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# Impulse Response Identification of Minimum and Non Minimum Phase Channels

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### *Abstract*

*In this work we propose an algorithm based on third order cumulants for identification of the linear system (Finite Impulse Response (FIR)) with Minimum Phase (MP), and Non Minimum Phase (NMP) excited by non-Gaussian sequences, independent identically distributed (i.i.d). The proposed algorithm, for different signal to noise ratios (SNR) and for different sample sizes, is compared to the Zhang method for 50 Monte-Carlo runs. The simulation results show that the proposed algorithm is more accurate than the Zhang method, despite in high noise environment and weak sample sizes.*

***Keywords:*** *Higher Order Cumulants; FIR systems; Identification; NMP and MP channels*

## 1. Introduction

The interest in higher order cumulants (HOC) or higher order statistics (HOS) is permanently growing in the last years. Principally finite impulse response system identification based on HOC of system output has received more attention [1, 2, 3]. In the literature we have important results [6], established that blind identification of finite impulse response (FIR) single-input single-output (SISO) communication channels is possible only from the output second order statistics (AutoCorrelation Function ACF and power spectrum) of the observed sequences [9]. But these approaches are sufficient only to identify Gaussian processes with minimal phase. However, in several applications, the observed signals are non Gaussian and can be considered as the output of linear system excited by non Gaussian distribution input or a non linear system excited by Gaussian distribution input. Moreover, the system to be identified has no minimum phase and is contaminated by a Gaussian noise where the autocorrelation function ACF does not allow identifying the system correctly. To overcome these problems, another approach was proposed by several authors [2, 7, 9]. This approach allows the resolution of the insoluble problems using the second order statistics.

However, identification of linear time-invariant (LTI) systems with only output measurements is very important in many signal processing areas such as seismic deconvolution, channel equalization (in communications), radar, sonar, oceanography, speech signal processing, and image processing [4, 2]. In this paper, only the linear algebra solutions are considered because they have simpler computation and are free of the problems of local extremes that often occur in the optimization solutions [7].

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In this paper, we will consider a NMP and MP channel excited by non Gaussian distribution input, for different signal to noise ratio (SNR) and for different size data input. The method proposed in this paper is based on third order cumulants exploiting only *(q+1)* equations to estimate q unknown parameters. In order to evaluate the proposed algorithm, we compared it to the Zhang one. The results show the performance of the proposed algorithm for all data input in noisy environment.

## 2. Problem Statement

The output of a FIR channel, excited by an unobservable input sequences, i.i.d. zero-mean symbols with unit energy, across a selective channel with memory q and additive noise (Figure 1). The output time series is described by the following equation

$$r(k) = h_q x(k) + n(k) \quad (1)$$

Where $\{x(i)\}$ is the input sequence, $\{h(k)\}$ is the impulse response coefficients, q is the order of FIR system, $\{y(k)\}$ is the output of system and $\{n(k)\}$ is the noise sequence.

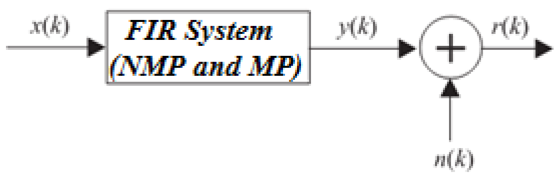


**Figure 1. Channel model**

The completely blind channel identification problem is to estimate $h_q$ (impulse response parameters) based only on the received signal $r(k)$ and without any knowledge of the energy of the transmitted data, $x(k)$, nor the energy of noise.
The output channel is given by the following equation:

In noise free case:

$$y(k) = \sum_{i=1}^{q} x(i) h_q(k-i) \quad (2)$$

In presence of noise:

$$r(k) = y(k) + n(k) \quad (3)$$

The principal assumptions can be presented as follows:

- The input sequence $\{x(i)\}$ is independent and identically distributed (i.i.d) zero mean, the variance is $\sigma_x^2$, and non Gaussian.
- The system is causal and truncated, i.e. $h(i) = 0$ for $i < 0$ and $i > q$ , and where $h(0) = 1$.
- The measurement noise sequence $\{n(k)\}$ is assumed to be zero mean, (i.i.d), Gaussian and independent of $\{x(k)\}$ with unknown variance.

