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MULTIRESOLUTION TEXTURE CLASSIFICATION AND ANALYSIS

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ABSTRACT

The aim of this method is to introduce a general hierarchical process for texture classification and analysis. It is more exactly intended for discriminating between micro and macrotextures. Objective features are then extracted according to the evolution of some parameters during a bottom-up process through an intensity pyramid, making them perceptually valuable. Moreover, this efficient tool is not inherently very costly in terms of computation.

Keywords : image analysis, multiresolution process, pyramid, texture.

INTRODUCTION

Texture is still a problem in computer vision, particularly because there is none standard definition (Rao, 1990). The word texture has in fact a rich range of meanings even in image analysis. Let then describe random textures in terms of texture primitives (Haralick, 1979). In fact, the larger the primitives are, the more macrotextured the image is considered. When an image is microtextured, there is none extractible primitive. As a possible utilization in an industrial process, in textile domain for example, the wearing aspect can be quantified through the evolution from a microtextured surface to a macrotextured one. Let now present our hierarchical process potentially useful for texture classification and analysis.

THE CONTRIBUTION OF MULTIRESOLUTION PROCESS IN TEXTURE ANALYSIS

As a possible taxonomy of textures is to divide them into microtextured or macrotextured ones according to the size of their primitives, a hierarchical process is well adapted. Indeed, let use a pyramid (Tanimoto et al., 1975) to implement a multiresolution approach in decreasing order : it contains by definition the same image at different resolution levels decreasing from one to another.

This concept is so attractive because the lower resolutions provide a global view of the image, while the higher resolutions provide the details. Specifically, the information of a microtextured image is lost in the lower resolutions while it is still present in the higher resolutions for a macrotextured one. Thus, the "window size problem" (Burt, 1982) becomes solvable.

In fact, our approach is not to compute another statistical parameter that is only suitable for one kind of textures. Our process, that is in agreement with human perception, is more general because each image is characterized by its multiresolution evolution. Actually, in order to classify different textures, their evolution through a bottom-up process in an intensity pyramid is compared, making this process perceptually valuable.

First of all, let then present the construction of an intensity pyramid. It is a hierarchy of fine to coarse resolution versions of an image, where the resolution decreases usually twofold between consecutive levels. Generally, the values of the current level are computed by convolving the gray values at the previous level with a *KxK* kernel and by sampling them at half the current spatial frequency. Thus, each element (x,y) at level h is computed as follows :

$$f_h(x,y)=\sum_{i=0}^{K-1}\sum_{j=0}^{K-1} w(i,j)\cdot f_{h-1}(2x+i-z,2y+j-z) \qquad \text{where} \qquad z=\left\lfloor \frac{K-1}{2} \right\rfloor \tag{1}$$

By definition, the K^2 pixels $(2x+i-z,2y+j-z)$ at level h-1 are the sons of (x,y) at level h. When (x,y) is used to compute an element at level h+1, each of them is one of his father.

Different forms of the generating kernel $w(i,j)$ have been studied by Burt (1981). The Gaussian one tends to preserve the shape of the objects and the contrast of the image (Konik, 1994). Such a kernel defines the overlapped gaussian pyramid, that is presented in Fig.1.

Let consider two test images, "micro" and "macro" presented in Fig.2 and Fig.3 respectively. The first levels of their Gaussian pyramids are illustrated in Fig.4 and Fig.5 respectively. All levels are presented with the same resolution as the original ones.

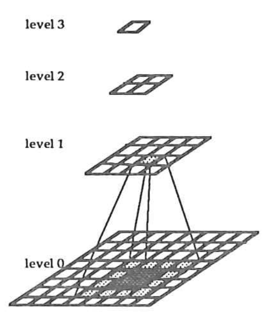

Fig.1. A 2^3x2^3 overlapped pyramid.

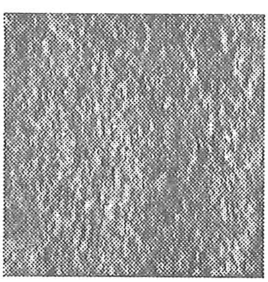

Fig.2. Image test "micro".

