TEXTURED IMAGES SEGMENTATION BY A MULTIRESOLUTION MORPHOLOGICAL DECOMPOSITION METHOD

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ABSTRACT

This contribution deals with the textured images segmentation. The model exploits morphological operators and order filters properties. A morphological decomposition filters bank is built to isolate elementary patterns by decomposing the textural image characteristics. The 1 and 2 order statistic moments and the gradient means are computed in order to select the best feature component image which allows to perform the image segmentation. The method is illustrated by a real image randomly textured.

1 INTRODUCTION

This paper describes an hierarchical algorithm based on a multiresolution morphological decomposition approach to segment natural textured images. The analysis model consists in combining morphological operators and order filtering properties. The order filters [1][2] are largely appreciated with the context of image processing on account of their impulse noise immunity and their ability of edges preservation and contrast enhancement. Many successful applications were found in the image preprocessing at this day [3]. Parallely, others filters patterns based on the ensemblist theory [4] are developed in patterns recognition. The mathematical morphology is very attractive in the decomposition processing model : its iterated operators allows to extract the objects topology until satisfactory result and its algebraic properties allows to build from basic structuring elements higher order primitives, which leads to deal efficiently with geometrical features. From these principles, a texture analysis strategy based on morphological filters is proceeded in several stages and implemented recursively :

(i) a local and growing statistic classification is realized by an order statistic approach ;

(ii) a texture attribute extraction is accomplished by a morphological decomposition filters bank ;

(iii) a comparative observation of a texture attribute vector by computing the 1 and 2 order statistic moments and the gradient means can segment a real textured image.

2 ORDER STATISTIC CLASSIFICATION

2.1 Order filters

In the within of the image analysis, the order filters presence is justified in the focus of resolving the considered pixel assignment problematic with the best value from the surrounding observations set. They are characterized by a statistic study based on a growing data ordering. This statistic set is performed either by a implicit or explicit Φ function [3] or by a classification criteria defined by order statistics [5] to provide an unique output value.

2.2 Order statistic determination

On account of the great filters variety concerned by the statistic studies, we propose in this framework the use of rank order based filters model [5] belonging the nonlinear filters class in order to optimize filtering features. This filter pattern is built on the design of a dual order filters pair whom principle can be described in the following way.

Let f(x,y) denote an original image point and B_n a flat structuring element of size n.

The point set under the mask referenced as :

$$f\big((x,y)+z\big) \text{ with } z \in B_n$$

is unfolded on a one dimensional vector X.

$$X = \{x_1, \ldots, x_i, \ldots, x_n\}$$

The vector X is sorted in the growing order.

Let $g^k(X)$ denote the k^{th} smaller value among X. Under these conditions, the output of the k^{th} order filter at the location (x,y) is :

$$\begin{aligned} RO^k_{r,B_n}(x,y) &= \mathrm{Rank}_k\left[f\big((x,y)+z\big) / z \in B_n\right] \\ &= g^k(X) \end{aligned}$$

where r defines the order k of the filter by the relation :

$$k = NI[(n-1)r+1]$$

with $0 \le r \le 0.5$ and where $NI[.]$ is the rounding to the nearest integer operation.
The output of the dual fikter that corresponds to the one we have just described is given by taking the complement r' of r towards 1, that is to say $r' = 1 - r$. This leads to choose a new indice k' defined as :

$$k' = NI[(n-1)(1-r)+1]$$

.

The output of the dual filter is then :

$$RO_{1-r,B_n}^{k'}(x,y) = \mathrm{Rank}_{k'}\left[f((x,y)+z)/z \in B_n\right] = g^{k'}(X).$$

It is interesting to notice that the order filter Rank becomes the mathematical morphology erosion for multi-gray levels when $k = 1$ (i.e. $r = 0$). Under this condition, the corresponding dual order filter is the mathematical morphology dilatation (i.e. $k' = n$ for $r = 0$). For $r = 0.5$ Rank and its dual become the median filter.

