TEXTURE CHARACTERIZATION USING 2D CUMULANT-BASED LATTICE ADAPTIVE FILTERING

Mounir Sayadi[2], *Véronique Buzenac-Settineri*[3] *and Mohamed Najim* [1]

[1] Equipe Signal & Image, ENSERB, BP 99, F33402 Talence, France
Email : najim@goelette.tsi.u-bordeaux.fr

[2] ESSTT, 5 Av Taha Heussien, 1008, Tunis, Tunisia

[3] LESTER-UBS, 2 rue Le Coat St Haouen, 56100 Lorient, France

ABSTRACT:

In this work, we take into account the non gaussian properties of textures and we propose a new approach for their characterization based on bidimensional adaptive modelisation using higher order statistics. The 2D-OLRIV (Bidimensionnal Overdetermined Lattice Recursive Instrumental Variable) algorithm allows accurate texture model estimation. Sets of 2D-AR coefficients obtained from the 2D reflection coefficients of the lattice model are used to characterize the texture model. This algorithm has the advantage of yielding non biased estimates of the 2D-AR model even when the texture image is disturbed by gaussian noise. A multilayer neural network deals with these coefficients in order to classify different textures. In order to evaluate the performance of this approach, classification sensitivity is evaluated on a set of eight different textures. This characterization approach gives very promising results.

1. INTRODUCTION

Bidimensionnal autoregressive models (2D-AR) have now proved to be very useful in many applications in image processing, such as restoration, adaptive noise cancelling, coding [2] ... In texture classification, 2D-AR models are also of great help and have been used by several researchers (see [1] [7] for example). Indeed, the 2D-AR parameters are used for the characterization of the texture, and can then be the input of a classifier. As an alternative, reflexion coefficients (PARCOR) can replace the 2D-AR parameters at the input of the classifier, as is done in [1].

2D-AR coefficients are obtained by solving the bidimensionnal normal equations, which can be done either by inverting the autocorrelation matrix or with adaptive algorithms such as 2D-LMS (Least Mean Square), or 2D-RLS (Recursive Least Square). Fast versions of the 2D-RLS algorithm can also be used. Among them, we can mention the 2D Lattice Fast RLS [9], which has the main advantage of yielding the PARCOR coefficients used in [1].

However, all these methods are based only on second order statistics, and provide biased AR parameters (or PARCOR) when images are disturbed by noise, leading to wrong classification when dealing with textures. In this paper, we propose to use cumulant-based estimation of the 2D-AR parameters in order to classify textures. Indeed, as the cumulants of gaussian processes are zero [11], it is possible to obtain non-biased estimates of the 2D-AR parameters of noisy textures, provided that the noise is gaussian and that only high order cumulants are used. Note that cumulants have other properties, such as phase sensitivity, which are not taken into consideration here, but which are used by some authors [5][6][7][12].

In our approach, the 2D-AR parameters are obtained with the 2D-OLRIV (Overdetermined Lattice Recursive Instrumental Variable) algorithm [2], which solves the bidimensionnal high order normal equations. This algorithm can be seen both as a cumulant-based version of the 2D-Fast Lattice RLS [9], and as a non-immediate extention to the bidimensionnal case of Swami's double lattice [13]. The 2D-OLRIV algorithm is described in part 2.

Part 3 deals with the classification procedure. A multilayer neural network classify the textures from the 2D-AR parameters previously obtained. This network is trained with a backpropagation algorithm [8]. We give results obtained by training the network with a part of the available data, and then testing it with the remaining part.

2. THE BIDIMENSIONNAL CUMULANT-BASED ADAPTIVE ALGORITHM

In this part, we give a description of the 2D-OLRIV algorithm. As its derivation is too long, we will only recall the main points. A complete derivation is given in [2].

2.1. Cumulants of 2D processes

Let us first recall a few definitions about cumulants of bidimensionnal processes. All the material is taken from [14], where the reader can find a complete description of the HOS of bidimensionnal processes and their properties.

For a zero-mean bidimensional process $y(i,j)$, the second and third order cumulants are defined as follows:

$$c_{2y}(m_1,m_2)=E\{y(i,j)y(i-m_1,j-m_2)\}$$

$$c_{3y}(m_1,m_2;n_1,n_2)=E\{y(i,j)y(i-m_1,j-m_2)y(i-n_1,j-n_2)\}$$

The 2D processes cumulants verify the same properties as 1D processes.