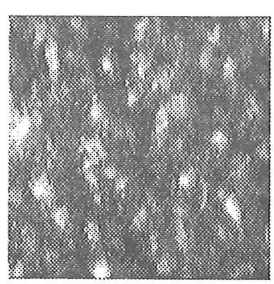

Fig.3. Image test "macro".

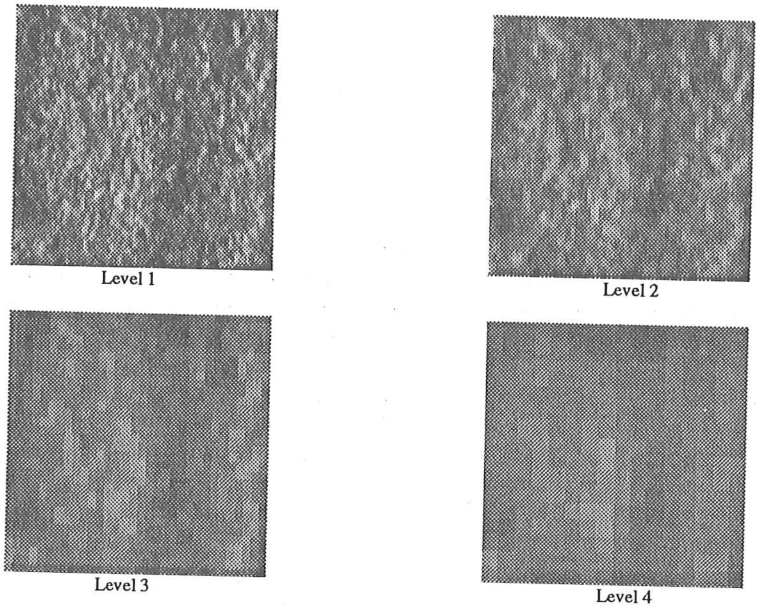

Fig.4. Pyramid of the image "micro". All levels appear in the same resolution.

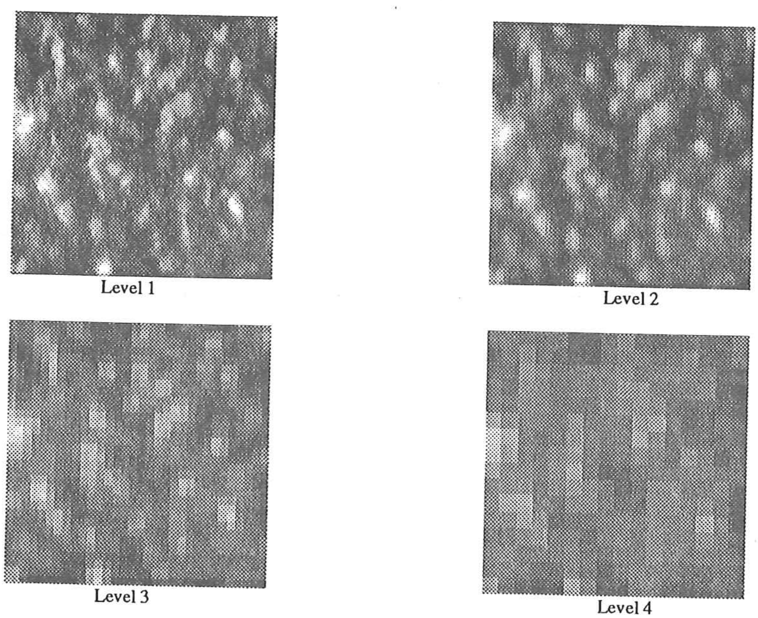

Fig.5. Pyramid of the image "macro". All levels appear in the same resolution.

These examples show the difference between a microtextured image and a macrotextured one. Considering the image "micro", its information is smooth rapidly and there is no more contrast from the third level up. On the contrary, the relevant primitives are still present at the fourth level for the image "macro". Let now develop our hierarchical process that uses these comments in order to determine texture features.

