ACTA STEREOL 1994; 13/2: 499-504
PROC 6ECS PRAGUE, 1993
ORIGINAL SCIENTIFIC PAPER

# ADAPTIVE TEXTURE IMAGE SEGMENTATION USING LOCAL-BASE PYRAMIDS

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ABSTRACT

This paper presents an approach to textured image segmentation. It is more exactly intended for detecting and extracting compact objects from an image. Because multiresolution or pyramidal techniques set problems, local-base pyramids are introduced. They are called "local pyramids" and simulate the human vision in its attention focusing process. Moreover, our method has the advantage to be adaptive with respect to the image texture.

Key words: image segmentation, texture, pyramid, local methods.

## INTRODUCTION

The final aim of our research is an automatic vision system for visual aspects quantification of textile surfaces. Such surfaces can generally be decomposed both as an image of structure and as an image of texture (Redortier et al., 1992). The first one contains the periodic organization of the yarn. The second one is composed with non-periodic events, such as tufts due to abrasion, pile tearings or other rearrangements of fibres...

In fact, we have to quantify these local events automatically. To realize this operation, we have developped the present process:

Segmentation ---> Analyze ---> Data ---> Quantification.

The first step, i.e. the segmentation, must resume the image information by extracting objects from the noisy background. Consequently, this paper presents a segmentation method. It uses a pyramid or a hierarchy of fine to coarse resolution versions of a picture. This tool was first explored in order to speed up several picture processing operations (Tanimoto et al., 1975). Such techniques have been successfully applied to segmenting images on the basis of texture, contours (Rosenfeld, 1986).

## 1. LOCAL PYRAMID VERSUS CLASSICAL PYRAMID

### 1.1. Greylevel pyramid definition

First of all, let f be the $2^n \times 2^n$ image to be segmented. The corresponding pyramid is the reduced resolution versions of this original image. Usually, the resolution decreases twofold between consecutive levels, so at each level h the size is $2^{n-h} \times 2^{n-h}$. An example of a $2^3 \times 2^3$ image pyramid is given in Fig.1.

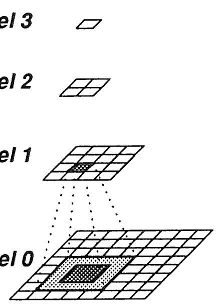


Fig.1. An example of a $2^3 \times 2^3$ pyramid.

Let $f_h(x,y)$ be the value of pixel (x,y) at level h. In fact, $f_0$ is the bottom level and corresponds to the original image f.
Actually, we compute the values of the next level by convolving the greylevel values at the current level with a 4 by 4 kernel, w, and by sampling them at half the current spatial frequency. The pixels that are used during this process are by definition the sons of the current element.
Given $f_{h-1}$, $f_h(x,y)$ is then obtained by:

$$f_h(x,y) = \sum_{i=1}^{i=k} \sum_{j=1}^{j=k} f_{h-1}(2x+i-2, 2y+j-2) \cdot w(i,j) \tag{1}$$

Different generating kernels have been studied (Burt, 1981). Our choice is a 4 by 4 unweighted averaging kernel. There is 50 percent overlap between adjacent kernels along both horizontal and vertical directions, which implies that each element generates four fathers.

### 1.2. Introduction of the local pyramids

Pyramid structure seems to be ideally adapted to implement human vision (Burt, 1988). Indeed, the extraction of an object does not suppose to "look at" the greatest resolution. Attention is not perturbed by irrelevant details. In high levels of the pyramid, the noise has been averaged out so that only relevant parts appear. On the contrary, an object can only be delineated if all details are present. Lowest levels provide it. In fact, the segmentation consists in using vertical interactions between neighbouring elements in the pyramid.

Nevertheless, classical structures give poor results when they are experimented on our images. Fig.2 shows a 256x256 image studied in the experimental results.