 

## 3. Proposed Algorithm: Alg3ZS

The $m^{th}$ order cumulants of the $\{y(n)\}$ can be expressed as a function of impulse response coefficients $\{h(i)\}$ as follows [3, 5, 11]:

$$C_{my}(t_1, \dots, t_{m-1}) = \gamma_{mx} \sum_{i=0}^{q} h(i)h(i+t_1)\dots h(i+t_{m-1}) \qquad (4)$$

Where $\gamma_{mx}$ represents the $m^{th}$ order cumulants of the excitation signal $\{x(i)\}$ at origin.

If $m = 3$, Eq. (4) yield to

$$C_{3y}(t_1, t_2) = \gamma_{3x} \sum_{i=0}^{q} h(i)h(i+t_1)\, h(i+t_2) \qquad (5)$$

The same, if $m = 2$, Eq. (4) becomes

$$C_{2y}(t) = \gamma_{2x} \sum_{i=0}^{q} h(i)h(i+t) \qquad (6)$$

The Fourier transforms of the $2^{nd}$ and $3^{rd}$ order cumulants are given respectively by the following equations [7, 10]:

$$S_{2y}(\omega) = TF\{C_{2y}(t)\} = \gamma_{2x} \sum_{i=0}^{q} \sum_{t=-\infty}^{+\infty} h(i)h(i+t)\exp(-j\omega t) = \gamma_{2x} H(-\omega)H(\omega) \qquad (7)$$

With

$$H(\omega) = \sum_{i=0}^{+\infty} h(i)\exp(-j\omega t)$$

$$S_{3y}(\omega_1, \omega_2) = TF\{C_{3y}(t_1, t_2)\} = H(-\omega_1 - \omega_2)H(\omega_1)H(\omega_2) \qquad (8)$$

If we suppose that $\omega = (\omega_1 + \omega_2)$, Eq. (7) becomes

$$S_{2y}(\omega_1 + \omega_2) = \gamma_{2x} H(-\omega_1 - \omega_2)H(\omega_1 + \omega_2) \qquad (9)$$

Then, from Eqs. (8) and (9) we obtain the following equation

$$S_{3y}(\omega_1, \omega_2)H(\omega_1 + \omega_2) = \mu H(\omega_1)H(\omega_2)S_{2y}(\omega_1 + \omega_2) \qquad (10)$$

With $\mu = \frac{\gamma_{3x}}{\gamma_{2x}}$

The inverse Fourier transform of Eq. (10) demonstrates that the 3rd order cumulants, the autocorrelation function (ACF) and the impulse response channel parameters are combined by the following equation

$$\sum_{i=0}^{q} C_{3y}(t_1 - i, t_2 - i)h(i) = \mu \sum_{i=0}^{q} h(i)h(t_2 - t_1 + i)\, C_{2y}(t_1 - i) \qquad (11)$$

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

If we suppose that $t_1 = 2q$ the Eq. (11) becomes:

$$\sum_{i=0}^{q} C_{3y}(2q - i, t_2 - i)h(i) = \mu h(q)h(t_2 - q)\, C_{2y}(q) \qquad (12)$$

Else, if we suppose that $t_2 = 2q$, Eq. (11) will become

$$C_{3y}(q,q)h(q) = \mu h^2(q)C_{2y}(q) \qquad (13)$$

Using Eqs. (11) and (12) we obtain the following relation

$$\sum_{i=0}^{q} C_{3y}(2q - i, t_2 - i)h(i) = C_{3y}(q,q)\, h(t_2 - q) \qquad (14)$$

