TEXTURE CHARACTERIZATION BASED ON 2-D REFLECTION COEFFICIENTS.

O. ALATA, P. BAYLOU, M. NAJIM
Equipe Signal/Image and GDR-134-CNRS
ENSERB. 351, cours de la Libération
33405 Talence Cedex
FRANCE

ABSTRACT

In the framework of model based image processing, we propose a new parametric approach for classifying textured images. The image, considered as a two-dimensional stochastic process, is characterized by a set of *reflection coefficients* computed using a two-dimensional adaptive lattice filter based on RLS criterion. The corresponding algorithm is named Two-Dimensional Fast Lattice Recursive Least Squares.
In order to evaluate this method, classification rates are calculated on a set of 8 different textures from the Brodatz album. We carry out performance comparisons with methods of characterization based on two-dimensional AR coefficients computed with two-dimensional transversal filters or based on statistical features calculated from co-occurrence matrices and neighbouring matrices.

1. INTRODUCTION

Many applications in image processing such as medical imaging, teledetection or TV images compression may lead to a problem of characterization of textured images. One can distinguish two groups of textures: deterministic and stochastic textures. Deterministic textures are described by a set of primitives and a set of placement rules. Characterization of stochastic textures is still an open field and many attemps have been achieved using different approaches such as linear prediction theory [6] [7], or co-occurrence matrices [8].
A two-dimensional adaptive lattice filter with RLS criterion has been developed by Liu & al [1]. Some significant results have been obtained in noisy images restoration using an adaptive noise canceler [2].
Considering the well known results obtained for characterization of vocal signals by mono-dimensional reflection coefficients, we propose the set of two-dimensional reflection coefficients as a new parametric approach for characterizing textures.
Our approach is compared with parametric approaches (i.e., *transversal filters* such as Two-Dimensional Fast Recursive Least Squares filter [3] and Two-Dimensional Normalized Least Mean Squares filter [5]) and with non-parametric approaches (co-occurrence matrices [8] and neighbouring matrices [9]).
In section 2, the two-dimensional linear prediction theory is briefly recalled. In section 3, we present some details upon the extraction methods of the different parameters for each representation. Finaly in Section 4, a discussion upon the classification rates obtained with additive noise is provided.

2. LINEAR FILTERING

If we consider an image as a realization of some bidimensional random field process, it would be possible to represent it by a parametric model. The corresponding bidimensional AR model is defined by extending the one-dimensional model so as to express the dynamic characteristic of discrete data on a two-dimensional plane. The prediction filter and the prediction error are given by the relations:

$$\hat{x}(i,j) = \sum_{(m,n)\in D} a(m,n,i,j)\, x(i-n,j-m) \qquad (1)$$

$$e(i,j) = x(i,j) - \hat{x}(i,j) \qquad (2)$$

where D is the prediction support and, at coordinates (i,j), x(i,j) is the pixel value, e(i,j) is the prediction error, {a(m,n,i,j)} is the set of transversal AR coefficients.
The definition of the past and the future for a pixel leads to different kinds of support D. The use of a Quarter-Plane (QP) support leads to a causal model where the order is a couple (M,N). The prediction support D_{QP} is defined as follows:

$$D_{QP} = \{(m,n)/\ 0\leq m\leq M,\ 0\leq n\leq N,\ (m,n)\neq(0,0)\} \text{ (Fig.1)}$$

so that all x(i-n,j-m) are contained in the past of x(i,j).
A QP support will be implemented for all different filters presented in this paper.

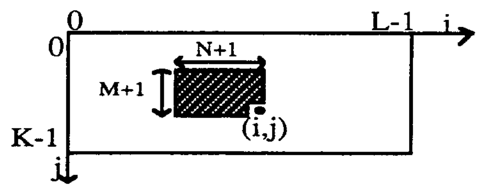

Fig. 1. QP AR Model Support Region.