Suppose now that $y(i,j)$ can be represented as a 2D-AR model of order (p_1,p_2) with quarter plan support:

$$\sum_{(i,j)=(0,0)}^{(p_1,p_2)} a_{i,j}\,y(n_1-i,n_2-j)=x(n_1,n_2) \qquad \text{with } a_{0,0}=1$$

$x(i,j)$ is the input noise of the model supposed to be white, zero-mean, non-gaussian and non-symmetric.

The 2D-AR parameters verify the cumulant-based normal equations:

$$\left.\begin{array}{l}\displaystyle\sum_{(i,j)=(0,0)}^{(p_1,p_2)} a_{i,j}c_{3y}(m_1,m_2;n_1-i,n_2-j)=0 \\ for(m_1,m_2;n_1,n_2)\neq(0,0;0,0) \\ \displaystyle\sum_{(i,j)=(0,0)}^{(p_1,p_2)} a_{i,j}c_{3y}(0,0;-i,-j)=\gamma_{3x}\end{array}\right\} \qquad (1)$$

where γ_{3x} is the skewness of the input noise $x(i,j)$. By taking different lags in (1), one can build linear systems whose resolution yields the 2D-AR parameters.

2.2. Analogy between multichannel and bidimensionnal modelisation

In [15], it has been shown that the autocorrelation matrix of an 2D-AR model could be seen as the autocorrelation matrix of a multichannel process. We have shown in [2] that if we choose some specific lags (m_1, m_2; n_1, n_2) in equations (1), the same kind of analogy can be done with cumulant matrices. As this analogy is needed for the derivation of the 2D-OLRIV algorithm, we recall it in the sequel.

By collecting equations (1) for all the lags contained in

$$M(p_1,p_2)=\begin{Bmatrix} n_1=0,1,\cdots,p_1;m_1=n_1,n_1-1,\cdots,n_1-p_1 \\ m_2=0;n_2=0,1,\cdots,p_2\end{Bmatrix}$$

the following system is obtained:

$$\begin{bmatrix} \mathbf{C}(0) & \mathbf{C}(-1) & \cdots & \mathbf{C}(-p_2) \\ \mathbf{C}(1) & \mathbf{C}(0) & & \mathbf{C}(-p_2+1) \\ \vdots & & \ddots & \vdots \\ \mathbf{C}(p_2) & \cdots & \cdots & \mathbf{C}(0)\end{bmatrix}\begin{bmatrix}\underline{a}_0\\ \underline{a}_1\\ \vdots \\ \underline{a}_{p_2}\end{bmatrix}=\begin{bmatrix}\underline{\gamma}\\ \underline{0}\\ \vdots\\ \underline{0}\end{bmatrix} \qquad (2)$$

with: $\underline{a}_j=\begin{bmatrix}a_{0j} & a_{1j} & \cdots & a_{p_1 j}\end{bmatrix}^T$, $\underline{\gamma}=[\gamma_{3x}\ \ 0\ \ \cdots\ \ 0]^T$,

and

$$\mathbf{C}(k)=\left[\begin{array}{cccc} c_{3y}(0,0;0,k) & c_{3y}(0,0;-1,k,) & \cdots & c_{3y}(0,0;-p_1,k) \\ c_{3y}(-1,0;0,k) & \cdots & \cdots & c_{3y}(-1,0;-p_1,k) \\ \vdots & & & \vdots \\ c_{3y}(-p_1,0;0,k) & \cdots & \cdots & c_{3y}(-p_1,0;-p_1,k) \\ \hdashline c_{3y}(0,0;k,1) & & & \vdots \\ \vdots & & & \vdots \\ \hdashline c_{3y}(0,0;p_1,k) & c_{3y}(0,0;p_1-1,k) & \cdots & c_{3y}(0,0;0,k) \\ c_{3y}(-1,0;p_1,k) & \cdots & \cdots & c_{3y}(-1,0;0,k) \\ \vdots & & & \vdots \\ c_{3y}(-p_1,0;p_1,k) & \cdots & \cdots & c_{3y}(-p_1,0;0,k)\end{array}\right]$$

It must be noted that the cumulant matrix involved in (2) is block-Toeplitz, but the blocks are not square. Then (2) is not a square system.