Else, if we suppose that the system is causal, i.e., $h(i) = 0$ if $i < 0$. So, for $t_2 = q, \ldots, 2q$, the system of Eq. (13) can be written in matrix form as

$$\begin{pmatrix} C_{3y}(2q-1, q-1) & \cdots & C_{3y}(q,0) \\ C_{3y}(2q-1, q) - \alpha & \cdots & C_{3y}(q,1) \\ \vdots & \ddots & \vdots \\ C_{3y}(2q-1, 2q-1) & \cdots & C_{3y}(q,q) - \alpha \end{pmatrix} \times \begin{pmatrix} h(1) \\ \vdots \\ h(i) \\ \vdots \\ h(q) \end{pmatrix} = \begin{pmatrix} \alpha - C_{3y}(2q,q) \\ -C_{3y}(2q, q+1) \\ \vdots \\ -C_{3y}(2q, 2q) \end{pmatrix} \qquad (15)$$

Where $\alpha = C_{3y}(q,q)$

Or in more compact form, the Eq. (15) can be written as follows:

$$Mh_q = d \qquad (16)$$

 

Where M is the matrix of size $(p+1) \times (p)$ elements, $h_q$ is a column vector constituted by the unknown impulse response parameters $h(k): k = 1, \ldots, p$ and d is a column vector of size $(p+1)$ as indicated in the Eq. (15).

The least squares (LS) solution of the system of Eq. (16), permits blindly identification of the parameters $h(k)$ and without any information of the input selective channel. So, the solution will be written under the following form

$$\hat{h} = \left(M^T M\right)^{-1} M^T d \tag{17}$$

## 4. Zhang Algorithm

Zhang *et al.* [3, 12] developed an equation based on the cumulants of order n, given by:

$$\sum_{i=0}^{q} h(i)\, C_{ny}^{n-1}(i-t, q, \ldots, 0) = C_{ny}(t, 0, \ldots, 0) C_{ny}^{n-3}(q, \ldots, 0) C_{ny}(q, q, \ldots, 0) \tag{18}$$

For $n = 4$, from the equation (18), we obtain the following equation:

$$\sum_{i=0}^{q} h(i)\, C_{4y}^{3}(i-t, q, 0) = C_{4y}(t, 0, 0) C_{4y}(q, 0, 0) C_{4y}(q, q, 0) \tag{19}$$

For $t = -q, -q+1, \ldots, q$.

Then, the Eq (19) can be written as follows:

$$M h_q = d \tag{20}$$

Where *M* is the matrix of size $(2q+1) \times (q)$ elements, $h_q$ is a column vector constituted by the unknown impulse response parameters $h(k): k = 1, \ldots, q$ and d is a column vector of size $(2q+1)$.

The least squares (LS) solution of the system of Eq. (20), permits blindly identification of the parameters $h(k)$ and without any information of the input selective channel. So, the solution will be written under the following form

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

## 5. Simulation Results

In order to evaluate the performance of the proposed algorithm, we consider a Non-Minimum and Minimum phase, channels in which the order is known. The channel output was corrupted by an Additive White Gaussian Noise (AWGN) for different sample sizes and for 50 Monte Carlo runs.

### 5.1. First channel

We consider the channel described by the model FIR-MP(2), given by the following equations:

$y(k) = e(k) - 0.86\, e(k-1) + 0.74\, e(k-2)$, in noise free case.

$r(k) = y(k) + n(k)$, in presence of Gaussian noise.

Where the signal to-noise-ratio (SNR) is defined by

$$SNR = 10 \log \left( \frac{\sigma_y^2(k)}{\sigma_w^2(k)} \right) \quad (22)$$

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

$$MSE = \frac{1}{q} \sum_{i=1}^{q} \left( \frac{h(i) - \hat{h}(i)}{h(i)} \right)^2 \quad (23)$$

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

The following figure (Figure 2) shows that the zeros are inside of the unit circle (*i.e.*, minimum phase channel).

