A Hierarchical Representation for Texture Classification

Barbara Caputo, Antonella Troncone and Domenico Vitulano *

Istituto per le Applicazioni del Calcolo "M. Picone"
C. N. R.
Viale del Policlinico 137
00161 Rome, Italy
E-mail: {caputo,troncone,vitulano}@iac.rm.cnr.it

Abstract

In this paper [1] we present and test a model based on a Weak Continuity Representation to classify textures. In particular, the edges, extracted on windows having a given size and centered on the image, are an efficacious representation to design a neural network oriented to classify textures on the basis of their coarseness. The results obtained on real textures, relative to pudding stones having different grains, show that this kind of features constitute an efficacious approach for the material recognition.

1 Introduction

In the last years a big effort devoted to develop techniques and methodologies able to solve problems relative to Cultural Heritage field has been made by many researchers. A unified approach has been proposed in [10] where, considering digital images, many attempt have been faced, and in particular to make objective the "naked eye" analysis traditionally carried out by Cultural Heritage experts.

One of the more interesting aspects is, there, the recognition of different kinds of materials degradation. To do this, a first step has been made in [11] where, with the help of a neural network, two kinds of degradation such as fissures and cavities have been classified. An example of the examined shapes is shown in Fig. 1. Since, we are dealing with degradation kinds characterized by lack of material, the hypothesis that the most information is contained in the contours of the examined shapes seems to be good. In fact, in these cases, basing the analysis on the information contained in digital images, the texture inside the regions analyzed can be coarsely considered an uniform background. So the model is able to recognize these two classes considering both Fourier descriptors and the frequential information contained in the binary images of the contours.

Nevertheless, a noticeable improvement of an automatic recognizer could be attained by means of a preliminary classification of the material where the degradation kinds are. In other words, a preliminary recognition of the material we are considering could allow us to focus on a small set of possible degradation kinds.

In this sense this paper proposes a texture classification using a *Weak Continuity* based (*WC*) representation. Particularly, our model

*Correspondence to: Dr. Barbara Caputo, Istituto per le Applicazioni del Calcolo (M. Picone) C.N.R., 00161 Rome Italy, tel. +39-6-88470210, telefax +39-6-4404306 E-mail b.caputo@caspur.it

[1]This paper has been partially supported by the CNR Finalized Project: "Cultural Heritage".

is based on the characterization of textures using statistics of their coarseness ([1] p. 396 and [2]). The coarseness is, in fact, one of the features that the human eye takes into account when a discrimination is required. Furthermore, different types of degradation are, generally, mapped to different material coarseness. Obviously, the coarseness depends strongly on the scale level we are considering the scene. So, an useful tool should detect the discontinuities of an image, at many scale levels — even if only one, opportunely selected, is sufficient.

It is well known that the *WC* approach is a very efficacious tool for edge detection. In particular, besides allowing a multi scale detection, its non linearity leads to a selective smoothing and thus to a high robustness to the noise. Thus, considering squared windows of a given size, the edges detected can represent the input of a neural network oriented to classify different textures. The images we consider, are relative to pudding-stone ashlars which constitute the material of many buildings of historical importance. In particular, the images considered have been acquired from Roman Theatre in the city of Aosta. The problem of classifying different textures constitutes one of the aspects of a more general problem, within the Cultural Heritage, relative to the purpose to make quantitative the "naked eye" analysis. To do this, a unified approach has been proposed [10], where many purposes have been obtained.

With regard to the texture classification, this paper deals with the problem of discriminating between two classes of textures relative to the pudding-stone, that is the gross grain kind and the fine grain one. The preliminary results have been good, encouraging further generalization to other classes.

The paper is organized as follows. Section 2, presents a short review about the *WC* approach, successively introducing the proposed model. In Section 3 some experimental results are presented, providing to test the efficacy of our approach on some textures relative to buildings of historical importance. Finally, Section 4 draws the conclusions.

2 The Weak Continuity as Texture Representation for a Neural Network

In order to present in detail the model we utilize, a short review about the *Weak Continuity* (*WC*) approach is presented. The output of this process will constitute the input of a neural network.

The *WC* is an interesting approach for both edge detection and image restoration, having attractive performances in localization and detection in presence of high percentage of noise. It can be also shown that this approach can work at different scale levels.

The basic idea is to represent the input signal by a *weak string*, that is an elastic string satisfying the weak continuity constraints. Obviously, for two dimensional signals, such as images, the string will be substituted by an elastic membrane: the *weak membrane*.