3 MULTIRESOLUTION DECOMPOSITION MORPHOLOGIC METHOD

3.1 Top hat transform

The texture statistic properties are studied in an observation window of size n. Morphological operators allow to characterize them directly by using the top hat transform which is defined as being the difference between the original signal f and its opening γ_n and is described by the following relation :

$$h_n(f) = f - \gamma_n(f).$$

This transformation basically compensates for the smooth gray level fluctuations of the DC component of the signal while discriminating between positive and negative peaks.

3.2. Morphological decomposition approach

In this stage, a decomposition algorithm based on top hat transform is elaborated by taking from Wang [6] works. As that mentioned in [4], the texture attributes extraction by the opening design is generaly contaminated by the presence of noise. The top hat transform is here controlled by the morphological opening. This opening operation is combination of an erosion ε_n followed by a dilatation δ_n, so :

$$\gamma_n(f) = \delta_n \varepsilon_n(f).$$

In order to obtain a robust textural discrimination, we substitute the rank order filter concept described previously for the classical morphological operators. The erosion which operates on the local minima is replaced by $RO_{r,B_n}^{k}(x,y)$, while the dilation which operates on the local maxima is replaced by $RO_{1-r,B_n}^{k'}(x,y)$. The result of opening operation is thus defined as :

$$RO_{1-r,B_n}^{k'}\left[RO_{r,B_n}^{k}(f)\right].$$

To obtain a multiresolution decomposition, this process of analysis is iterated in the way described here after to obtain a generalized decomposition algorithm. The iteration concerns the size of the structuring element. We start with a size equal to the dimension of the bigest object that may be found in the image. The opening of the original image is computed. The result showing the occurences of objects of this particular dimension is substracted to the original image to obtain an image on which a new opening operation is processed using a decreased size of structuring element. The process is repeted until the size becomes equal to one. This can be descripted as :

(i) $f_0 = f$ start with the original image
(ii) $s_0 = RO_{1-r,B_n}^{k'}\left[RO_{r,B_n}^{k}(f_0)\right]$; $f_1 = f_0 - s_0$
(iii) $s_1 = RO_{1-r,B_{n-p}}^{k'}\left[RO_{r,B_{n-p}}^{k}(f_1)\right]$; $f_2 = f_1 - s_1$
:
(i...) $s_i = RO_{1-r,B_{n-ip}}^{k'}\left[RO_{r,B_{n-ip}}^{k}(f_i)\right]$; $f_{i+1} = f_i - s_i$

where p is the step of decrease of the structuring element size.
We thus obtain a set of component images $\{s_0,\ldots,s_i,\ldots\}$ that represent the original texture. Different attributes, like 1 and 2 order statistc moments and the gradient means, may be computed on these components to recognize a particular texture or to obtain a segmentation of several textured regions.

4 APPLICATIONS AND RESULTS

4.1 Method consideration

The tool we have described in the previous section is the starting point of the design of a textured image segmentation process. It is achieved by using a morphological decomposition filters bank which does not compute frequencies but rather window size variation. At the end of processing, each output channel provides a particular component of the textured image. These components are to be taken int account differently depending on what, interpretation or treatment, is to be performed.

4.2 Application to texture segmentation

Three textures that are not visualy very different from each other have been used to show the ability to give a good segmentation. The first is a synthetic pure geometric one, the second is a natural geometric texture, and the third is a random texture. The figure 1 shows the resulting components in each case. It is visible that the energy is radicaly differently distributed.

