Blind Identification Using Higher Order Statistics and Eigendecomposition

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Summary

In this paper we develop a new approach to identify noncausal AR models driven by non-Gaussian i.i.d input. Under a few moderate assumptions, we derive the necessary and sufficient conditions of rebuilding the parameters of the AR models from 2nd and higher order statistics. We show that the AR model parameters are directly related to the solution of an eigenproblem. Based on the result, we present a method of AR model identification, applying eigenvector computation. The unique solution of AR parameters is guaranteed up to sign and linear phase ambiguity. Model order determination is not crucial in the method. If the order is overestimated, several equivalent AR models with different linear phases will be obtained.

Keyword: Higher order statistics, Non-minimum phase, Blind identification, Noncausal AR model

1. Introduction

The blind identification of non-minimum phase systems has received extensive attention in recent years. Higher order statistics provide us a powerful tool to reconstruct non-minimum phase systems only from observing the output, if the systems are driven by non-Gaussian, independent, identically distributed (i.i.d) input. Many successful methods of identifying MA, AR and ARMA models have been developed based on higher order cumulants. Two excellent overviews can be found in [1][2].

The correlation based approach only solves the spectrally equivalent minimum phase systems because 2nd-order statistics do not carry complete phase information. For AR models, Yule-Walker equation is solvable only if the systems have causal impulse responses, i.e. they are minimum phase systems. To handle non-minimum phase, the systems are often considered as MA [4][5] or ARMA [8][7] models that have causal impulse responses. However it has been found very convenient to specify non-minimum phase processes as noncausal

AR models in certain applications such as spatial signal processing, astronomical data processing and blind equalization.

As pointed out in [2], the identification of non-minimum phase systems is classified into three categories: exhaustive search, nonlinear optimization, and linear algebraic solution. Since we are more interested in linear approach, the exhaustive search and optimization methods will not be taken into our consideration. For noncausal AR models, most methods essentially convert the problem to the related MA model identification [2][3][7][9]. For example in [3], the identification of noncausal AR models is studied, where an equivalent MA model is employed to make the normal equation solvable. Consequently the result is sensitive to the choice of the MA model order and may suffer greatly from the poles located near the unit circle. Other methods that essentially convert the problem to MA model identification can be found in [7].

In our study, we propose a linear approach of identifying noncausal AR models. First we present the conditions of uniquely determining AR parameters, using

both correlation lags and higher order cumulant samples. We find that the AR model coefficients are directly related with a typical eigenproblem. Based on the result, eigendecomposition is applied and the AR coefficients are obtained from the proper choice of the eigenvectors. Singular value decomposition(SVD) may also be used as a more general method. Order determination is not crucial in the method. The overestimated model order simply leads to linear phase ambiguity among the solutions yielded by the proposed algorithm. The method is valid when some poles are located near the unit circle. But it does suffer from the zeros near $|z| = 1$, because the data are not suitable to fit AR models in this situation.

The paper is organized as follow. In Section 2, the problem is formulated under some moderate constraint. An indirect form of the correlation function is introduced to cope with additive Gaussian noise. In Section 3, we give the proof of uniquely determining AR coefficients, and then present an algorithm of AR model identification, using eigenvalue analysis. The simulation results of this approach are demonstrated in Section 4.

2. Problem Formulation

(2.1) Blind identification Consider a linear system that has impulse response $h(t)$, the output of the system is given by

$$y(t) = \sum_{i=-\infty}^{\infty} h(t-i)x(i) \dots\dots\dots(1)$$

where the input $x(t)$ is a non-Gaussian i.i.d sequence with zero mean. Now the system is specified by an AR model as

$$H(z) = \frac{A}{\prod_{i=1}^p (1-u_i z) \prod_{i=1}^q (1-v_i z^{-1})} = \frac{1}{\sum_{i=-p}^q a(i)z^{-i}} \dots\dots\dots(2)$$

In the expression, we assume $|u_i| < 1$ and $|v_i| < 1$, so that $\prod_{i=1}^p (1-u_i z)$ is the maximum phase factor with anti-causal impulse response and $\prod_{i=1}^q (1-v_i z^{-1})$ is the minimum phase factor with causal response. In the time domain (2) is equivalent to

$$\sum_{i=-p}^q a(i)y(t-i) = x(t) \dots\dots\dots(3)$$

Thus the problem of blind identification is described as reconstructing the coefficient $\{a(i)\}$ from observing

$y(t)$ when $x(t)$ is not accessible. Since neither the linear phase (delay) nor the sign of $H(z)$ can be measured from $y(t)$, we formulate the problem in an alternative way.