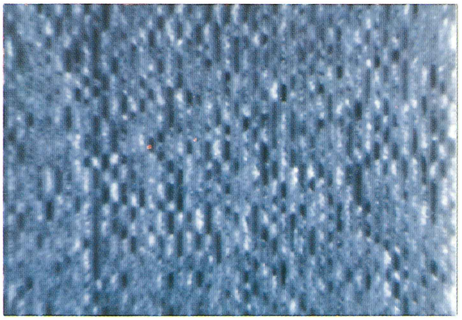

Fig.2. Test image.

Actually, the classical structure generates many problems (Jolion et al., 1992). It can not be adapted to objects that are extremely different. It is the case for our images. Though they are globally inhomogeneous, they are characterized by local topographic irregularities in a noisy background. Obviously, objects have different contrasts, different sizes and different homogeneities.
Moreover, on seeing an image, human sight systems seem to take into account image texture. They don't look for the same objects if the image is macro-perturbed or on the contrary micro-perturbed (Redortier, 1992). These terms classify images into different textures. An image where quite large objects appear is macro-perturbed, when another one with a "sandy" aspect is micro-perturbed. It is our hypothesis that no segmentation method can be efficient without being adaptive with respect to image texture.

The principle of our pyramidal approach is that attention is focused on more relevant parts of the image. In fact, we construct not only one pyramid for the entire image but one for each relevant part. This one has to be correctly contained in each local pyramid base. This base size is defined in accordance with the image texture and constitutes an a priori decision obtained during a general analysis (Redortier, 1992). The appropriate size is linked to the smallest square window containing the object. The more macro-perturbed the image is, the larger the base of each local pyramid is. This size is always chosen larger so that none object can be "truncated".

The question is now to extract relevant parts of the image. In our context, we use the notion of spot. A pixel is by definition a spot if its greylevel value is higher (white objects) than all the greylevel values in its neighbourhood, whose size depends on the macro/micro perturbation of the image. This definition can easily be adapted for other applications. An example of local pyramids approach is shown in Fig.3.

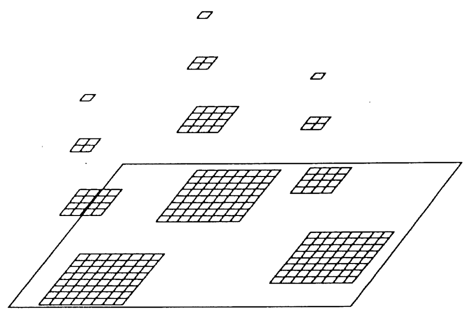

Fig.3. Local pyramids for each spot.

The spots are now labelled. In the next part of this paper, we will use each local pyramid in the same way. So, let only consider the spot i and its local pyramid $P_i$ centred on it.

## 2. USING THE LOCAL PYRAMID

### 2.1. Bottom-up process

A severe problem of the classical structure is linked to the hypothesis that it exists a level where the object could be represented by an unique pixel. It seems to be too restrictive for the objects we are concerned with. A solution can be found observing that the central pixels in a pyramid are important. Actually, the spot i generates 4 and only 4 fathers at each level of $P_i$. We can also introduce the notion of 4 orientations during the bottom-up process (Fig.4).

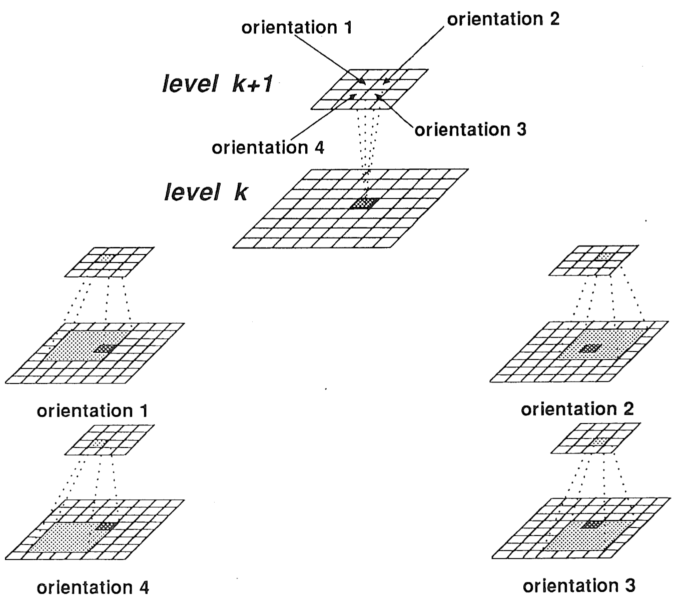


Fig.4. The 4 orientations in the local pyramid and their correlations with the current element.