We assume a cylindric connexity to solve boundary problems and particularly to initialize the filter parameters at the begining of each line:

$$y(-i,j)=y(L-i,j-1) \qquad (i>0,j>0) \qquad (3)$$

$$y(i,j)=0 \qquad (j<0) \qquad (4)$$

0-7803-2431-5/95 $4.00 © 1995 IEEE

In a stationary case, the set {a(m,n,i,j)} of AR coefficients do not depend on the position of the pixel (i,j). This hypothesis enables us to derive the bidimensional adaptive algorithms and {a(m,n,i,j)} is simply denoted {a(m,n)}.
As a stochastic texture is supposed to be a homogeneous bidimensional field, filtering it by a bidimensional adaptive filter will provides a specific set of parameters which may be used for characterization.

3. PARAMETERS EXTRACTION

3.1. Two-Dimensional Fast Lattice Recursive Least Squares Algorithm (TDFLRLS)

The prediction filter (1) is represented using the bidimensional reflection coefficients obtained with the TDFLRLS lattice filter [1][2]. Lattice filters present nice properties, e.g. modularity, convergence, stability and robustness [1].
In a general way, the optimal least squares filter minimizes the accumulated squared error:

$$\varepsilon(i,j) = \sum_{l=0}^{i}[e(l,j)]^2 + \sum_{l=0}^{L-1}\sum_{k=0}^{j-1}[e(l,k)]^2 \qquad (5)$$

The TDFLRLS algorithm which provides an exact growing-order least squares solution to the deterministic normal equations is derived from the multichannel and geometrical approaches of the bidimensional linear prediction [1] [4]. Due to limited space, we can't detail the algorithm in this paper.

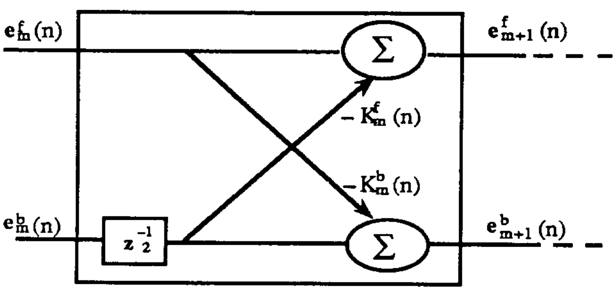

Fig.2. Internal structure of the 2D RLS lattice cell.

For a D_{QP} support, N+1 lattice cells (Fig. 2) are necessary to implement a (M,N) order TDFLRLS filter. The forward and backward lattice coefficients K are matrices with dimension M(M+1) at the first stage and (M+1)(M+1) at other stages. The image is filtered using order (2,3) support providing 66 reflection coefficients.

3.2. Transversal filters

3.2.1. Two-Dimensional Fast Recursive Least Squares Algorithm (TDFRLS)

The textured image will be characterized by the AR coefficients estimated with TDFRLS [3]. This algorithm uses the same multichannel and geometrical approach as the TDFLRLS, involving the concepts of linear vector spaces, orthogonality, projection operators and relation to linear least squares prediction [3] [4].

3.2.2. Two-Dimensional Normalized Least Mean Squares Algorithm (TDNLMS)

The AR coefficients are estimated by a transversal 2D-Normalized LMS filter [5]. The NLMS is derived with the prediction error equation (2) and the following equation (see (1) for a(m,n) and x(i,j)):

$$\hat{a}_{i+1,j}(m,n) = \hat{a}_{i,j}(m,n) + \frac{2\mu e(i,j)x(i-m,j-n)}{\sum_{(k,l)\in D_{QP}}(x(i-k,j-l))^2} \qquad (6)$$

Where $e_{(i,j)}$ is the prediction error (2), $\{\hat{a}_{i,j}(m,n)\}$ the set of AR coefficients estimated by the filter at pixel of coordinates (i,j) and μ the step chosen to optimise the convergence of the AR coefficients. The step used in the experiments is a compromise between convergence speed and stability of AR coefficients.
The number of AR coefficients is (M+1)(N+1)-1 for D_{QP} support with (M,N) order. In this paper, we have used order (3,3) support providing 15 coefficients for transversal filter.