For a given set of $\{a(i)\}_{i=-p}^q$, we define a residual function as

$$f(t) = \sum_{i=-p}^q a(i)h(t-i) \dots\dots\dots(4)$$

Here $\{a(i)\}$ will be considered as the solution of the AR model $H(z)$ if $f(t)$ has only one nonzero, i.e.

$$f(t) = \begin{cases} \pm 1 & \text{if } t = d \\ 0 & \text{otherwise} \end{cases} \dots\dots\dots(5)$$

where d is an arbitrary integer. If the model order is overdetermined, i.e. $a(-p) = 0$ or $a(q) = 0$, another AR model whose parameters are specified by shifting $\{a(i)\}_{i=-p}^q$ also satisfies (5). In this case the two models are viewed identically from the perspective of blind identification. In other words, $H(z)$ and $z^r H(z)$ are equivalent in our study. The sign ambiguity in (5) does not make much sense and can be ignored.

The idea behind the formulation is that we use an FIR filter that has coefficients $\{a(i)\}$ to compensate $H(z)$. The the identification of the unknown system $H(z)$ is achieved if a delayed version of $x(t)$ is obtained from the filter.

(2.2) Higher order statistics The explicit definition of higher order cumulants is given in [2]. For the zero-mean stochastic process $y(t)$, the 3rd-order cumulant takes identical form to its 3rd-order moment, i.e.

$$C_{3y}(\tau_1, \tau_2) = E\{y(t)y(t+\tau_1)y(t+\tau_2)\} \dots\dots\dots(6)$$

In the case of the linear system $H(z)$ driven by $x(t)$, it is easy to show that

$$C_{3y}(\tau_1, \tau_2) = \gamma_{3x} \sum_{i=-\infty}^{\infty} h(i)h(i+\tau_1)h(i+\tau_2) \dots\dots\dots(7)$$

where $\gamma_{3x} = E\{x^3(t)\}$ is the skewness of $x(t)$.

In our study we will use 3rd-order cumulant for simplicity because the obtained result can be easily extended to 4th-order cumulant.

An important property of higher order cumulants is that they are insensitive to additive Gaussian noise^[2]

The fact that relation (7) remains valid even if $y(t)$ is corrupted by Gaussian noise allows us to ignore the presence of Gaussian noise theoretically, if the estimates are based on higher order statistics. But in our method, both 3rd-order cumulant $C_{3y}(\tau_1, \tau_2)$ and correlation $r(\tau) = E[y(t)y(t+\tau)]$ are used. To cope with

Gaussian noise, we can make use of an indirect form of correlation function given by

$$r(\tau) = \frac{\sigma_x^2}{\gamma_{3x} \sum_{n=-\infty}^{\infty} h(n)} \sum_{n=-\infty}^{\infty} C_{3y}(\tau, n) \\ \approx \alpha \sum_{n=-L}^L C_{3y}(\tau, n)$$

where L must be large enough and α is a constant since $\sum_{n=-\infty}^{\infty} h(n) \neq 0$ for AR models. We need not worry about the unknown constant α too much because its effect is similar to that of unknown γ_{3x} .

Therefore with higher order cumulant the following assumptions are made reasonable for further analysis:

1. The AR model is free from additive noise;
2. $x(t)$ is non-Gaussian i.i.d and $E\{x(t)\} = 0$, $\gamma_{3x} \neq 0$; furthermore we assume $E\{x^2(t)\} = 1$ instead of $h(0) = 1$.
3. $H(z)$ does not have zeros and poles on the unit circle.

3. Identifying Noncausal AR Models

The blind identification of non-minimum phase AR models is described as finding the coefficients $\{a(i)\}$ so that the residual function $f(t)$ defined in (4) has only one nonzero. Now we present the following theorem.

Theorem 1 For a given coefficient set $\{a(i)\}_{i=-p}^q$, the residual function $f(t)$ has only one nonzero if and only if the following conditions are satisfied for all m and some k ,

$$\sum_{n=-p}^q C_{3y}(m-k, m-n)a(n) = \lambda_k \sum_{n=-p}^q r(m-n)a(n) \quad (8)$$

$$\lambda_k = \gamma_{3x} \sum_{n=-p}^q r(k-n)a(n) \neq 0 \quad (9)$$

$$\sum_{n=-p}^q \sum_{l=-p}^q r(l-n)a(n)a(l) = 1 \quad (10)$$

Proof: First we prove that (8)-(10) can be obtained if $\{a(i)\}$ are the true AR coefficients.

