A Comparative Study of Speech Modeling Methods

A. MADDI [1], A. GUESSOUM [2], D. BERKANI [3]

[1], [2]: Department of Electronic, University of Blida,
Road of Soumaa, PB 270, Blida,
ALGERIA

[3]: Department of Electrical Engineering, National Polytechnic School of El Harrach,
Road of Hassan Badi, PB 182, Algiers,
ALGERIA

Abstract: - In this paper, we present two stochastic methods, to identify the parameters of a physical process with unbiased estimates based on whitening error of prediction. These methods incorporate a recursive procedure that makes successive corrections in determining, a linear mathematical model, based on the data of observation, to represent the system considered. The ARMA model is a typical example. Several tests of simulation were carried out to show the abilities of the least mean squares algorithm LMS and stochastic Newton algorithm. An application is provided then to identify the parameters of AR model corresponding to the speech signal.

Key-Words: - Modeling, Identification, Unbiased estimator, Newton method, Gradient method, Speech signal.

1 Introduction

The majority techniques of identification were developed for the identification of the models of dynamic systems, when the parameters are, either unknown, or vary in time. Thus the method of parametric identification consists to determine, in a recursive way, a linear mathematical model, based on the available data of observation, to represent the system considered.

The proposed structural identification method can incorporate as much as possible structural information known a priori into the structural identification process to improve the identification accuracy. To avoid the practical difficulty often associated with unbiased estimator measurement, two methods are proposed.

The Least Mean Square algorithm, introduced by Widrow and Hoff in 1959 is an adaptive algorithm, which uses a gradient method based on a step decent. LMS algorithm uses the estimates of the gradient vector from the available data and incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error.

2 Gradient Method Formulation

Let us consider a quadratic functional J(x). The method of the gradient is given by:

$$\hat{x}(t) = \hat{x}(t-1) + \mu\left[-\frac{\partial J(x)}{\partial(x)}\right]_{x=\hat{x}(t-1)} \quad (1)$$

Where μ: the step size parameter.

Autoregressive moving average model noted ARMA (n, m) is defined by the following equation [1]:

$$\sum_{i=0}^{n} a_i \ y\ (t-i) = \sum_{i=0}^{m} b_i \ u\ (t-i) + e(t) \quad (2)$$

Where $a_0 = 1$, $b_0 = 0$

u (t), y (t): Input and output signals

e (t): White noise.

As we can represent this last equation in a matrix form:

$$y(t) = \theta^T \varphi(t) + e(t) \tag{3}$$

Let us pose these notations [5]:

$$\theta^T = [a_1 \quad a_2 \quad \dots \quad a_n \ , \ b_1 \quad b_2 \quad \dots \quad b_m]$$
$$\varphi^T(t) = [-y(t-1)\dots-y(t-n)\ , u(t-1)\dots u(t-m) \quad]$$

With

θ^T : Parameters vector to be identified

φ^T : Data vector.

The identification of the vector parameters θ within the meaning of the average quadratic error is:

$$J(\theta) = \frac{1}{2} E\left[e^2(t)\right] \tag{4}$$

With

$E[\,.\,]$ Indicate the expectation.

However the error of prediction is defined as is followed:

$$e(t) = y(t) - \hat{\theta}^T(t-1)\varphi(t) \tag{5}$$

The minimization of the criterion $J(\theta)$ consists to find the optimum; it means to find the point where the derivative is cancelled, so we write:

$$\left[\frac{\partial J(\theta)}{\partial \theta}\right]^T = -E\{\varphi(t)[y(t) - \varphi^T(t)\theta\}\Big|_{\theta=\hat{\theta}} = 0 \tag{6}$$

From where the algorithm of the gradient will be written:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + \mu\left[-\frac{\partial J(\theta)}{\partial \theta}\right]^T \Big|_{\theta=\hat{\theta}(t-1)} \tag{7}$$

By replacing Eq.6 in Eq.7, we obtain:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + \mu E\{\varphi(t)[y(t) - \varphi^T(t)\hat{\theta}(t-1)]\} \tag{8}$$

This algorithm is called: Algorithm of the deterministic gradient, in general the stochastic ones of $(\varphi(t), y(t))$ are unknown. However, we replace the average value by the instantaneous value, and in this case, the algorithm is called by the algorithm of the stochastic gradient.

