AN IDENTIFICATION METHOD FOR TEXTURE AR-2D MODELLING BASED ON AUTO- AND PARTIAL CORRELATION MEASURES

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ABSTRACT

This paper deals with the identification of the model order for a bidimensional autoregressive (AR-2D) texture model. It means the automatic choice of the number of neighbours in the prediction set of the model and their spatial position. The method, called *mixed correlation method* is based on partial and auto-correlation measures and fastly and efficiently allows to find an adapted model for all microtextures. In a textured samples classification procedure, these adapted models improve the percentage of good classification in comparison with a classical approach consisting in taking the same prediction set for all the textures.

1 INTRODUCTION

In this paper, we focus on texture modelling by bidimensional autoregressive models (2D-AR models). Typically, a textured image is represented by a two-dimensional stochastic stationary field defined over a rectangular square lattice. The model fitted to the image is a spatial-interaction model characterizing the statistical dependency between the gray value at a site and those of its neighbouring sites. In 2D-AR model, a gray level is assumed to be a linear combination of the neighbouring gray levels plus an additive noise.

Let Ω be the set of sites or pixels of an image Y of size I x J :

$$\Omega = \{s = (i,j); 1 \leq i \leq I, 1 \leq j \leq J\} \tag{1}$$

Let $y(s)$ be the state (generally gray level value) at the pixel s. The AR model can be expressed as follows :

$$\begin{aligned} y(s) = y(i,j) = & \sum_{(m,n)\in D} a(m,n) \\ & \times y(i-m, j-n) + be(i,j) \end{aligned} \tag{2}$$

where

- e is a zero mean white noise with unit variance,
- D is the neighbouring set of model prediction
- and b and $a(m,n)$ are the parameters of the model.

The predictive value at the site s is defined by :

$$\begin{aligned} \hat{y}(s) = \hat{y}(i,j) = & \sum_{(m,n)\in D} a(m,n) \\ & \times y(i-m, j-n) \end{aligned} \tag{3}$$

The selection of the set D requires two choices : the number of selected neighbours and their spatial layout determination. A survey of the litterature shows that the first stage of model identification is often ignored and only the second stage of parameters estimation is considered. However, we can suppose that the significant neighbours for pixel value prediction differ from a texture to another. This assumption is confirmed by the visual quality of synthesized textures when we use different models. Among the few works dealing with the identification of 2D-AR models, we can cite those of Akaike [1], Schwarz [2] and Kashyap [3]. They have partially treated this problem. They proposed a criterion to select the best model among a set of potential models. But, it needs the previous selection of this set of potential models. Kartikeyan [4] has given a more complete solution based on multiple partial autocorrelation, but the models obtained are difficult to use in texture segmentation because of their too wide layout.

Thus, we present a new method of neighbourhood identification. This approach is significantly different from the methods that we have already proposed [5, 6]. They differ in the way of obtaining the models, but meet the same requirements : to provide adapted texture models usable for image segmentation.

2 DESCRIPTION OF THE METHOD

This method is called *mixed correlation method*, because it is based on autocorrelation and partial correlation measures. Similarly to some methods of AR-1D model identification, our method consists in two stages :

1. we select the neighbour which has the highest correlation with the central pixel.

2. we classify the other neighbours in descending order of their partial correlation with the central pixel.

In other words, we choose the most correlated neighbour when the influence of the previously selected neighbours has been removed. In this way, we build a set of neighbourhoods with an increasing number of elements. Now, we can select the best model in this set by using the well-known Schwarz Information Criterion. This criterion takes the number θ of model parameters and the value of b (see equation (2)) into account. It is defined as follows :

$$SIC = \log b^2 + \frac{\theta \log (n-\theta)}{(n-\theta)} \qquad (4)$$

where n is the number of observations.

We can also determine the neighbourhood by choosing a given number of elements.

Figure 2 shows these partial correlation measures on a 9x5 non symetric half plane (NSHP) support for leather and wool textures (figure 1). A gray value is assigned to each site according to its partial correlation value (black for the first selected neighbour and white for the last one).