TEXTURE ANALYSIS PROCESS

First of all, a coarse segmentation is obtained for each level using the maxima, that are useful texture descriptors (Mitchell et al., 1977). Nevertheless, because they are noise sensitive, the detection is performed using the 4-directional neighbourhood (Fig.6) that is valuable during the bottom-up process according to the construction (Konik et al., 1993). By this way, the more relevant parts of each image are extracted as spots. An element is by definition a spot if its gray value is higher than all the gray values in its neighbourhood for at most one direction. Finally, coarse connected primitives are labelled for each level. Some parameters are then obtained considering the evolution of the extracted primitives through the pyramid, such as their size, their number, etc. The evolution of the standard deviation of the image is useful too. Generally speaking, the contrast constitutes a good characterization of the texture.

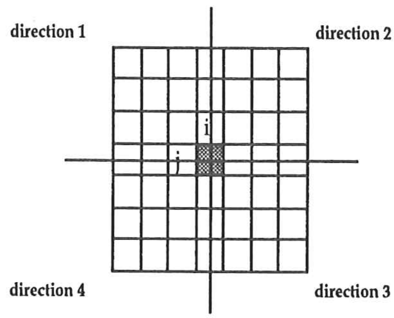

Fig.6. The 4-directional neighbourhood of (i,j).

A contrast is associated to each primitive as follows : it is computed as the difference between the primitive and its local background, that is the difference between the dilated primitive and itself. Microtextured surfaces are characterized by low contrast that decreases progressively.

The level where the contrast is optimal constitutes a good quantifier. In fact, we consider the curve representing the contrast according to the level of the pyramid and we associate the curvature for each level as follows :

$$curv(h) = 2cont(h) - cont(h-1) - cont(h+1) \quad (2)$$

RESULTS

Let consider two textile surfaces (Fig.7 and Fig.8). Their evolution during an abrasion test are shown respectively in Fig.9 and Fig.10. The values of the contrast are shown in Fig.11 and Fig.12. The contrast quantifiers are then resumed in Tbl. 1.

The sign of the curvature is negative in the convex case (microtextures) and positive in the concave one (macrotextures). With respect to these results, the original surfaces are clearly

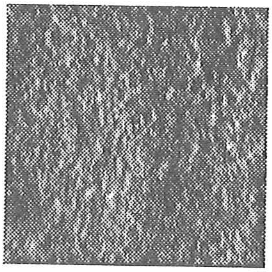

Fig.7. Surface a : original.

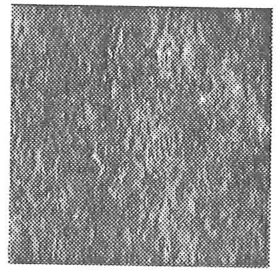

Fig.8. Surface b : original.

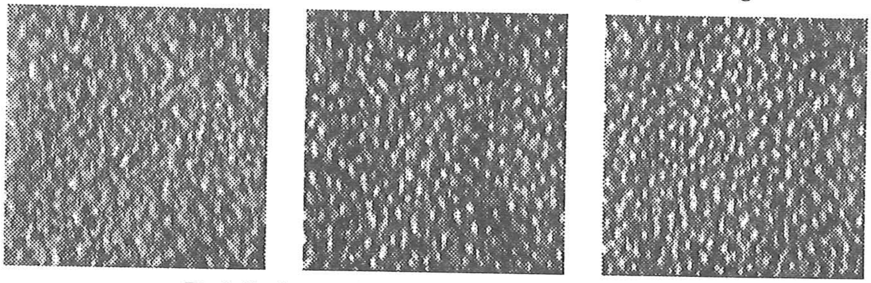

Fig.9. Surface a after respectively 5, 15 and 30 minutes.