The bottom-up process consists in analysing the evolution of the spot through the pyramid. For every orientation $\alpha$, ($\alpha$ = 1..4), the greylevel contrast is computed at each level. By definition, this contrast is the difference between the greylevel value of the current element and the average of the greylevel values of its neighbours (Rosenfeld et al., 1988).
By comparing the contrasts between successive levels, we can decide on the best element which can represent the object according to the orientation $\alpha$. This element is defined as the root in the orientation $\alpha$.
Obviously, if the element is within the object, while all its neighbours belong to the background, it should have a high contrast. So, the root representing the object in the orientation $\alpha$ is chosen as the one where the contrast begins to decrease for the first time. In fact, it is possible that the higher contrast, through the pyramid, represents an element where two objects have been connected (because of the sampling). However, it can not be the best root of the concerned object.
After the four roots representing the object have been found, we want now to get a more precise description of the object in the image.

## 2.2. Object delineation

In fact, we "project" the four roots, whose level can be different, on the base by keeping all its sons at each step.
An optimal enclosing base is also obtained. The local mean $m_i$ and the standart deviation $\sigma_i$ are then computed. The object detected by the spot i is defined by a virtual greylevel interval $I_i$ such as $I_i = [m_i - \sigma_i, f(i)]$.
As we said before, f is the greylevel function of the original image.
Finally, an agregation step extracts precisly the real object from the image. Beginning from i, it groupes all 8-connected neighbours with greylevel values in the interval $I_i$ until no further pixel can be added.

## 2.3. An application example

We have experimented with our segmentation method on 256x256 images. The test image, shown in Fig.2, represents a textile surface where tufts (due to abrasion) appear as compact regions that differ in average greylevel from their background. Fig.5 shows the results.

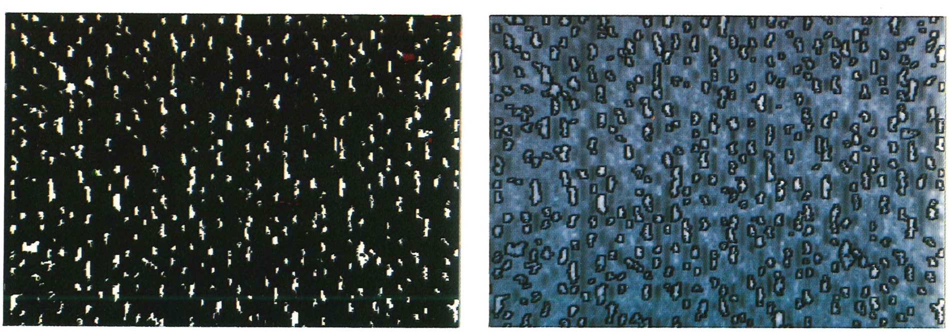

Fig.5. Experimental results on the test image.
(a)extracted objects. (b)extracted objects within the original image.

## CONCLUSION

We have exhibited an adaptive method of image segmentation using local pyramids. It simulates the human vision in its attention focusing process by extracting an object from its local background. Actually, each object is extracted locally and with respect to the image texture.

This method was applied to a set of 256x256 images. The results were very satisfactory. They enable a classification of textile surfaces in terms of pilling and abrasion resistance. However, the detection of spots is adapted to our objects. For other applications, another approach would be more efficient, in term of scene analysis for example.

## ACKNOWLEDGEMENTS

This work was supported by Région Rhône-Alpes through a research grant.

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