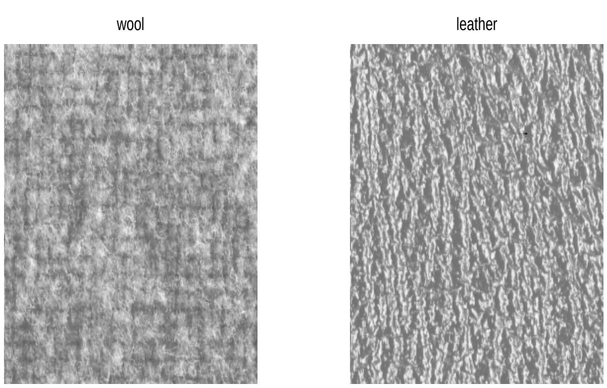

Figure 1: *Textures of wool and leather*

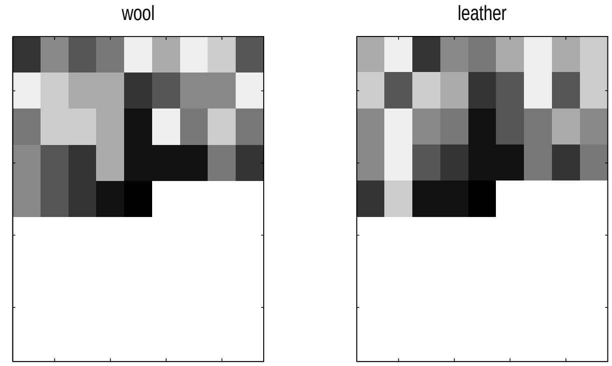

Figure 2: *Partial correlation maps of wool and leather textures*

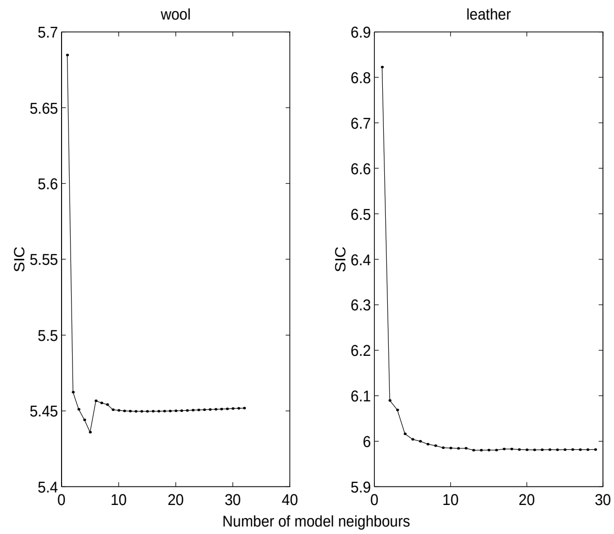

Figure 3: *Evolution of SIC according to the number of elements in the models*

Figure 3 gives the evolution of the Schwarz Information Criterion (SIC) when we include the neighbours in decreasing order of their partial correlation measure.

Figure 4 represents the selected set D, called mixed correlation models (MCM), for the 2 textures under consideration.

3 EVALUATION OF THE ADAPTED MODELS OBTAINED

3.1 Comparison in synthesis processing

We generate textured images with several models estimated on original textures in order to visually compare the performance of the models. We use a non-correlated gaussian noise as an entry of the regeneration processing. Globally, the differences are small but the adapted models allways give an image closer to the original image. For example the water is better synthesized with its adapted model than with a classical NSHP ones (see

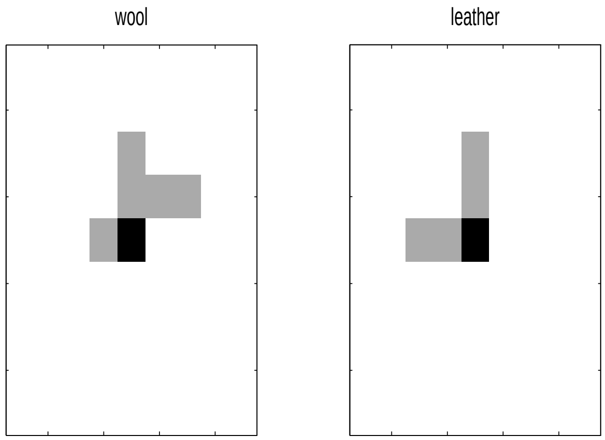

Figure 4: *The adapted neighbourhood (MCM)*

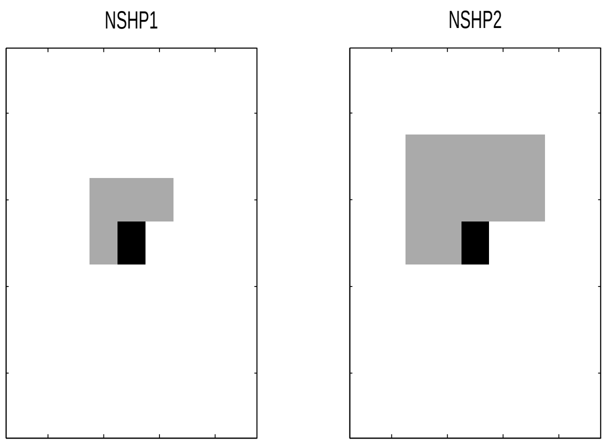

Figure 5: *NSHP models of order 1 and 2*

figure 6).

3.2 Comparison in classification processing

We assess the adapted models obtained in comparison with the classical NSHP models of order 1 or 2 given in figure 5. The comparison processing consists in the classification of textured samples with the help of the criterion defined as :

$$C(k) = \frac{1}{b_k} \exp - \frac{(\bar{e}^{(k)})^2}{2b_k^2} \qquad (5)$$

where

$$\bar{e}^{(k)} = \frac{1}{IJ} \sum_{i}^{I} \sum_{j}^{J} (y(i,j) - \hat{y}^{(k)}(i,j))^2 \qquad (6)$$

is the prediction error for the model k. We use different sample sizes of 8 textures of the Brodatz album [7].