Strictly speaking, the general model consists on determining the minimum of an energy related to the image, i.e.:

$$E = D + S + P \tag{1}$$

with

$$D = \int\int_{\Omega} (f(x,y) - d(x,y))^2 dxdy \tag{2}$$

$$S = \lambda \int\int_{\Omega} (f_x^2 + f_y^2) dxdy \tag{3}$$

$$P = \alpha |Z| \tag{4}$$

and where $d(x,y)$ are the input data, $f(x,y)$ is the function that will be restored, f_x and f_y the derivatives with respect to x and y directions respectively, $|Z|$ is a measure of the contours contained in the image and, finally, λ and α are two input parameters. The last two terms are weights determining a compromise among the three terms above.

The first term in 1 is to assure the closeness of the computed f to the input data. We can say that, by means of this term, we lead the solution to be faithful to the data.

The second term regulates the elasticity of the membrane: high values of λ produce a smoothing of f while low values of the parameter itself assure that f is close to the input data d. The peculiarity of this technique is that the continuity of the solution is weak: the solution tries to be continuous but some discontinuity points are allowed.

Finally, the third term takes into account the "penalties" of the contours, that is for each discontinuity point there's a price to pay. This term produces the non linearity of the model.

We have seen that the above representation is very useful for the edge detection at many scale levels. This representation can be, then, utilized for our model, in order to discriminate and so classify textures having different coarseness. There are many cases where this feature is able to solve the discrimination problem ([1] p. 396 and [2]). So, for this aim, we will utilize $|Z|$, which is the set of the contours of an image at a given scale level.

The recognition will be then based on the extraction of a (squared) subregion of the considered image, applying on it an edge detection. The image containing the edges shall be the features in input to the neural network.

Strictly speaking, be f a scalar function on a domain $\Omega \in \Re^2$.

So starting from f over Ω, we are looking for the set K_{w_1,w_2} such that:

$$E(u,K) = \int_{\Omega}(u-f)^2 + w_1 \int_{\Omega/K} \nabla u \cdot \nabla u + w_2 \int_K d\sigma \qquad (5)$$

be minimized.

Starting from K_{w_1,w_2}, we can define the characteristic function $\chi : \Omega \rightarrow \{0,1\}$, taking into account of K_{w_1,w_2}, defined as:

$$\chi(x,y) = \begin{cases} 1 & \text{if } x,y \in K_{w_1,w_2} \\ 0 & \text{otherwise.} \end{cases} \qquad (6)$$

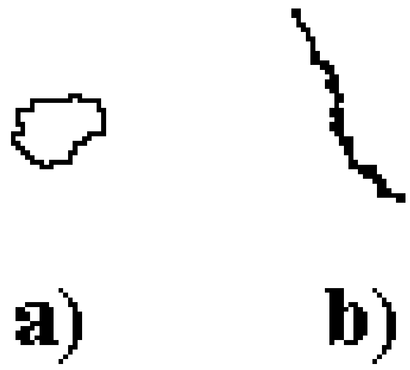

Figure 1: Two kinds of degradation belonging to the class of lack of material: a cavity (left) and a fissure (right).

Database Size	60
Windows Size	64×64
Scale Parameter Value	$l = 10$
Noise Immunity	$h = 5$

Table 1: Feature of the image data-base set and of the Weak Continuity parameters.

The region Ω is a subregion of the domain of the considered image. In other words, we don't need to consider all the image in input, but a significant subregion, containing no degradation shapes, is sufficient. To determine the size of this subregion we need to know the periods of the considered textures and then select a size being at least equal to the maximum of them. This is possible on synthetic textures but on real images this information has to be obtained by qualitative considerations.

Learning File Dimension	10	20	30
Testing File Dimension	50	40	30
Recognition (%)	36	78	88

Table 2: Network results.

Figure 2: An image of pudding-stone (gross grain).

Figure 3: An image of pudding-stone (thin grain).

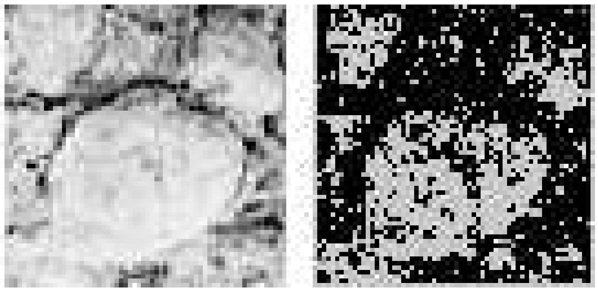

Figure 4: Extracted window and its Weak Continuity representation from a gross grain pudding-stone.

3 Experimental Results

In order to show the obtained results, some 8-bits images relative to the Aosta Roman Theatre have been considered. In particular, these images show pudding stones, i.e. gross and fine, without any kind of degradation (only texture). From them, windows having the same size have been extracted, in order to detect their edges by a WC model.

It has to be small enough to not contain too much information, but large enough to describe the texture inside. Since we are dealing with natural textures, the choice has been made following qualitative criteria. So, the size has been fixed at 64×64.

Moreover, it is to be also outlined that the choice of the scale parameter is very important. In fact, the scale level characterizes the binary matrix, containing the edges of the selected windows, which constitutes the input to our neural network.