Since $\{a(i)\}$ are the true coefficients, relation (3) holds. Multiply (3) by $y(t-m)$ and take average, we have

$$\sum_{n=-p}^q r(m-n)a(n) = h(-m) \quad (11)$$

This relation can be viewed as Yule-Walker equation for noncausal AR models. Similarly, multiply (3) by $y(t-k)y(t-m)$ and recall (7), we get

$$\sum_{n=-p}^q C_{3y}(m-k, m-n)a(n) = \gamma_{3x}h(-k)h(-m) \quad (12)$$

Let $\lambda_k = \gamma_{3x}h(-k)$ and use (11), we obtain (8) and (9). It is not difficult to demonstrate that for the AR model (2), $h(t)$ can not be equal to zero for all $t \in [-p, q]$. Thus there exists $-k \in [-p, q]$ so that $\lambda_k = \gamma_{3x}h(-k) \neq 0$. Relation (10) is obvious because

$$\sum_{n=-p}^q \sum_{l=-p}^q r(l-n)a(n)a(l) = E\{x^2(t)\} = 1$$

Up to now we proved that (8)-(10) are necessary conditions if $\{a(i)\}$ are the true AR parameters. Now we will show they are also sufficient for recovering the AR model.

Let us examine the residual function $f(t)$ defined in (4) when $\{a(i)\}$ satisfies (8)-(10). From $r(\tau) = \sum_{i=-\infty}^{\infty} h(i)h(i+\tau)$, it can be found that (9) and (10) are equivalent to

$$\lambda_k = \gamma_{3x} \sum_{i=-\infty}^{\infty} h(i-k)f(i) \neq 0 \quad (13)$$

and

$$\sum_{i=-\infty}^{\infty} f^2(i) = 1 \quad (14)$$

respectively. Also we get

$$\sum_{n=-p}^q r(m-n)a(n) = \sum_{i=-\infty}^{\infty} h(i-m)f(i) \quad (15)$$

Substitute (7) and (15) into (8), we can rewrite (8) as

$$\sum_{i=-\infty}^{\infty} h(i-m)[\gamma_{3x}h(i-k) - \lambda_k]f(i) = 0 \quad (16)$$

Since (16) holds for all m and $H(z)$ does not have zeros on $|z|=1$, it must be

$$[\gamma_{3x}h(i-k) - \lambda_k]f(i) = 0 \quad \text{for all } i \quad (17)$$

Take the sum over index i and use (13), we find

$$\lambda_k[1 - \sum_{i=-\infty}^{\infty} f(i)] = 0 \quad (18)$$

Since $\lambda_k \neq 0$, it must be

$$\sum_{i=-\infty}^{\infty} f(i) = 1 \quad (19)$$

The function $f(t)$ satisfies both (14) and (19) if and only if it has one nonzero, or equivalently $\{a(i)\}$ represents the true AR model up to a linear phase. The above deduction is valid if $a(-p)$ or $a(q)$ is equal to zero. Thus the theorem holds for all the equivalent AR models if the model order is overdetermined. $\square$

Now we present an algorithm based on the theorem. In fact the model order (p, q) is unknown. But it is

possible for us to choose $P \geq p$ and $Q \geq q$. Let $m = -P, \dots, Q$, we rewrite (8)-(10) in the matrix forms of

$$C_k \mathbf{a} = \lambda_k \mathbf{r} \mathbf{a} \dots\dots\dots (20)$$

$$\lambda_k = \gamma_{3x} \mathbf{I}_k^T \mathbf{r} \mathbf{a} \neq 0 \dots\dots\dots (21)$$

$$\mathbf{a}^T \mathbf{r} \mathbf{a} = 1 \dots\dots\dots (22)$$

where the entries of matrices and vectors are

$$\begin{aligned} C_k(m, n) &= C_{3y}(m-k, m-n) \quad m, n = -P, \dots, Q \\ \mathbf{r}(m, n) &= r(m-n) \\ \mathbf{a}^T &= (a(-P), a(-P+1), \dots, a(Q)) \\ \mathbf{I}_k^T &= (0, \dots, 1, \dots, 0) \quad (1 \text{ at } k\text{th}) \end{aligned}$$

It can be observed that C_k and $\mathbf{r}$ are symmetric and $\mathbf{r}$ is always positive definite. Therefore Cholesky decomposition can be applied to $\mathbf{r}$, i.e. the correlation matrix is decomposed as $\mathbf{r} = \mathbf{L} \mathbf{L}^T$, where $\mathbf{L}$ is a lower triangular matrix and $(\mathbf{L}^T)^{-1} = (\mathbf{L}^{-1})^T$. Thus the conditions (20)-(22) are rewritten as

$$P_k \mathbf{v} = \lambda_k \mathbf{v} \dots\dots\dots (23)$$

$$\lambda_k = \gamma_{3x} \mathbf{I}_k^T \mathbf{L} \mathbf{v} \neq 0 \dots\dots\dots (24)$$

$$\mathbf{v}^T \mathbf{v} = 1 \dots\dots\dots (25)$$

where $P_k = \mathbf{L}^{-1} C_k (\mathbf{L}^{-1})^T$ is also symmetric and $\mathbf{v} = \mathbf{L}^T \mathbf{a}$.