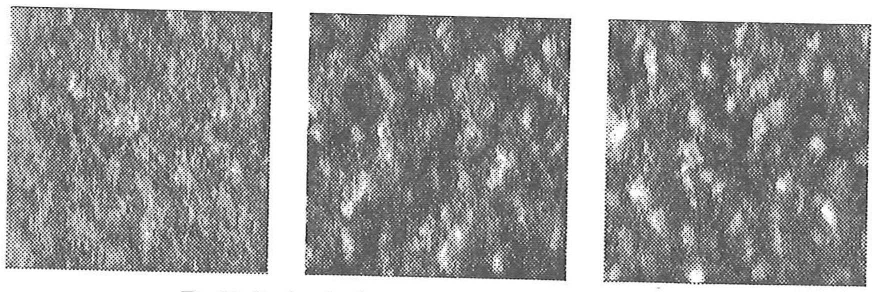

Fig.10. Surface b after respectively 5, 15 and 30 minutes.

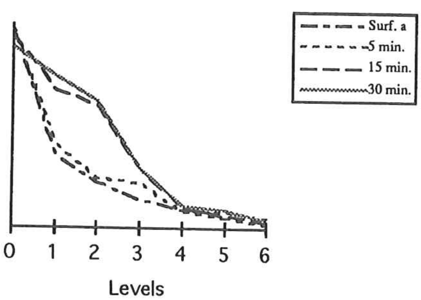

Fig. 11. Contrast evolution through the pyramid for surface a.

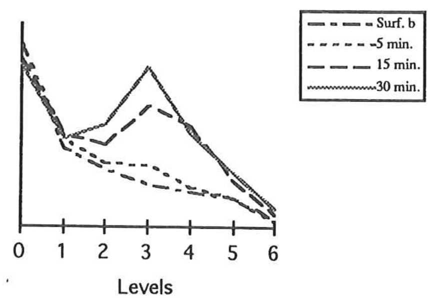

Fig. 12. Contrast evolution through the pyramid for surface b.

microtextured. Moreover, surface b is more macrotextured. Finally, these quantifiers are in close relation with the visual evaluation by an expert.

Table 1. Contrast quantifiers for the surfaces a and b.

Quantifier	*a*	*a.5*	*a.15*	*a.30*	*b*	*b.5*	*b.15*	*b.30*
Optimal level	2	2	2	2	2	3	3	3
Curvature	-3,58	3,46	16,52	15,09	-1,11	3,47	10,41	21,29

CONCLUSION

We have described a multiresolution process for texture analysis using an intensity pyramid. The retained quantifiers are objective because their evolution through different levels is characteristic. Moreover, the pyramide structure is well matched to the human visual encoding (Wandell, 1995). This method is applied to textile surfaces. The results are then satisfactory enough to enable a classification in terms of abrasion resistance.

Actually, we work on fractional pyramid (Burt, 1981) to increase the number of levels. In fact, the number of cells in the next higher level is 1/4 of that in the lower one and some applications have shown that this growth rate may be too fast. We will have then a more extremely computationally efficient tool.

REFERENCES

Burt PJ. Fast filter transforms for image processing. Comp Graphics Image Processing 1981; 16: 20-51.

Burt PJ. Pyramid-based extraction of local image features with applications to motion and texture analysis. Proceed SPIE 1982: 114-24.

Haralick RM. Statistical and structural approaches to texture. Proceed of the IEEE 1979; 67(5): 786-804.

Konik H. Contribution de l'approche pyramidale à la segmentation des images texturées. PhD thesis, University of Saint-Etienne, 1994.

Konik H, Calonnier M, Laget B. Adaptive texture image segmentation using local-base pyramids. Acta Stereol 1993; 13: 499-504.

Mitchell OR, Myers CR, Boyne W. A max-min measure for image texture analysis. IEEE Trans Computers 1977; 25: 408-14.

Rao AR. A taxonomy for texture description and identification. Springer-Verlag, 1990: 2-4.

Tanimoto S, Pavlidis T. A hierarchical data structure for picture processing. Comp Graphics Image Processing 1975; 4: 104-19.

Wandell BA. Foundations of vision. Sunderland: Sinauer Associates, 1995: 265-67.

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