non-minimum phase impulse response channel, given by the following equation:
\[
y(n) = e(n) + 0.327e(n-1) - 0.815e(n-2) + 0.470e(n-3),
\]
in noise free case.
\[
r(n) = y(n) + w(n),
\]
in presence of an AWGN.

The channel characteristics are illustrated in the following figure (Fig. 14). The magnitude of the channel impulse response is more selective in frequency and the phase response are not linear. We have selected the third algorithm \((ALG3)\), i.e. for

\[
\lambda = 0
\]
in which we use the maximum information of the estimated signal using higher order cumulants. In the TABLE VIII we represent the estimated impulse response parameters. From the TABLE VIII we conclude that the algorithm \((ALG3)\) gives a good impulse response parameters estimation, for
In this paper, we have proposed a family of algorithms based on third and fourth order cumulants. These algorithms are used for the estimation of parameters of non-minimum phase channel. The results show the performance of all the proposed algorithms mainly for (ALG3). The proposed algorithms can be used for all channel (minimum phase or non-minimum phase). Therefore, these algorithms will be used for modeling the internet traffic. It is important to know that we can use all family of random PAM input (i.e.: PAM (2), PAM (4), PAM (8)). The current work is aimed to show the performance of the proposed algorithms to a practical channel such as BRAN. In order to minimize the influence of the bias cumulants estimator, we consider in the following Table (TABLE IX) the influence of noise and for a data input N = 1024. The influence of noise is not very important, this influence is due, principally, to the use of cumulants biased estimator.

In the following figure (Fig. 13), we represent the estimation of the magnitude and phase of the channel impulse response for different SNR and for a data input N = 1024.

![Fig. 13. Estimated magnitude and phase of the second channel impulse response, using the ALG3 algorithm, when the data input is N = 1024 and for different SNR.](image)

In order to minimize the influence of the bias cumulants estimator, we consider in the following Table (TABLE IX) the influence of noise and for a data input N = 2048. The simulation results are illustrated for different SNR.

The TABLE IX demonstrate a light improvement of channel impulse response parameters estimation, especially on the variance estimation -no more fluctuation comparing to the TABLE VIII- and a small MSE.

In Fig.14 so below, we represent the estimation of the magnitude and phase of the third channel in the case of input data length N = 2048.

The Fig. 14 prove that the ALG3 gives a very good estimation for phase response, the estimated phase are closed to the true ones, and an important estimation on the magnitude estimation. To conclude, the proposed algorithms are able to estimate the phase and magnitude of the non minimum phase channel impulse response in very noisy environments, this is due to the cumulants properties such as: the cumulants of the Gaussian noise are zeros.

### IV. CONCLUSION

In this paper, we have proposed a family of algorithms based on third and fourth order cumulants. These algorithms are used for the estimation of parameters of non-minimum phase channel. The results show the performance of all the proposed algorithms mainly for (ALG3). The proposed algorithms can be used for all channel (minimum phase or non-minimum phase). Therefore, these algorithms will be used for modeling the internet traffic. It is important to know that we can use all family of random PAM input (i.e.: PAM (2), PAM (4), PAM (8)). The current work is aimed to show the performance of the proposed algorithms to a practical channel such as BRAN A and BRAN E used in mobile communication.

### APPENDIX A

**PROOF OF THE EQUATION (10)**

From the equation (9)

\[ \epsilon H (\omega_2 + \omega_3) S_{13}(\omega_1, \omega_2, \omega_3) \]

\[ = H (\omega_2) H (\omega_3) S_{13}(\omega_1, \omega_2 + \omega_3) \]

(24)
If we take the inverse Fourier Transform of the above equation (24) we obtain the following equation

\[
\sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} \sum_{l=-\infty}^{+\infty} \sum_{k=-\infty}^{+\infty} C_{3q}(n, l) e^{-jn\omega_1} e^{-j(\omega_2 + \omega_3)}
\times \left( h(m) e^{-j(m+\omega_2)} h(k) e^{-(j+k)\omega_3} \right)
= \epsilon \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} \sum_{l=-\infty}^{+\infty} \sum_{k=-\infty}^{+\infty} h(m) h(t_2 - t_1 + m) C_{3q}(n, t_1 - m)
\times \left( e^{-j(m+\omega_2)} e^{-(j+t_2)\omega_3} \right)

\times \left( e^{-(j+t_1)\omega_2} e^{-(j+t_2)\omega_3} \right)
\]

so, we have obtained the equation (10)

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REFERENCES


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