On the other hand, consider a multichannel process $\underline{Y}(n)$ which is supposed to be the output of an AR model of order p with parameters A_i ($A_0=I$). A cumulant-based normal equations system can be built:

$$\begin{bmatrix} \overline{\mathbf{C}}_{3Y}(0,0) & \overline{\mathbf{C}}_{3Y}(0,-1) & \cdots & \overline{\mathbf{C}}_{3Y}(0,-p_2) \\ \overline{\mathbf{C}}_{3Y}(0,1) & \overline{\mathbf{C}}_{3Y}(0,0) & & \overline{\mathbf{C}}_{3Y}(0,-p_2+1) \\ \vdots & & \ddots & \vdots \\ \overline{\mathbf{C}}_{3Y}(0,p_2) & \cdots & \cdots & \overline{\mathbf{C}}_{3Y}(0,0)\end{bmatrix}\begin{bmatrix}\mathbf{A}_0\\ \mathbf{A}_1\\ \vdots\\ \mathbf{A}_{p_2}\end{bmatrix}=\begin{bmatrix}\overline{\Gamma}_{3X}\\ \mathbf{0}\\ \vdots\\ \mathbf{0}\end{bmatrix} \qquad (3)$$

where

$$\overline{\mathbf{C}}_{3Y}(i,j)=unvec(\underline{c}_{3Y}(i,j))$$
$$=E\{\underline{Y}^T(n)\otimes\underline{Y}^T(n+i)\otimes\underline{Y}(n+j)\}$$

$\otimes$ is the Kronecker product.

$\overline{\Gamma}_{3X}=unvec(\Gamma_{3X})$, Γ_{3X} : skewness of the multichannel input noise $\underline{X}(n)$.

Once again, the cumulant matrix involved in (3) is rectangular-block Toeplitz.

Suppose:

$\underline{Y}^T(n)=\begin{bmatrix}y(m,n) & y(m-1,n) & \cdots & y(m-p_1,n)\end{bmatrix}$.

Then $\mathbf{C}(k)=\overline{\mathbf{C}}_{3Y}(0,k)$, and the bidimensional cumulant matrix is the same as the multichannel cumulant matrix.

Therefore, if

$$\underline{\gamma} = \overline{\Gamma}_{3X}\, \underline{a}_0 \quad (4)$$

then $\underline{a}_i = \mathbf{A}_i\, \underline{a}_0 \; i = 1,2,\ldots,p_2 \quad (5)$

Then the 2D-AR parameters can be obtained by the following procedure:
1- Solve the multichannel cumulant-based normal equations for A_i $i = 1$ to p_2.
2- Solve equations (4) for $\underline{a}_0$.
3- Deduce $\underline{a}_i$ from $\underline{a}_0$ and A_i, for $i = 1$ to p_2.

2.3. The 2D-OLRIV algorithm

The bidimensionnal Overdetermined Lattice Recursive Instrumental Variable (2D-OLRIV) is based on the previous analogy. Here are its main steps:

1. First, the cylindric connexity is introduced: we suppose that for a point at the end of a row, the next one is the beginning of the following row. This allows us to define a linear index n such that: $n = n_1 * K + n_2$, where K is the number of columns of the image.
2. Then we define the multichannel process $\underline{Y}(n)$ so that:
$y_1(n) = y(n_1, n_2)$
$y_i(n) = y(n_1 - (i-1), n_2) = y_1(n - (i-1)K), i = 1,\ldots,p_1 + 1$
3. To obtain directly the 2D-AR parameters from the multichannel prediction parameters, we must perform the forward prediction of a multichannel process with same support as the 2D process. Therefore we consider the forward prediction of the following vector:
$\underline{Y}_F^T(n) = \left[y_2(n+1) \;\; \cdots \;\; y_{p_1+1}(n+1) \;\; y_1(n)\right]$
along the quarter plane support.
4. Then we perform the multichannel prediction of Y_F with the OLRIV algorithm [3]. OLRIV is a fast algorithm solving overdetermined block-Toeplitz systems, where the blocks are allowed to have more lines than columns. It uses an instrumental variable which can have more components that the original process to take into consideration the rectangular character of the blocks. It lies on a double lattice structure, one lattice predicting the original process and the other the instrumental process. In the context of the present application, we choose the instrumental process as $\underline{Z}(n) = \underline{Y}(n) \otimes \underline{Y}(n)$ so that the solved system is (2).
5. Then we deduce the 2D-AR parameters from the multichannel forward prediction coefficients.