And we write:

$$e(t) = y(t) - \hat{\theta}^T(t-1)\varphi(t) \tag{9}$$
$$\hat{\theta}(t) = \hat{\theta}(t-1) + \mu\ \varphi(t)\, e(t) \tag{10}$$

With μ represent the step of adaptation.

So the convergence and stability of the LMS algorithm [1], [8] must to verify:

$$0 < \mu \le \frac{2}{\lambda_{\max}}$$

Or

$\lambda_{\max}$: The greatest eigen value of $E\{\varphi(t)\varphi^T(t)\}$ matrix

3 Stochastic Newton Method

The stochastic algorithm of Newton is indicated for the identification of the parameters. It makes it possible to minimize the error in a more effective way. This algorithm is used in several applications of the signal processing. Thus we can write the general formula [6]:

$$x(t) = x(t-1) - \frac{f[x(t-1)]}{f'[x(t-1)]} \tag{11}$$

Let consider a quadratic functional $J(x)$ and to find the optimal by the stochastic Newton method is given by:

$$Min\ J(x) \Rightarrow \frac{\partial J(x)}{\partial x}\Big|_{x=\hat{x}} = 0 \tag{12}$$

We put:

$$f(x) = \frac{\partial J(x)}{\partial x} = J'(x) \tag{13}$$

And

$$f'(x) = \frac{\partial^2 J(x)}{\partial x^2} = J''(x) \tag{14}$$

By replacing in the equation (Eq.11), we write:

$$x(t) = x(t-1) - \frac{J'[x(t-1)]}{J''[x(t-1)]} \tag{15}$$

This last equation is called: scalar Newton algorithm.

The minimization of the criterion $J(\theta)$ described in Eq.4 consists to find the optimum; it means to find the point where the derivative is cancelled, so we write:

$$\left[\frac{\partial J(\theta)}{\partial\theta}\right]^T = -E\{\varphi(t)[y(t)-\varphi^T(t)\theta\}\Big|_{\theta=\hat{\theta}} = 0 \quad (16)$$

$$\left[\frac{\partial^2 J(\theta)}{\partial\theta^2}\right] = E\{\varphi(t)\varphi^T(t)\} = R \quad (17)$$

The use of the stochastic procedure of approximation, the Eq.15 will be written:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + \gamma_1(t)R^{-1}(t)\varphi(t)\left(y(t)-\varphi^T(t)\hat{\theta}(t-1)\right) \quad (18)$$

Where

$\gamma_1(t)$: Scalar function.

If R is unknown, then R can be estimated by:

$$E\left(\varphi(t)\varphi^T(t)\right) = R \Rightarrow E\left(\varphi(t)\varphi^T(t) - R\right) = 0 \quad (19)$$

By applying the procedure of approximation, we write:

$$R(t) = R(t-1) + \gamma_2(t)\left(\varphi(t)\varphi^T(t) - R(t-1)\right) \quad (20)$$

From the equations Eq.18, and Eq.20, the algorithm of stochastic Newton can be summarized as:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + \gamma_1(t)R^{-1}(t)\varphi(t)e(t) \quad (21)$$

$$R(t) = R(t-1) + \gamma_2(t)\left(\varphi(t)\varphi^T(t) - R(t-1)\right) \quad (22)$$

$$e(t) = y(t) - \hat{\theta}^T(t-1)\varphi(t) \quad (23)$$

4 Example of Simulation

Let us consider a stable system [5], [9] with minimal phase of order 2, having the following transfer function:

$$H_1(z) = z^{-1}\frac{1+0.5z^{-1}}{1+0.3z^{-1}+0.8z^{-2}}$$

With

$a_1 = 0.3$, $a_2 = 0.8$, $b_1 = 1$, $b_2 = 0.5$

The results obtained by algorithm LMS and Newton algorithm are illustrated on tables Tab.1, Tab.2, Tab. 3 and Tab.4.