From an original database of 35 images of pudding stone we selected, with the help of Cultural Heritage experts, 10 images showing pudding stone with gross and thin grain textures. From every image we extracted six windows, obtaining a final database of 60 thin grain textures and gross grain ones. The selected windows have no evident material degradation shapes inside, in order to obtain quite uniform textures to be computed. The technique described in Section II was applied on every window, choosing $l = 10$ and $h = 5$ — the choice of these values came from qualitative considerations and with the help of

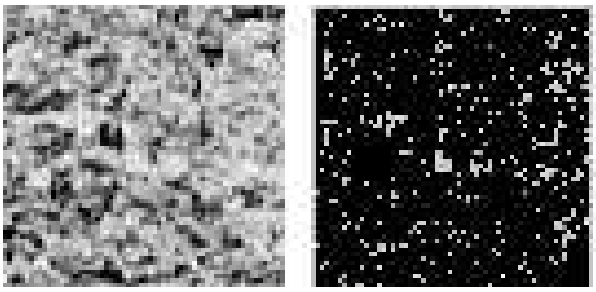

Figure 5: Extracted window and its Weak Continuity representatino from thin grain pudding-stone.

Cultural Heritage experts. We want to stress that the choice of the parameters, and particularly the choice of l (the scale parameter), it's a crucial point for the success of the model. Actually, the scale level characterizes the binary matrix containing the edges of the selected windows, which is our neural networks input. A too large value of l should lead to a characterization with few features, while small values of the same parameter provide an accurate description.

In Tab. 1 we resume the database features.

A three-layers feedforward, backpropagation network (with one neuron in the middle unit) was learnt to separate thin grain texture from gross grain one. The first time we made the learning stage on 1/6 of the whole database and tested the results on the 5/6 of the database obtaining 36 % of recognition.

We next made the learning stage on 1/3 of the whole database and tested the results on the remaining 2/3 of the database, obtaining 78 % of recognition.

We made the learning stage on 1/2 of the finally of the whole database and tested the results on the remaining 1/2 of the database, obtaining 88 % of recognition.

These results are summarized in Tab. 2.

4 Conclusions

In this paper, we presented a model, based on a Weak Continuity representation, able to classify images containing textures. In other words, the hypothesis that different textures can be classified using their coarseness has been made. The edges obtained by the weak membrane constituted the input features for a neural network oriented to classify between two classes of pudding-stones ashlars: gross grain and fine grain. The results obtained on stones relative to the Aosta Roman Theatre show the efficacy of this representation and, at same time, encourage the development of this approach.

5 Acknowledgements

We would like to thanks Arc. Paolo Salonia (ITABC-CNR) and Dr. Lorenzo Appolonia (Sovrintendenza Beni Culturali- Aosta) for their cooperation as cultural heritage experts.

References

[1] A. K. Jain, Fundamentals of Digital Image Processing. *Prentice Hall, Englewood Cliffs*, 1986.

[2] A. Rosenfeld, Visual Texture Analysis: An Overview, Tech. Rep. TR-406, Computer Science Center, University of Maryland, August 1975.

[3] M. Gokmen and A. K. Jain, $\lambda\tau-$Space Representation of Images and Generalized Edge Detector, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 19, No. 6, June 1997, pp. 545-563.

[4] G. A. Hewer, C. Kenney, and B. S. Manjunath, Variational Image Segmentation Using Boundary Functions, *IEEE Trans. on Image Processing*, Vol. 7, No. 9, September 1998, pp. 1269-1282.

[5] A. Blake and A. Zissermann, *Visual Reconstruction.* MIT Press, 1987.

[6] A. Laine and J. Fan, Frame Representation for Texture Segmentation, *IEEE Trans. on Image Processing*, Vol. 5, No. 5, September 1996, pp. 771-780.

[7] T. S. Lee, D. Mumford, A. Yuille, Texture Segmentation by Minimizing Vector-Valued Energy Functionals: The Coupled-Membrane Model, *Proc. of*

Computer Vision ECCV '92, Vol. 588, LNCS Springer, May 1992.

[8] S. L. Horowitz, T. Pavlidis, Picture Segmentation by a Directed Split-and-Merge Procedure, *Proc. 2th ICPR*, pp. 424-433, 1974.

[9] R. M. Haralick, Digital Step Edges from Zero Crossing of Second Directional Derivatives, *IEEE Trans. on PAMI*, 6, pp.58-68, 1984.

[10] D. Vitulano, A syntactic approach applied to materials degradation, *Pattern Recognition Letters*,Vol. 20, 1999, pp. 75-80.

[11] B. Caputo, L. Moltedo, D. Vitulano, Neural Nets applied on Investigations about Cultural Heritage Shapes, *Proc. EVA'99 Florence*, pp. 48-51, 1999.