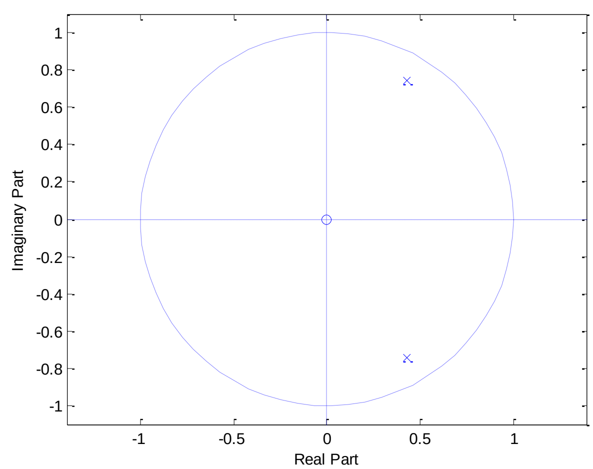


**Figure 2. The zeros of first channel**

The true parameters are $h(1) = -0.860$, $h(2) = 0.740$

The results of simulation are shown in the Tables 1 and 2 for different values of sample sizes and different values of signal to noise ratio (SNR).

 

**Table 1. Estimated parameters of the first channel of SNR=30dB (50 monte carlo runs)**

| $N$ | Algo | $\hat{h}(1) \pm \sigma$ | $\hat{h}(2) \pm \sigma$ | $MSE$ |
|---|---|---|---|---|
| 300 | Alg3ZS | $-0.8565 \pm 0.1300$ | $0.7892 \pm 0.1178$ | 0.0015 |
| | Zhang | $-0.4618 \pm 0.2827$ | $0.5927 \pm 0.3322$ | 0.0847 |
| 600 | Alg3ZS | $-0.8271 \pm 0.0980$ | $0.7452 \pm 0.0680$ | $5.034 \times 10^{-4}$ |
| | Zhang | $-0.6567 \pm 0.1333$ | $0.6811 \pm 0.1255$ | 0.0207 |
| 900 | Alg3ZS | $-0.8633 \pm 0.0924$ | $0.7496 \pm 0.0658$ | $6.1177 \times 10^{-5}$ |
| | Zhang | $-0.6800 \pm 0.1216$ | $0.6692 \pm 0.1043$ | 0.0177 |

From the simulation results, presented in Tables 1, we can conclude:

For the input data length N=300 (the sample are very small), the values of MSEs of the proposed algorithm are very small, than those obtained by the Zhang algorithm, this implies the true parameters are near the estimates parameters.

If we increase the data input (N=900) we can conclude that the proposed algorithm more precise and gives a very good estimation, than those obtained by the Zhang algorithm. Indeed, the value of MSEs of the proposed algorithm is lower than that obtain by Zhang algorithm 290 once. This is due to the complexity of the equations systems of for each algorithm (the proposed algorithm exploiting only *(q+1)* equations compared to the Zhang algorithm exploiting *(2q+1)*).

We observe that the value of the variance estimations obtained by the proposed algorithm is good, equal almost half the value of the variance estimations given by the Zhang algorithm.

**Table 2. Estimated parameters of first channel in noise case for different snr (50 monte carlo runs, N=1000)**

| $SNR$ | Algo | $\hat{h}(1) \pm \sigma$ | $\hat{h}(2) \pm \sigma$ | $MSE$ |
|---|---|---|---|---|
| 0dB | Alg3ZS | $-1.0305 \pm 0.1781$ | $0.7727 \pm 0.1407$ | 0.0137 |
| | Zhang | $-0.4997 \pm 0.4417$ | $0.6833 \pm 0.6186$ | 0.0605 |
| 10dB | Alg3ZS | $-0.8945 \pm 0.0868$ | $0.7600 \pm 0.0657$ | $7.7971 \times 10^{-4}$ |
| | Zhang | $-0.6720 \pm 0.2015$ | $0.6276 \pm 0.1257$ | 0.0236 |
| 20dB | Alg3ZS | $-0.8742 \pm 0.0726$ | $0.7361 \pm 0.0638$ | $9.9797 \times 10^{-5}$ |
| | Zhang | $-0.6700 \pm 0.1387$ | $0.6598 \pm 0.0925$ | 0.0202 |
| 30dB | Alg3ZS | $-0.8610 \pm 0.0794$ | $0.7487 \pm 0.0640$ | $4.6051 \times 10^{-5}$ |
| | Zhang | $-0.6839 \pm 0.1263$ | $0.6794 \pm 0.1269$ | 0.0162 |

 

The results (Table 2) permit to conclude that:

The proposed algorithm able to estimate the parameters of linear MP(2) model blindly with good precision, than those obtained by the Zhang algorithm, when the measured data are affected by an additive Gaussian noise, this be due to the fact that the proposed algorithm is based on the third order cumulants, which are zero for Gaussian process and non linear of the cumulants in Zhang algorithm.