3.3 Co-occurrence matrices & neighbouring matrices

A well known non-parametric approach for texture classification uses statistical information derived from the enumeration of grey-levels in an image: the co-occurrence matrices [8] and neighbouring grey-level dependance matrices [9].
A texture descriptor composed of nine parameters is computed from these statistical data:

- from the co-occurrence matrices: second angular moment, contrast, correlation, difference inverse moment and entropy.
- from the neighbouring grey-level dependance matrices: little number of neighbours accentuation, great number of neighbours accentuation, non-uniformity of the grey levels, second moment.

4. CLASSIFICATION RESULTS

4.1. Classification procedure

Eight images (256x256) taken from the Brodatz Album [10] have been used in these experiments: wood, bubbles, canvas, water, grass, wool, ivy, and sand (See Fig. 3. left to right, top to bottom). The simulation have been performed within the framework of the SIMPA Library [11].
Each image is divided into 5 overlapping subimages (128x128), 25 overlapping subimages (64x64) and 25 non-overlapping subimages (32x32) in order to test the sensitivity to the size of images.
Using the set of vectors extracted from the 40 (128x128) images (called Learning set), a Fisher-Snedecor test is performed on each parameter in order to keep only the

features which bring information and we eliminate correlated variables so as to avoid information redundancy (those operations were efficient especially for the reflection coefficients. We have kept only a set of 14 parameters belonging to an order (2,2) D_{QP} support).

The scattering matrix $W^{-1}(W+B)$ is computed from the "within class" scatter matrix W and the "between class" scatter matrix B. Applying a Karhunen-Loeve transform, a reduced subspace is derived according to the main eigenvalues of KL matrix (Discriminant Factorial Analysis).

A Mahalanobis distance to the centroïd of each class is used to classify all the unknown vectors extracted from the sets of (64x64) and (32x32) subimages. Results are shown in Tab. 1 and 2 and in Fig. 4 to 9.

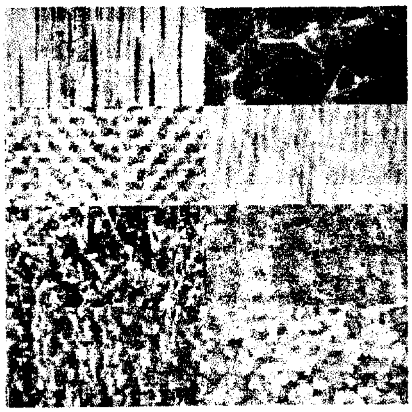

Fig. 3. Textures from the Brodatz Album.

4.2. Comments

4.2.1. Convergence considerations

The convergence to a unique set of asymptotic values of the TDFLRLS reflection coefficients on one hand and the TDFRLS AR coefficients on the other hand occurs for (32x32), (64x64) and (128x128) images. Some parameters of the TDNLMS filter need more than 4000 iterations to reach the final value. This explains its poor classification rates result (Tab. 1). For TDFRLS algorithm, the use of higher initialization value for autocorrelation matrix in order to have fast convergence has caused the divergence of AR coefficients.

4.2.2. Size considerations

Results were improved using (64x64) test images comparatively with (32x32) test images, especially for statistical features extracted with co-occurrence and neighbouring matrices (Tab. 1 and 2). For the filtering methods, convergence of parameters can be just obtained with a good stability of the coefficients especially for parameters calculated on the boundaries of the support.

4.2.3. Noise considerations

All the images of the test sets are corrupted with an additive zero-mean white gaussian noise with different SNR (Tab. 1 and 2). In this case, all the coefficients are biased. Tab. 1 and 2 shows the mean classification and Fig. 4 to 9 the classification results for each texture.

The noise robustness for filtering methods is efficient up to a SNR of 15dB. A too weak SNR causes an important bias on the measure for the three methods.

5. CONCLUSION

This paper presents preliminary results. Nevertheless, we can conclude that the new approach proposed for textured image characterization reveals fast convergence and good noise robustness. High classification rates are obtained with reflection coefficients up to a SNR of 15dB SNR. A 100% classification rate is obtained with noiseless (64x64) test images.