N	Estimated Parameters				SDV
	$\hat{a}_1$	$\hat{a}_2$	$\hat{b}_1$	$\hat{b}_2$	
256*2	0.2962	0.7912	0.9738	0.4363	0.0272
256*4	0.2716	0.7975	0.9612	0.4641	0.0165
256*10	0.3123	0.7987	0.9959	0.4864	0.0107
256*20	0.2971	0.8041	0.9932	0.4845	0.0082
256*50	0.3023	0.7963	0.9867	0.4985	0.0067

Tab.1: Effect of the samples N using LMS algorithm (μ=0.012, $\sigma_v^2 = 0.25$)

μ	Estimated Parameters				SDV
	$\hat{a}_1$	$\hat{a}_2$	$\hat{b}_1$	$\hat{b}_2$	
0.0123	0.2990	0.7998	1.0001	0.4985	0.0007
0.0244	0.3003	0.8005	1.0022	0.5013	0.0008
0.0498	0.2995	0.8018	0.9972	0.4970	0.0023
0.1304	0.3054	0.7985	0.9997	0.4974	0.0035

Tab.2: Effect of factor μ using LMS algorithm (N = 256*4, $\sigma_v^2 = 0.01$)

N	Estimated Parameters				SDV
	$\hat{a}_1$	$\hat{a}_2$	$\hat{b}_1$	$\hat{b}_2$	
256*2	0.2896	0.8068	0.9726	0.4506	0.0240
256*4	0.2865	0.7920	1.0175	0.4943	0.0137
256*10	0.3029	0.8016	0.9892	0.4904	0.0072
256*20	0.2915	0.7986	1.0046	0.4915	0.0063
256*50	0.3017	0.8033	0.9981	0.5055	0.0031

Tab.3: Effect of the samples N using NS algorithm ($\sigma_v^2 = 0.25$)

σ_v^2	Estimated Parameters				SDV
	$\hat{a}_1$	$\hat{a}_2$	$\hat{b}_1$	$\hat{b}_2$	
1.00	0.2931	0.8071	0.9875	0.5164	0.0132
0.25	0.3086	0.8028	1.0068	0.5150	0.0051
0.04	0.3054	0.7984	1.0063	0.5051	0.0037
0.01	0.3008	0.8011	0.9981	0.5019	0.0016

Tab.4: Effect of the variance using NS algorithm, (N=256*10)

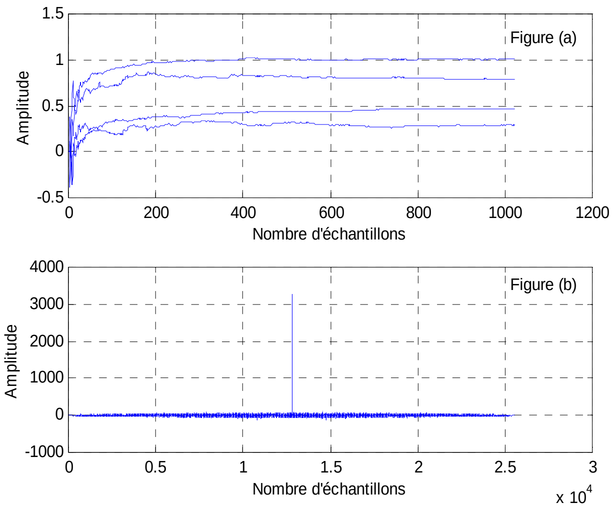

Fig.1: (a) - Evolution of the parameters ($N = 256*4, \sigma_v^2 = 0.25$)