3.3 Results of classification

Figure 7 summarizes the classification results and shows the improvement brought by the adapted models

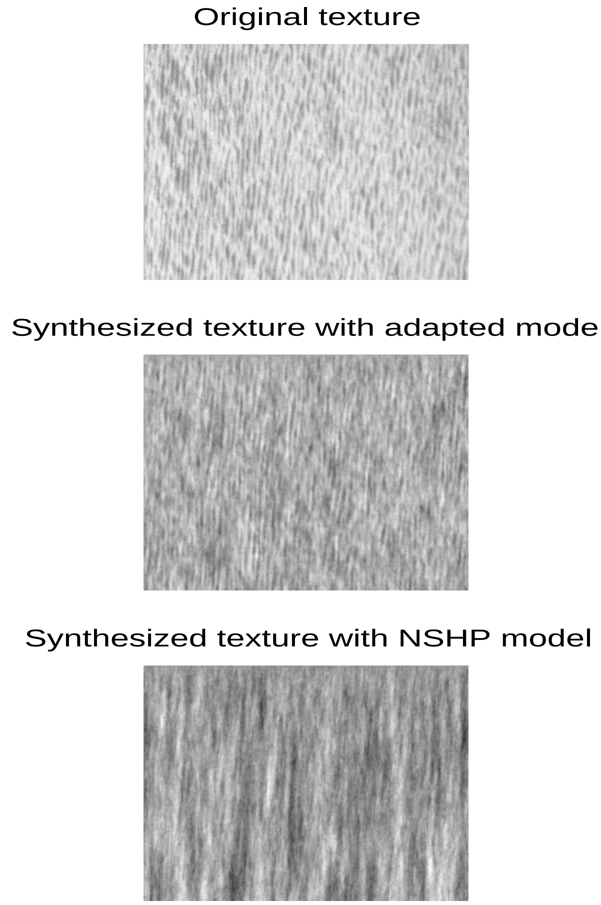

Figure 6: *Synthesis of water texture*

in terms of percentage of good classification. The improvement is globally of 2%.

4 CONCLUSION

In this paper, we have studied the influence of the choice of the neighbourhood for the texture representation and for the discrimination power of the AR model. We have presented our method of neighbourhood identification based on auto- and partial correlation measures.
The results show that the adapted models obtained improve the visual aspect of synthesized textures and the percentage of good classification in a textured samples classification processing.

References

[1] H. Akaike. On entropy maximization principle. *Symposium on applications on statistics*, pages 138–141, 1972.

[2] A.B. Koelher and E.S. Murphree. A comparison of akaike and schwarz criterion for selecting model order. *Applied Statistics*, 37(2):187–195, 1988.

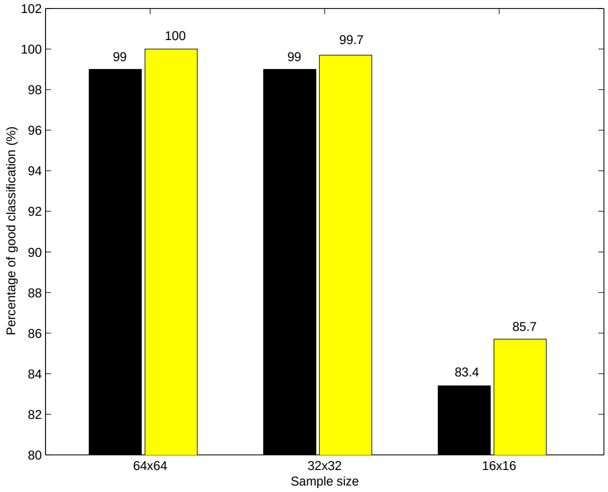

Figure 7: *Percentage of good classification according to the model used (in black, the NSHP models and in grey, the MCM models)*

[3] R.L. Kashyap and R. Chellapa. Estimation and choice of neighbors in spatial-interaction models of images. *IEEE Transactions on Information Theory*, 29(1):60–72, 1983.

[4] B. Kartikeyan and A. Sarkar. An identification approach for 2d autoregressive models in describing textures. *CVGIP: Graphical Models and Image Processing*, 53(2):121–131, 1991.

[5] I. Claude and A. Smolarz. Choice of neighbours for autoregressive modelling in texture analysis. *Applications in Computer Systems*, 1996.

[6] I. Claude and A. Smolarz. Mesure de corrélation partielle pour le choix d'un voisinage adapté en modélisation autorégressive de textures. *Colloque GRETSI*, 1997.

[7] P. Brodatz. Textures : A photographic album for artists and designers. 1966.