SNR	∞	30dB	15dB	10dB
TDNLMS	69,5%	25%	/	/
co-oc. neighbour.	89,5%	88%	77%	55,5%
TDFRLS	96,5%	96,5%	95%	70,5%
TDFLRLS	100%	98%	96%	79%

Tab. 1. Classification rates, 64x64.
Learning set: 5 (128x128) images per texture (40 images).
Test set: 25 (64x64) images per texture (200 images).

SNR	∞	30dB	15dB	10dB
co-oc. neighbour.	38%	40,5%	39,5%	31,5%
TDFRLS	83%	84,5%	82%	68%
TDFLRLS	87,5%	87%	87,5%	74%

Tab. 2. Classification rates, 32x32.
Learning set: 5 (128x128) images per texture (40 images).
Test set: 25 (64x64) images per texture (200 images).

6. REFERENCES

[1] X. Liu, M. Najim, "A new 2D fast lattice RLS algorithm", Proc. ICASSP 92, vol. 3, pp. 329-332 (a comprehensive paper is under review for the IEEE Transactions on Signal Processing).

[2] X. Liu, M. Najim, B. Ténèze and H. Youlal, "A new 2D fast lattice RLS algorithm: Application for Restoration of Images", Proc. GRETSI_91, pp. 813-816.

[3] A. M. Sequeira, C. W. Therrien, "A new 2-D fast RLS algorithm", Proc. ICASSP 90, vol. 3, pp. 1401-1404.

[4] H. Lev-Ari, T. Kailath, J. Cioffi, "Least-Squares Adaptive Lattice and Transversal Filters: A Unified Geometric Theory", IEEE Trans. on Information Theory, vol. IT-30, n°2, pp.222-236, March 1984.

[5] M. M. Hadhoud,D. W. Thomas, "The Two-Dimensional Adaptive LMS", IEEE Trans. on Circuits and Systems, vol. 35, n°5, pp.485-494, 1988.

[6]J. M. Francos, A. Z. Meiri, "A 2-D autoregressive, finite support causal model for texture analysis and synthesis", Proc. ICASSP-89, pp. 1552-1555.

[7]Y. Boutalis, S. Kollias, G. Carayannis, "A fast technique for automatic segmentation and classification of textured images", Proc. ICASSP-88, pp. 1132-1135.

[8] C. C. Gotlieb, H. E. Kreyszig, "Texture descriptors on co-occurrence matrices", Computers Vision, Graphics, and Image Processing, vol. 51, pp.70-86, 1990.

[9] Sun, Wee, "Neighbouring gray-level dependance matrix to texture classification", Computers Vision, Graphics, and Image Processing, vol. 23, pp. 341-352, 1983.

[10] P. Brodatz, "Textures: a photographic album for artists and designers", Dover, 1966, New York.

[11] SIMPA: Signal and Image softwares PAckage, Reference Manual, CNRS-GDR134, Paris.

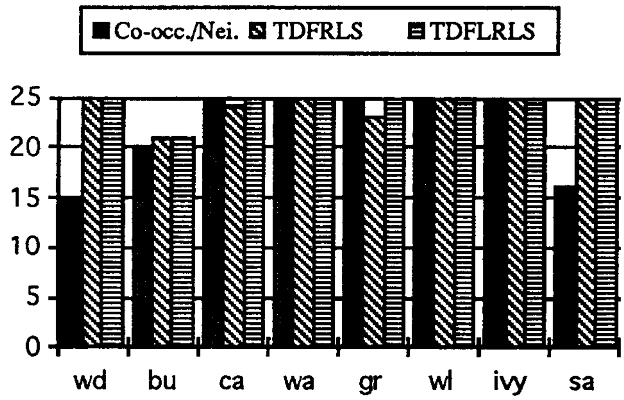

Fig. 4. Learning set: 5 (128x128) images per texture, test set: 25 (64x64) images per texture - 30dB

