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A NEW MULTI-SCALE APPROACH TO THE SEGMENTATION OF MULTI-TEXTURED IMAGES

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ABSTRACT

This article presents a new method for the segmentation of multi-textured images. This method, based on statistical criteria, is multi-scale. In fact the images are studying at any study scales and the best are automatically selected so that the segmentation can be done. The obtained results are in accordance with the segmentation realized by the human preattentive vision.

Key words : multi-scale, segmentation, study scale, textured images.

INTRODUCTION

The segmentation of multi-textured images is an area which concerns many fields of application (teledetection, applications in textile, industry etc...). Studies have been made either to describe textures or to segment multi-textured images. Best-known among the research on the subject are the works of Gagalowitz (1983) and Rao (1990) but also those of Redortier (1992) and Konik (1994). Thus we shall review in this article a variety of approaches for the description and segmentation of textures.

WHAT IS THE TEXTURE ?

Although texture has attracted a large amount of research in image analysis, it remains one of aspects of images which has the least definitions. For our part we have based our approach upon that of Gagalowitz (1983) who considers texture to be made up of two component features :

- one component whose law of intensity variation is periodic : i.e. the periodicity,
- one component whose law of intensity is not periodic : i.e. the pertubation.

It is the interaction between these two component features which makes up texture. This approach, which is very similar to the models used in synthesis imaging (Blinn and Newell, 76) allows for a classification of textures in two categories: stochastic textures and deterministic textures.

IMAGES OF STATISTIC MOMENTS

We have considered texture represented by in grey level images. These images can therefore be considered as discreet surfaces which can be analysed by a multi-scale approach. That means that for image considered, we define the corresponding **images of statistic moments** (Favier, 94) for each study level. The study scale is the size of the mask sliding on the image. Thus, for the image of statistic moments at 't' scale, each pixel is replaced by the statistic moment of the pixel corresponding to the neighbourgh pixels linked to the 't' scale of study (Fig. 1).

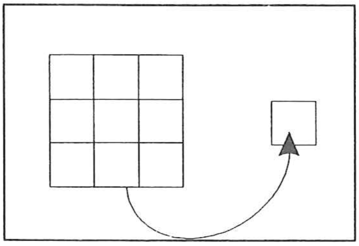


Fig.1. Neighbouring pixels linked to the 't' scale of study, t=1.

The study of these images of statistic moments at order one (the image of averages) and at order two (the image of standard deviation) shows that for images of reference as textures taken from the Brodaz's collection (Brodaz, 68) the histogram of these images becomes very rapidly unimodal with a low standard deviation (cf Fig 2). This is not very surprising reference to the description of textures presented above. We have also tested this property on gaussian images which are very good representations of stochastic textures. The idea is then to suppose that a texture can be characterized for a sufficiently large study scale by the data collected from the various statistic moments on a mask for which the size corresponds to the study scale placed randommless upon it. This idea may recall the preoccupations of G. Lowitz (1983) who studies the configuration of local histograms using Mahalanobi's distance on histogram, moreover also allows to dispense from computing these histograms. The problem is then to determine for each texture the study scale for which characterisation has been obtained (for larger scale characterisation remains identical).

ALGORITHM

We have used these properties to obtain an algorithm of segmentation of multitextured images. The images of statistic moments (order one and two) are calculated for each scale of study. The histogram of each of these images is studied so as to determine its multi-modal character. For images with two textures, we determine the scale of study to be considered and the image of statistic moments which permit segmentation. We illustrate our theory from multi-textured images by using Brodaz's textures (Fig 3.).