The reader is referred to [2] for more details.

3. RESULTS OF TEXTURE CLASSIFICATION WITH A NEURAL NETWORK

To test the proposed characterization approach, we take 8 textures images of 256×256 pixels (see Figure 1) from the Brodatz Album [4]. A total set of 320 images of 64×64 pixels (40 images of 64×64 pixels for each texture) are randomly chosen from the 8 initial texture images. For each image, we estimate a set of 2D-AR coefficients with the 2D-OLRIV algorithm presented below. The order of the 2D-AR model is chosen equal to (2,2).

To classify the different textures, the eight estimated 2D-AR coefficients are used as input vectors to a multilayer neural network, trained using the gradient descent back-propagation algorithm [8] with 75% of the available texture images (240 images of 64×64 pixels, i.e. 30 images for each texture) and tested with 25% of the available texture images (80 images of 64×64 pixels, i.e. 10 images for each texture). The training examples are grouped into sets of n examples for each texture. The network weights are updated upon each presentation of a feature vector. The order of presentation of the training examples is random within each set. At each iteration (total training vectors presented), 75 % of the training examples for each texture are presented. Every four iterations, the set of training examples is changed. For each texture, the classification sensitivity is the ratio of the number of positive tests to the total number of tests.

In order to determine the optimum neural network to achieve the best classification, we carried out several experiments using different architectures, that is different numbers of layers and different numbers of neurons in each layer. Both three binary coded outputs and eight uncoded outputs were investigated. The best result obtained is a network with 8 inputs, two hidden layers each containing 10 neurons, and three binary coded outputs. We use a training coefficient of 0.5. The momentum is 0.9 and the initial random values of the weights are set between -1 and 1. The threshold value of the sigmoïd is 0.2. There are n=6 parameter vectors in the training set for each texture.

For the noiseless case, a classification sensitivity of 100 % is obtained, that is all the images of the eight different textures are well classified. When the texture images are corrupted by an additive zero mean gaussian noise with SNR of 3 dB, (see Figure 2) and after 20000 training iterations, we obtain a high classification sensitivity of 96.25 %. In table 1, we present the classification sensitivity for each texture. The bubbles and grass textures are the most difficult to be classified. As a comparison, note that in [1], where only second order statistics were used, the classification robustness could not be assured for SNR lower than 5dB.

Texture	positive test	negative test	sensitivity
wood	10	0	100 %
bubbles	8	2	80 %
canvas	10	0	100 %
ivy	10	0	100 %
water	10	0	100 %
grass	9	1	90 %
wool	10	0	100 %
sand	10	0	100 %
Eight textures	77	3	96.25 %

Table 1: The classification sensitivity for each texture (SNR=3dB)

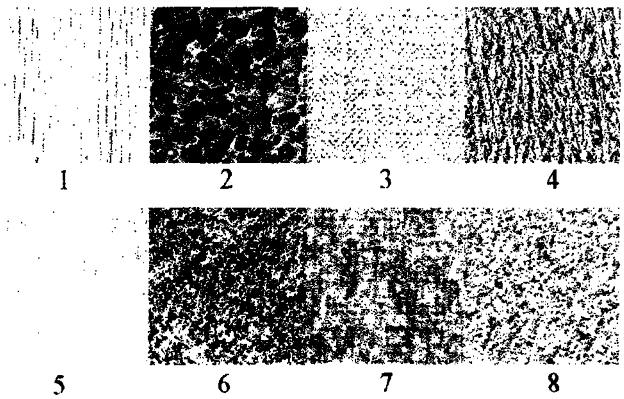

Figure 1: The eight classified textures from the Brodatz Album: 1:wood, 2:bubbles, 3:canvas, 4:ivy, 5: water, 6:grass, 7: wool, 8:sand