It is clear to see that $\mathbf{v}$ is the normalized eigenvector belonging to the eigenvalue λ_k . From eigenvalue decomposition we can obtain $P + Q + 1$ eigenvectors $\{\mathbf{v}_k^{(i)}\}_{i=0}^{P+Q}$, then we have to decide which one among them associates the true solution of the AR model. If γ_{3x} is known, we can do that by testing which one satisfies (24). Unfortunately, (24) will hold only when the true statistics of $y(t)$ are given. In practice we can only choose the eigenvalue-eigenvector pair which is most likely to fit the relation. For this purpose, we define a criterion as

$$\varepsilon = \frac{|\lambda^{(i)} - \gamma_{3x} \mathbf{I}_k^T \mathbf{L} \mathbf{v}_k^{(i)}|}{|\lambda^{(i)}| + |\gamma_{3x} \mathbf{I}_k^T \mathbf{L} \mathbf{v}_k^{(i)}|}$$

Among $P + Q + 1$ eigenvectors we chose the one which minimizes ε as the desired solution. The criterion does not guarantee the correct choice especially when the estimated cumulant is unreliable. However we find that it gives reasonably good results if more than 1000 samples are used to estimate the cumulants. (e.g. thirteen incorrect choices were made in 500 Monte Carlo runs when 1024 samples were used; and six failures were found in case of 4096 data samples.)

If γ_{3x} is unknown, the proper choice of eigenvectors can be made by comparing the $P + Q + 1$ possible solutions. When the model order is overestimated, i.e. $P > p$

Figure 1 The region where the 3rd-order cumulant samples are used in identification

or $Q > q$, totally $(P + Q) - (p + q) + 1$ desired eigenvectors that represent the same number of equivalent AR models will be obtained from the eigenvalue decomposition. The equivalent AR models are distinguishable, because they must be all similar to each other up to a shifted index. From the simulations it was found that the correct solutions can be determined if more 1000 samples are available to estimate the cumulants.

The free parameter k shifts the region where cumulant samples are used by the algorithm (see Fig.1). It is reasonable to let $k = 0$. Theoretically, the algorithm may fail if $h(-k) = 0$. By overestimating the model order, we can hardly expect that it happens for all the equivalent AR models unless $h(t)$ has many sequential zeros in $t \in [-p, q]$, where (p, q) is the true mode order. For AR models, the impulse responses rarely have many sequential zeros in the origin.

If the input $x(t)$ admits a symmetric distribution, we have to use 4th-order cumulant, because the odd order cumulants are all identical to zero. The definition of 4th-order cumulant in our study is given by

$$\begin{aligned} C_{4y}(\tau_1, \tau_2) &= E[y^2(t)y(t+\tau_1)y(t+\tau_2)] \\ &\quad - 2r(\tau_1)r(\tau_2) - r(0)r(\tau_1 - \tau_2) \end{aligned}$$

The condition for identifying noncausal AR models can be extended to the 4th-order case as follows

$$\begin{aligned} \sum_{n=-p}^q C_{4y}(k-m, k-n)a(n) &= \lambda_k \sum_{n=-p}^q r(m-n)a(n) \\ \lambda_k &= \gamma_{4x} \left(\sum_{n=-p}^q r(k-n)a(n) \right)^2 \neq 0 \\ \sum_{n=-p}^q \sum_{l=-p}^q r(l-n)a(n)a(l) &= 1 \end{aligned}$$

where $\gamma_{4x} = E[x^4(t)] - 3\{E[x^2(t)]\}^2$. The same algorithm can be applied to the formulations.

4. Simulations

In the simulations we use the presented algorithm to identify the noncausal AR model specified by

$$H_1(z) = \frac{1}{(1 + 0.3z)(1 - 0.6z^{-1} + 0.25z^{-2})}$$

$$= \frac{1}{0.3z + 0.820 - 0.525z^{-1} + 0.25z^{-2}}$$

Since $H_1(z)$ is not physically realizable, the truncated impulse response $h_{tr}(t)$ is employed to approximate $h(t)$. i.e.

$$h_{tr}(t) = \begin{cases} h(t) & -L_1 \leq t \leq L_2 \\ 0 & \text{otherwise} \end{cases}$$

where L_1 and L_2 are chosen as large enough so that the algorithm yields almost perfect identification of $H_1(z)$ when the true statistics calculated from $h_{tr}(t)$ are given.