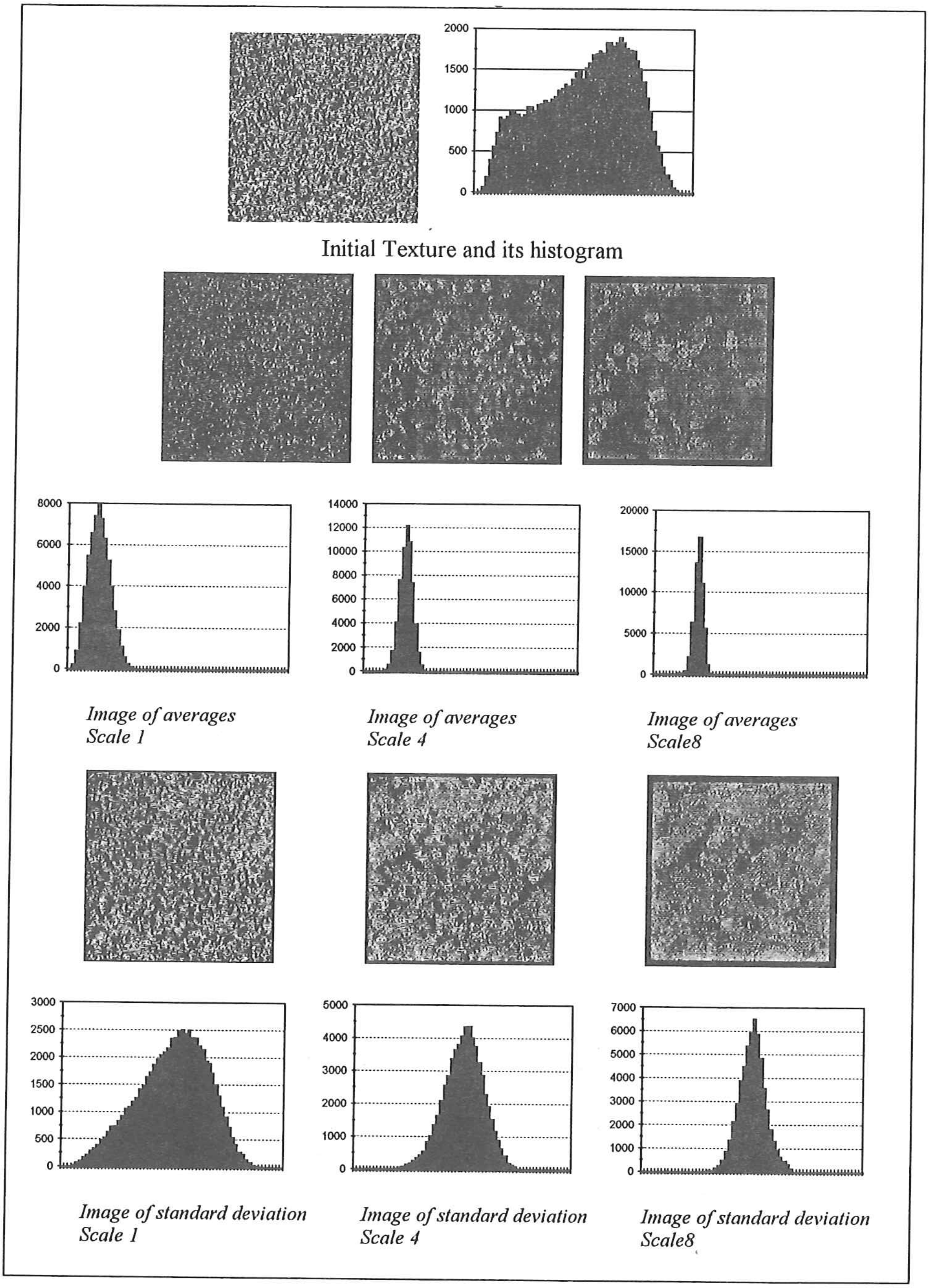
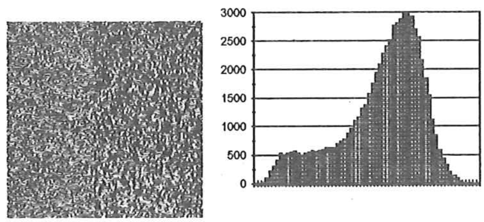


Fig. 2. Images of statistic moment and these histograms.