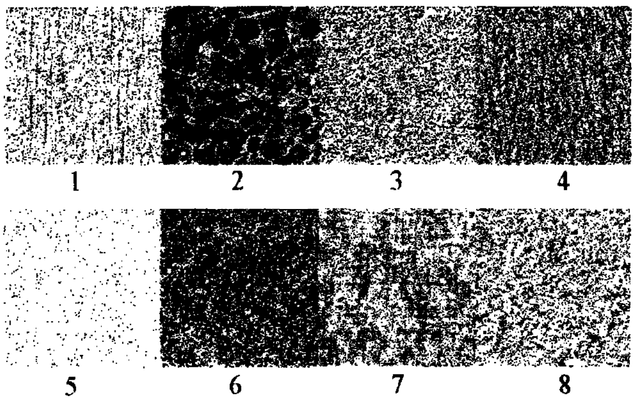

Figure 2: The eight noisy textures with SNR=3 dB: 1:wood, 2:bubbles, 3:canvas, 4:ivy, 5: water, 6:grass, 7: wool, 8:sand

4. CONCLUSION

In this work, we have proposed the use of 2D-AR coefficients obtained from the 2D-OLRIV algorithm as a new parametric approach for characterizing textures. In order to evaluate the performance of this approach, classification sensitivity has been evaluated on a set of eight different noisy textures. The obtained results in a noisy context are very promising when compared to similar approach using only second order statistics. Perspectives concern simulations with other kinds of noise (non gaussian but symmetric distribution) and classification based on PARCOR coefficients instead of 2D-AR coefficients. This last point may be of particular interest because the most complex part of the 2D-OLRIV algorithm is the computation of the AR parameters from the PARCOR coefficients.

REFERENCES

[1] O. Alata, P. Baylou and M. Najim, "Texture characterization based on 2 D reflection coefficients," *Proc. of IEEE ICASSP'95*, 9-12 May 95, Detroit, USA.

[2] V. Buzenac, R. Settineri and M. Najim, "A new cumulant-based lattice algorithm for adaptive identification of non gaussian bidimensional AR processes," *Proc. of IEEE ICASSP'96*, 7-10 May 96, Atlanta, USA.

[3] V. Buzenac, R. Settineri, M. Najim, "A Recursive Instrumental Variable (RIV) Lattice Algorithm for Adaptive Identification of Non Gaussian Multichannel AR Processes", GRETSI, Juan-les-Pins, Sept. 95.

[4] P. Brodatz, "Textures: a photographics album for artist and designers," Dovers, 1966, New York.

[5] V. Chandran, B. Carswell, B. Boashash and S. Elgar, "Pattern recognition using invariants defined from higher order spectra: 2-D image input," IEEE Trans. Image Processing, vol. 6, no. 5, May 1997, pp. 703-712.

[6] T. E. Hall and G. B. Giannakis, "Image modeling using inverse filtering criteria with application to textures," IEEE Trans. Image Processing, vol. 5, no. 6, June 1996.

[7] T. E. Hall and G. B. Giannakis, "Texture model validation using higher order statistics," Proc. IEEE ICASSP 91.

[8] R. P. Lippmann," An introduction to computing with Neural Networks," IEEE ASSP Mag., vol.4, no.2, April 87.

[9] X. Liu and M. Najim, "A two dimensional fast lattice recursive least squares algorithm", IEEE Transactions on Signal Processing, Vol. 44, No. 10, Octobre 96.

[10] P. A. Maragos, R. W. Schafer, R. M. Mersereau, "Two-Dimensional Line Prediction and Its application to Adaptive Predictive Coding of Images", IEEE Trans. on ASSP, vol. 32, n°6, pp. 1213-1229, Dec. 84.

[11] J. M. Mendel, "Tutorial on Higher Order Statistics (spectra) in signal processing and system theory: theoretical results and some applications", proc. IEEE, vol.79, n°3.

[12] S. Pagnan and C. Ottonello, "Experimental evaluation of cumulant based classifiers on noisy images," Proc. IEEE ICASSP 95, pp. 2419-2422.

[13] A. Swami and J. Mendel, "Adaptive system identification using cumulants," *Proceedings of IEEE ICASSP'88*, 11-14 April 1988, New York, USA.

[14] A. Swami, G.B. Giannakis and J. Mendel, "Linear modeling of multidimensinal non gaussian process using cumulant," *Multidimensional systems and signal processing*, Vol. 1, no. 1, March 1990.

[15] C. W. Therrien, "Relations between 2-D and Multichannel Linear Prediction", IEEE Trans on ASSP, vol. 29, n°3, June 1981.