The zero-mean exponentially distributed i.i.d input is generated with $\sigma_x = 1$ and $\gamma_{3x} = 2$. The correlation and 3rd-order cumulant are estimated from the output samples with data segment length of $N = 1024$ and $N = 4096$ respectively. The order of the AR model is predetermined as $P = Q = 2$. Table 1 shows the mean values and standard deviations of estimated AR coefficients from 500 Monte Carlo runs. Two solutions are obtained. The second one is approximately a shifted version of the true AR model.

Table 1. Two versions of estimated AR parameters

True parameter	$N = 1024$ (mean±std.dev)	
	Solution I	Solution II
$a(-2) = 0.000$	-0.003 ± 0.0488	0.300 ± 0.0572
$a(-1) = 0.300$	0.292 ± 0.0434	0.812 ± 0.0530
$a(0) = 0.820$	0.802 ± 0.0947	-0.514 ± 0.0402
$a(1) = -0.525$	-0.522 ± 0.1464	0.250 ± 0.0346
$a(2) = 0.250$	0.259 ± 0.0824	0.002 ± 0.0494
true parameter	$N = 4096$ (mean±std.dev)	
	Solution I	Solution II
$a(-2) = 0.000$	0.000 ± 0.0197	0.302 ± 0.0275
$a(-1) = 0.300$	0.300 ± 0.0175	0.819 ± 0.0261
$a(0) = 0.820$	0.818 ± 0.0215	-0.524 ± 0.0207
$a(1) = -0.525$	-0.520 ± 0.0640	0.252 ± 0.0200
$a(2) = 0.250$	0.248 ± 0.0320	0.000 ± 0.0263

The next simulation result in Fig.2 shows the locations of estimated poles of the noncausal AR model given by

$$H_2(z) = \frac{1}{(1 + 1.6z + 0.8z^2)(1 - 0.6z^{-1} + 0.25z^{-2})}$$

where the model order is predetermined as $P = Q = 3$. Because the order is overestimated, two extra poles

Figure 2 The estimated poles of $H_2(z)$

associated with linear phase factors are introduced and they are located far away from the circle.

5. Conclusions

We have presented an approach of identifying non-causal AR model, using 2nd and higher order statistics. Elegant results have been demonstrated by simulations. Generally, the performance of blind identification using higher order statistics highly depends upon the efficient use of all significant cumulant samples. However the methods in [3][9] exclude the cumulant samples lying in the rectangular regions that are nearly centered on the origin, and then heavily overdetermined equation systems are required in order to obtain acceptable estimates. Fig 1 illustrates the region where the 3rd-order cumulant makes contribution to estimate the AR parameters in our method. This region contains all the most significant samples of 3rd-order cumulant. Thus it can be expected that the algorithm yield better results. Moreover, the order determination often becomes a crucial issue when converting the AR identification to related MA problems. Imprecise system orders may seriously ruin the solutions [3][4]. In our method the overestimated order simply leads to equivalent solutions with different linear phases. One may argue that the problem of order determination is converted to that of eigenvector selection. However choosing the proper eigenvector is the final step in the algorithm and does not affect the performance of the estimation. It is superior to those algorithms in which overestimated model order may completely destroy all the computations. Finally, the unique solution is an important issue concerned with using higher order statistics and the unique identification is guaranteed in our method.

Now we briefly discuss the effect of additive Gaussian noise. This issue is also related to whether 2nd order statistics should be used. Generally the noise affects the estimates of both 2nd and higher order statistics. Noisy data will introduce bias to 2nd order statistics,

but higher order statistics can be unbiased. However the deviation of 2nd order statistics are usually much less. That could be one of the reasons why our simulation results show quite small deviation. Thus there is a trade off between the bias and deviation of the estimation. In case of high signal to noise ratio, 2nd order statistics definitely benefit the estimation. If one is particularly concerned with the biased estimation in lower signal to noise ratio situation, the proposed indirect form of correlation can be applied. In this case relatively large a number of data samples are required in order to obtain reliable estimates of $r(\tau)$ from $C_{3y}(\tau_1, \tau_2)$.

The proposed method is particularly suitable for blind equalization if an adaptive algorithm is developed. This will come to its turn as our further studies. The method can also be easily applied to non-minimum phase MA models, as long as the MA models do not have zeros at $|z| = 1$ because this approach essentially requires the systems be (noncausally) reversible.

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