(b) - Autocorrelation of error prediction

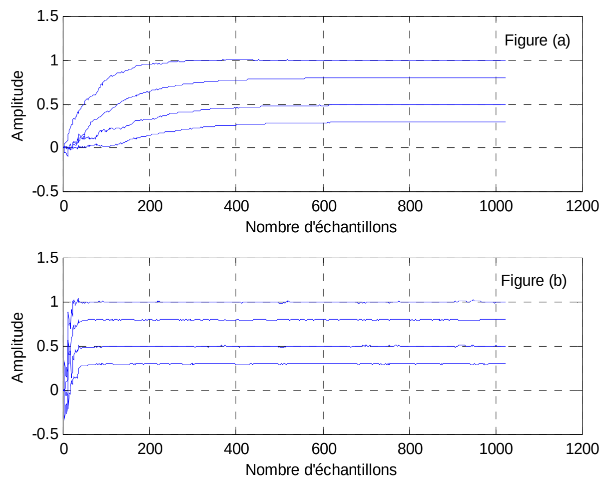

Fig.2: (a) – Slow convergence ($\mu = 0.0123$)

(b) – Fast convergence ($\mu = 0.1304$)

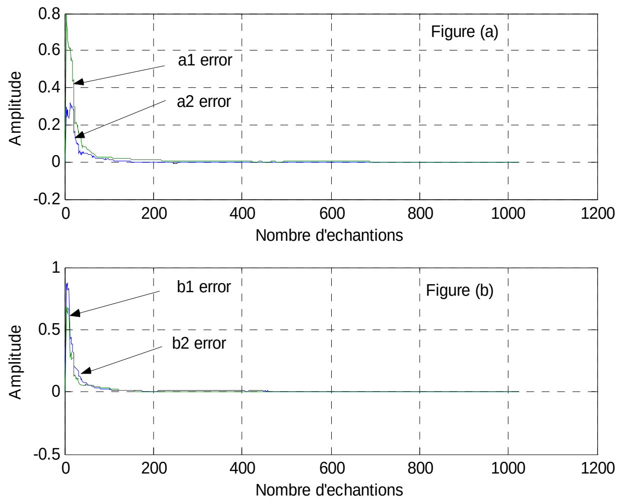

Fig.3: Error identification using stochastic Newton algorithm

(a) - Error identification of parameters a_1 and a_2

(b) - Error identification of parameters b_1 and b_2

5 Comparative Study of Stochastic Method

In this paragraph, we present an explanatory and comparative table of each estimator steady to a stable physical system.

According to table 1 and table 3, we notice that the algorithms applied give us an unbiased estimate with the order of 1%, but stochastic Newton algorithm remain always most powerful knowing that its bias can go until the 0.1%.

Bias Estimators	Algorithms used		
	Matlab Function	Stochastic Newton	Stochastic Gradient
$E\left[\hat{a}_1 - 0.3\right]$	0.0018	0.0102	0.0177
$E\left[\hat{a}_2 - 0.8\right]$	0.0048	0.0008	0.0176
$E\left[\hat{b}_1 - 1.0\right]$	0.0054	-0.0031	0.0187
$E\left[\hat{b}_2 - 0.5\right]$	-0.0034	0.0056	0.0397

Tab.5: Comparative bias of the estimators

6 Interpretation Results

It is noticed, according to the results obtained that when the number of samples N increases or the variance of the additive noise, the standard deviation SDV of error prediction still decreases until the estimated parameters are closer with actual values. Thus the position of the zeros of the system does not influence on the error of estimation parameters, on the other hand the position of the poles must be located inside the unit circle to ensure the stability of the system, and the convergence of the algorithms.

7 Application to the Speech Signal

In this part, an example application of clean speech signal is provided to show the abilities of the SN algorithm. The data file of speech signal used here is named (mf3.dat), which corresponds to the following sentence Fig.4: « un loup s'est jeté immédiatement sur la petite chèvre » [5]. The speech signal generally takes the structure of AR model [10] with the order varies between 8 and 12.

$$y(n)=\sum_{i=1}^{p}a_i y(n-i)+v(n)$$

Where

p: represent AR order.

v: noise sequence.