In the case, when the power of Gaussian noise is small (for example SNR=20dB) well obtain a very good estimation of the parameters channel impulse response using the developed algorithm. Indeed, the value of MSEs of the proposed algorithm is lower than that obtain by Zhang algorithm 202.41 once.

The Figures 3 give a good idea about the precision of the proposed algorithm.

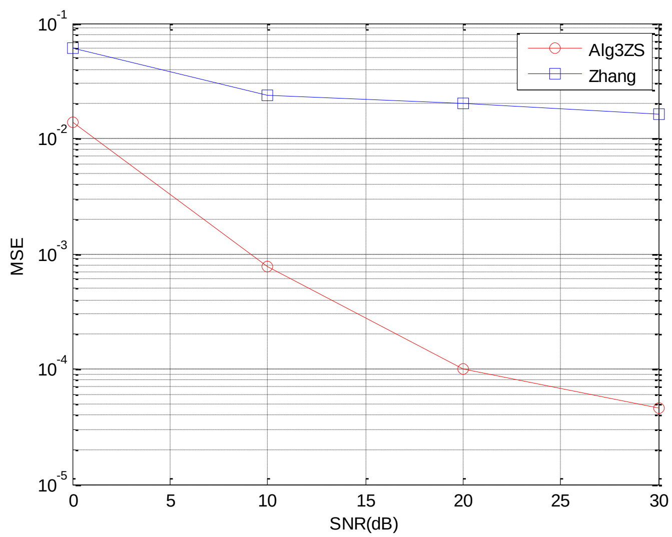


**Figure 3. Comparison of algorithms for first channel for N=1000**

In the following figure (Figure 4) we have presented the estimation of the magnitude and the phase of the impulse response using the proposed algorithm (Alg3ZS), compared to the Zhang algorithm. For data length N=900 (SNR =30dB); we remark that the phase estimation have the same form compared to the real one (Figure 4). The magnitude estimations corresponding to the data length N = 900, have the same allure comparatively to the true ones, than those obtained by the Zhang algorithm.

 

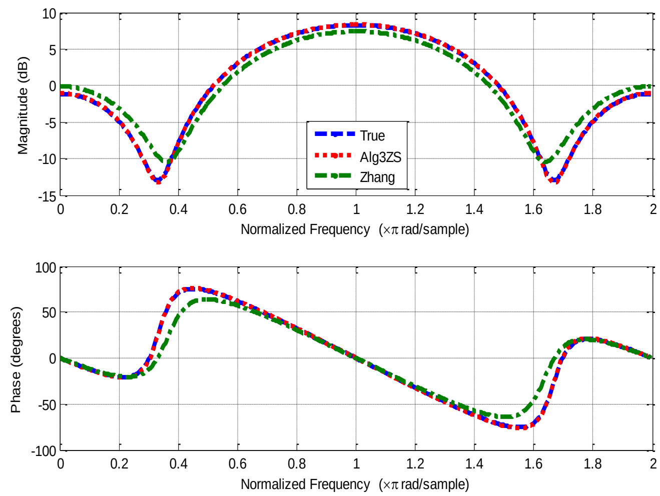


**Figure 4. Estimated magnitude and phase of Model 1, for N=900 and SNR =30dB**

### 5.2. 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:

$y(k) = e(k) - 1.083\, e(k-1) - 0.95\, e(k-2) + 0.95 e(k-3)$, in noise free case.

$r(k) = y(k) + n(k)$, in presence of Gaussian noise.

The following figure (Figure 5) shows that one of their zeros is outside of the unit circle (*i.e.*, non minimum phase channel).