DETERMINATION OF THE STUDY SCALE

To illustrate our purpose consider as example the case of study of an histogram with two different classes. We first have to determine the best treshold which correctly shares it in two different classes. In order to be optimum this sharing needs that the two detected classes present a maximal inter-class variance and, at the same time, minimal intra-class variances. The objective is then to maximize the inter-class variance and, at the same time, minimize intra-class variances. As far as we are concerned, we have to search the optimum solution in a set of two



Multi-textured image and its histogram

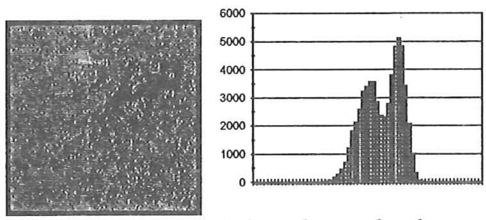


Image of averages at study scale 6 and its histogram

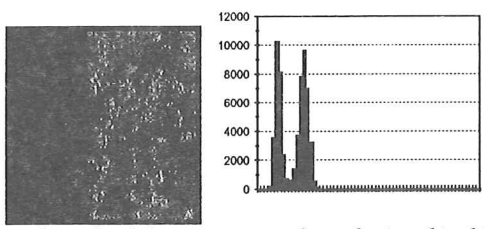
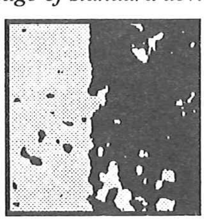
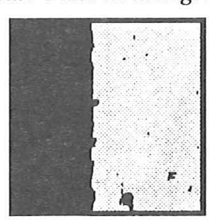


Image of standard deviation at study scale 6 and its histogram





Thresolding on image of averages | *Thresolding on image of standard deviation*

Fig. 3. Examples of segmentation on multi-textured image.

classes of histograms (histogram of images of averages and standard deviations). In fact, we first have to determine study scale and secondly we have to determine the division treshold of classes concerning the selected histogram.

In order to avoid a too long computation, it is much better to choose a threshold acceptability for the segmentation. This means that it would be preferable to find a criterion that would determine whether for the so-called study scale the segmentation is possible or not (either on the image of averages or on the image of standard-deviations), rather than studying all images of averages and all images of standard-deviations (one for each study scale). This criterion must depend on inter-class and intra-class variances. A simple solution to this problem is, for example, to impose a minimum value to the expression (1) :

$$\frac{V_{1,2}(k)}{(V_1(k)+V_2(k))} \tag{1}$$

where $V_{1,2}(k)$ is the inter-class variance at the study scale k and $V_1(k)$ and $V_2(k)$ are respectively the intra-class variance of each obtained class. The advantages of this principle is that it can be also applied to a number of classes superior to two. Actually, it is enough to impose a minimum value to the following expression:

$$\sum_{i=1}^{p-1} \frac{V_{i,i+1}(\alpha_i,k)}{V_i(\alpha_i,k)+V_{i+1}(\alpha_i,k)} \tag{2}$$

in the case of a p-classes decomposition where α_i is the threshold between the class i and i+1. So, the proposed algorithm for only two textures discrimination is as follows :

Algorithm

Let a bi-textured image I be segmented and the number p of texture known.
For all images of averages and standard deviation, and for each study scale the following value *m(k)* is computed:

$$m(k) = \sum_{i=1}^{p-1} \frac{V_{i,i+1}(\alpha_i,k)}{V_i(\alpha_i,k)+V_{i+1}(\alpha_i,k)} \tag{3}$$

For any existing k enabling *m(k)* maximal, the threshold is possible. Otherwise, the same thing must be done to the other value of k

This method is efficient for simple multi-textures images, i.e. presenting no micro texture and macro texture interweaving. In this last case, which is more complicated, one must not stop at the first possible study scale but continue after its detection in order to detect another possible study scale. Each segmentation based on these study scale gives us pertinent information on the micro or macro texture of the image.

CONCLUSION AND PERSPECTIVE

Parallel algorithm of these methods can be made if required. It is quite possible to study images of different statistic moments at different study scale simultanously. Moreower, these methods can be used to solve complex segmentation problems like the image of square. (e.g. the image of squares illustrated in Fig. 4)

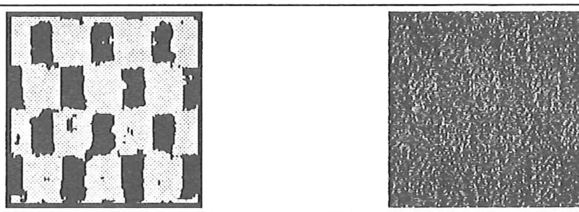


Fig 4. Multi-textured textile image : squares

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