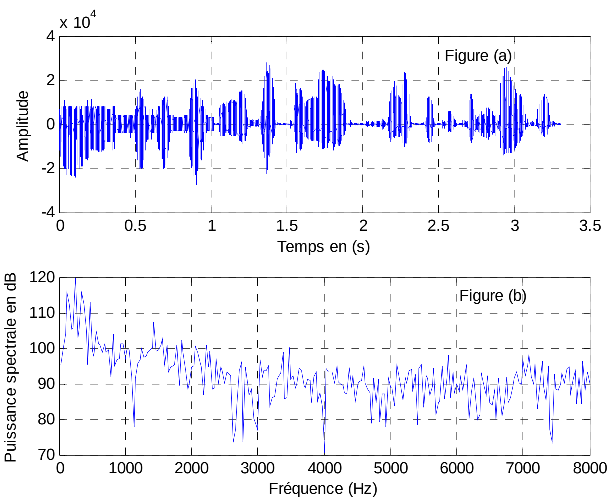

Fig.4: (a) - speech signal waveform
(b) - power spectrum magnitude of a partial waveform

AR Model Parameters	LMS Algorithm	Newton Algorithm	Matlab Function
a_0	1.0000	1.0000	1.0000
a_1	-0.6754	-0.7757	-0.7738
a_2	-0.1916	-0.1305	-0.1313
a_3	0.0371	0.0379	0.0371
a_4	0.0111	-0.0566	-0.0550
a_5	-0.0220	-0.0055	-0.0075
a_6	0.0718	0.0348	0.0364
a_7	-0.0169	0.0066	0.0038
a_8	-0.0366	-0.0587	-0.0589
a_9	0.0288	0.0498	0.0531
a_{10}	0.0708	0.0635	0.0619

Tab.6: Estimated parameters of AR model

8 Conclusion

The stochastic Newton algorithm is most commonly used adaptive algorithm because of its simplicity and a reasonable performance. Since it is an iterative algorithm it can be used in a highly time-varying signal environment. It has a stable and robust performance against different signal conditions. However it may not have a really fast convergence speed [5], [9] compared to other algorithms like the RLS and LMS.

We showed that the identification of the parameters of a speech signal using algorithm SN gives good results, but these performances are degraded quickly in the presence of disturbance compared to the algorithm of recursive least squares RLS [11]. In the representation time frequency of the disturbed signal, some of the parameters of the speech signal are masked by the noise [7]. In such a case the parameters of the clean speech cannot be estimated starting from the disturbed signal and are thus regarded as dubious.

References:

[1] Murant Kunt, Maurice Bellanger, Frederic de Coulon, « Techniques modernes de traitement numérique des signaux », collection électricité, traitement de l'information, Volume1, Année 1991.

[2] D. Arzelier, « Introduction à l'étude des processus stochastiques et au filtrage optimal », version 2, INSA, 1998.

[3] M.D.Srinath,P.k. Rajasekaran,R.Viswanathan, « Introduction to statistical signal processing with applications ». Prentice hall editor 1996.

[4] T.Chonavel, « Statistical signal processing, Modelling and estimation », Springer, January 2002.

[5] A. Maddi, A. Guessoum, D. Berkani, « Application the recursive extended least squares method for modelling a speech signal », Second International Symposium on Communications, Control and Signal Processing, ISCCSP'06, March 13-15, 2006 Marrakech, Morocco, In CD-ROM Proceedings.

[6] R.Ben Abdennour, P.Borne, « Identification et commande numérique des procédés industriels », April 2001.

[7] P.Renevey, « Speech recognition in noisy conditions using missing feature approach », thesis of doctorate, federal polytechnic school of Lausanne, 2000.

[8] D. Landau, « Identification et commande des systèmes, Hermes, Paris, 1998.

[9] A. Maddi, A. Guessoum, D. Berkani, « Using Recursive Least Squares Estimator for Modelling a Speech Signal », The 6th WSEAS International Conference on Signal, Speech and Image Processing SSIP '06 Lisbon, Portugal, September 22-24, 2006.

[10] O. Siohan, « Reconnaissance automatique de la parole continue en environnement bruité: Application à des modèles stochastiques de trajectoires », thesis of doctorate, university Henri Poincaré, Nancy I, September 1995.

[11] A. Maddi, A. Guessoum, D. Berkani, « Noisy Speech Modelling Using Recursive Extended Least Squares Method »,WSEAS TRANSACTIONS on SIGNAL PROCESSING Issue 9, Volume 2, September 2006 ISSN 1790-5022, pages: 1268-1274.