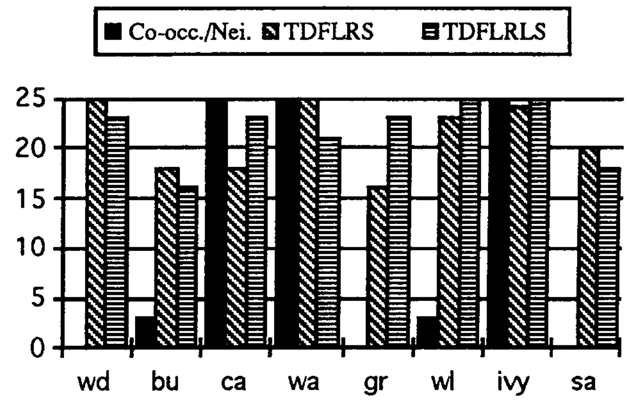

Fig. 5. Learning set: 5 (128x128) images per texture, test: 25 (32x32) images per texture - 30dB

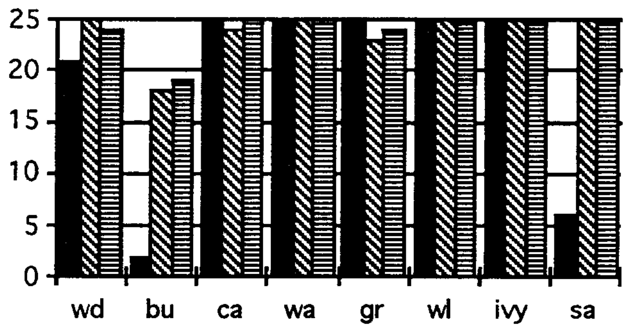

Fig. 6. Learning set: 5 (128x128) images per texture, test set: 25 (64x64) images per texture - 15dB

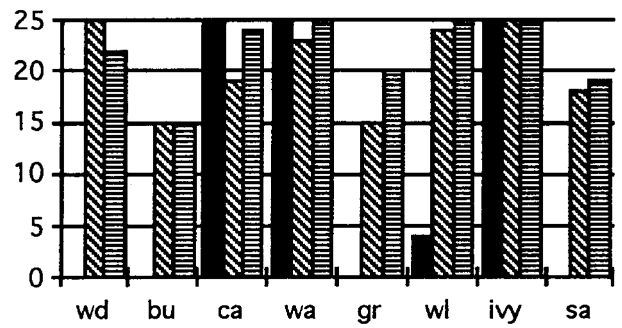

Fig. 7. Learning set: 5 (128x128) images per texture, test set: 25 (32x32) images per texture - 15dB

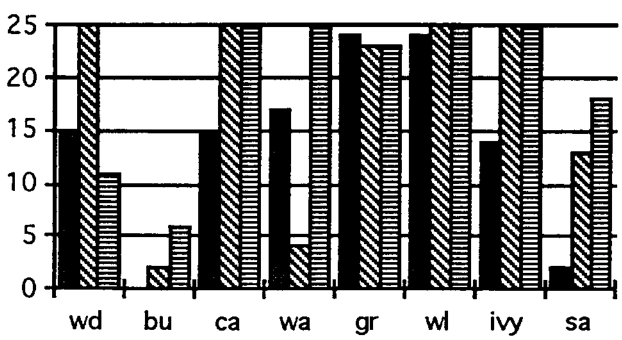

Fig. 8. Learning set: 5 (128x128) images per texture, test set: 25 (64x64) images per texture - 10dB

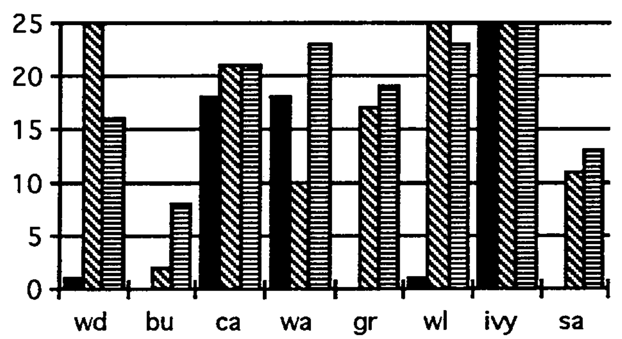

Fig. 9. Learning set: 5 (128x128) images per texture, test: 25 (32x32) images per texture - 10dB