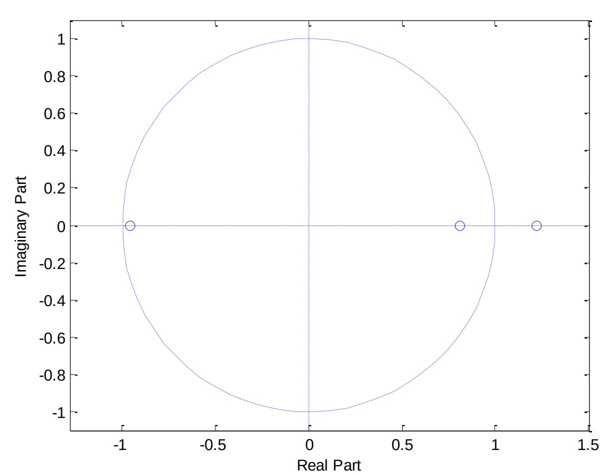


**Figure 5. The zeros of second channel**

The results of simulation are shown in the Tables 3 and 4 for different values of sample sizes and different values of signal to noise ratio (SNR).

The true parameters are $h(1) = -1.083$, $h(2) = -0.950$ and $h(3) = 0.950$

**Table 3. Estimated parameters of model 2 in noise case (SNR=30dB) for 50 monte carlo runs**

| N | Algo | $\hat{h}(1) \pm \sigma$ | $\hat{h}(2) \pm \sigma$ | $\hat{h}(3) \pm \sigma$ | *MSE* |
|---|---|---|---|---|---|
| 300 | Alg3ZS | $-1.0882 \pm 0.2076$ | $-0.8749 \pm 0.2252$ | $0.7815 \pm 0.1818$ | 0.0094 |
| | Zhang | $-0.2323 \pm 0.3379$ | $-0.0477 \pm 0.5121$ | $0.2687 \pm 0.5388$ | 0.5083 |
| 600 | Alg3Z3 | $-1.0135 \pm 0.1654$ | $-0.9549 \pm 0.1961$ | $0.9438 \pm 0.1811$ | 0.0010 |
| | Zhang | $-0.3780 \pm 0.5158$ | $-0.3204 \pm 0.9385$ | $0.3824 \pm 0.5548$ | 0.3050 |
| 900 | Alg3Z3 | $-1.1099 \pm 0.1251$ | $-0.9845 \pm 0.1420$ | $0.9488 \pm 0.1196$ | $4.8516 \times 10^{-4}$ |
| | Zhang | $-0.4461 \pm 0.4057$ | $-0.3631 \pm 0.4299$ | $0.5503 \pm 0.3193$ | 0.2261 |

**Table 4. Estimated parameters of model 2 in noise case for N=1000, different SNR and for 50 monte carlo runs**

| SNR | Algo | $\hat{h}(1) \pm \sigma$ | $\hat{h}(2) \pm \sigma$ | $\hat{h}(3) \pm \sigma$ | *MSE* |
|---|---|---|---|---|---|
| 0dB | Alg3ZS | $-1.3058 \pm 0.5034$ | $-0.9268 \pm 0.3507$ | $1.5004 \pm 0.5496$ | 0.0946 |
| | Zhang | $-0.2057 \pm 0.4004$ | $-0.0438 \pm 0.6794$ | $0.2901 \pm 0.6716$ | 0.5122 |
| 10dB | Alg3SZ | $-1.0753 \pm 0.1441$ | $-0.9276 \pm 0.1027$ | $0.9991 \pm 0.1372$ | $8.1800 \times 10^{-4}$ |
| | Zhang | $-0.5034 \pm 0.3463$ | $-0.1697 \pm 0.4419$ | $0.4545 \pm 0.2858$ | 0.3083 |
| 20dB | Alg3ZS | $-1.1246 \pm 0.1487$ | $-0.9440 \pm 0.1824$ | $0.9544 \pm 0.1409$ | $3.8351 \times 10^{-4}$ |
| | Zhang | $-0.5281 \pm 0.4072$ | $-0.3089 \pm 0.6009$ | $0.5507 \pm 0.3994$ | 0.2236 |
| 30dB | Alg3ZS | $-1.0667 \pm 0.1142$ | $-0.9752 \pm 0.1183$ | $0.9375 \pm 0.1249$ | $2.7545 \times 10^{-4}$ |
| | Zhang | $-0.5345 \pm 0.5384$ | $-0.4447 \pm 0.6033$ | $0.5566 \pm 0.3104$ | 0.1777 |

From the Table 3 and 4 we can conclude that:

The proposed algorithm gives a very good estimation compared to the Zhang algorithm (same if we increase system order on the parameters estimation), we observe the values of variance σ and MSE, for different input data length and for different signal to noise. To conclude, we observe that the system order on the parameters estimation have not the influence to the developed algorithm, but, had an influence on the Zhang algorithm. This is due to the complexity of the systems of equations for each algorithm, the proposed algorithm exploiting only *(q+1)* equations compared to the Zhang algorithm exploiting (2*q+1)*.

The following figure (figure 6) give a good idea about the precision of the proposed algorithm.

 

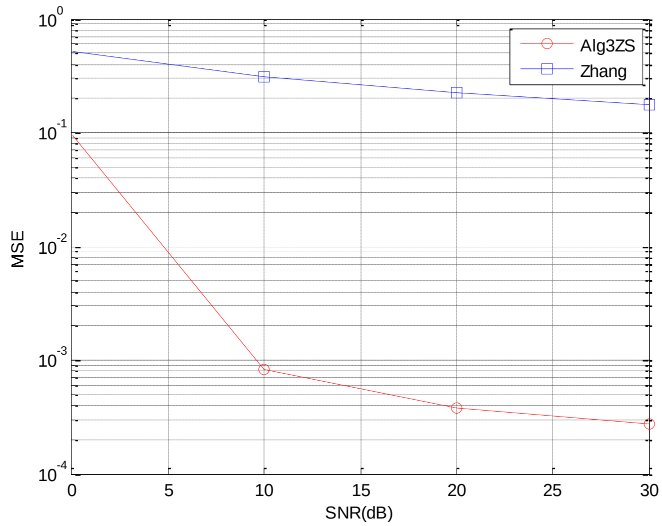


**Figure 6. Comparison of algorithms for second channel for N=1000**

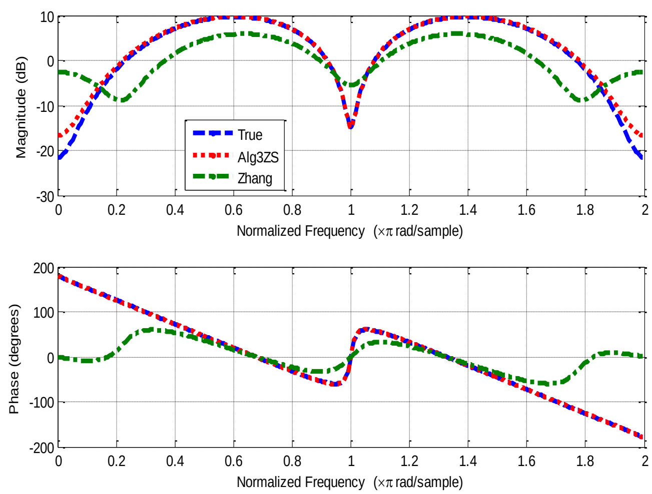


**Figure 7. Estimated magnitude and phase of Model 2, for N=900 and SNR =30dB**

The Figure 7 proof that the proposed algorithm (Alg3ZS) 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, compared to the Zhang algorithm. To conclude, the proposed algorithm is able to estimate the phase and magnitude of the non minimum phase channel impulse response in noisy environments.

## 6. Conclusion

In this paper, we have presented an algorithm based on third order cumulants. This algorithm are used for the estimation of parameters of minimum and non-minimum phase channels with a very good precision in noisy environment, same, in the case of small number of samples, compared with Zhang algorithm. In the future we will test the efficiency of the proposed algorithm for the identification of the mobile channel, especially MC-CDMA (Multi-Carrier Codes Division Multiple Access) systems.

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