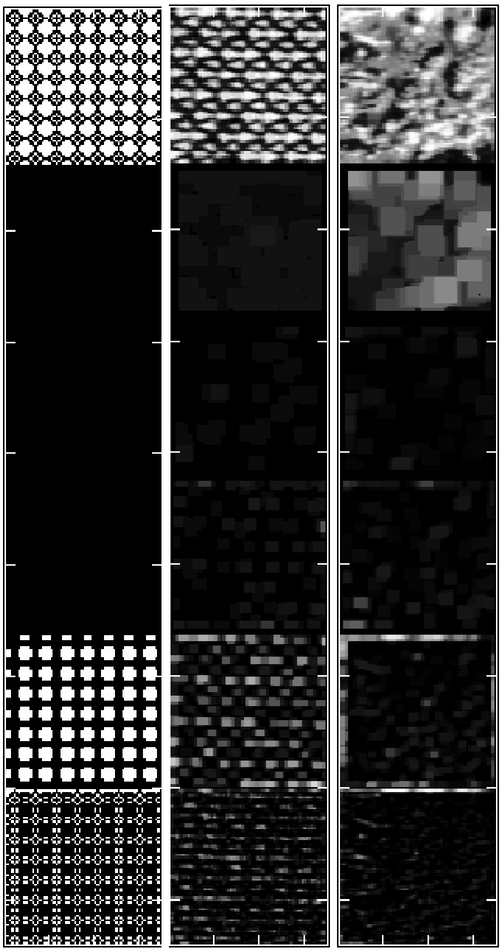
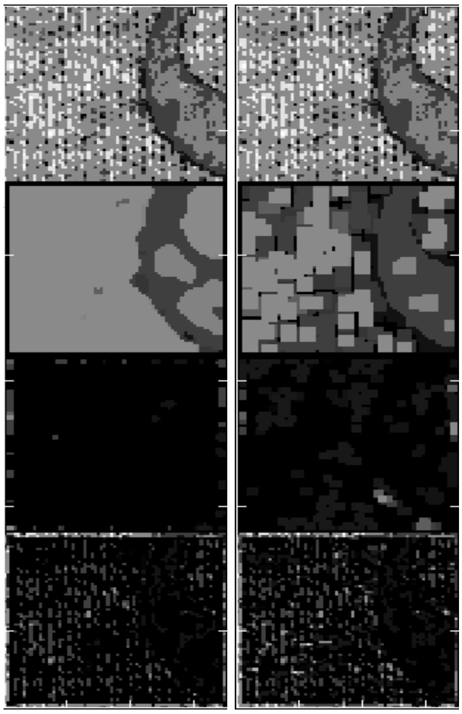


Figure 1

4.3 Performance gain in presence of noise

The use of order filters gives improved performance in terms of robustness to noises. The choice of a non zero value for r parameter forbids exact reconstruction of the original image, but it provides better components to perform segmentation. A test image containing an object on a noisy textured background is used to show this effect. Figure 2 shows the component results for two different values of r.

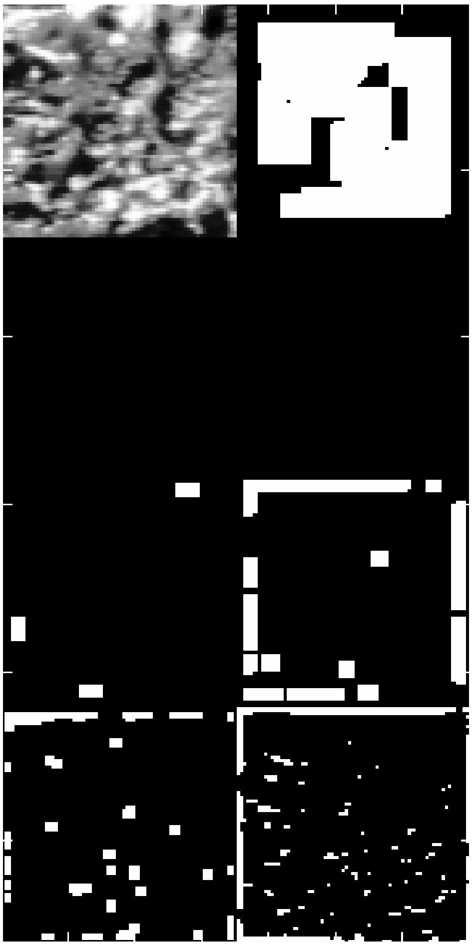


r = 0.1 r = 0.3

Figure 2

4.4 Application to defects detection

The images to analyze are showing rail flake rolling defects. These defects are issued from local failings owing to old component. They are characterized by irregular and variable size patterns yielding the heterogeneous nature and the random topography of images. We exploit here the two advantages of our method. For this practical work, seven square window sizes were used (13x13, 11x11, 9x9, 7x7, 5x5, 3x3, 1x1). It has proved to be a good compromise between sharpness analysis and heavy computation in order to isolate the texture random patterns. The figure shows an image and its decomposition. For an easier interpretation, the resulting components are binarized. It is clear that this random texture is composed mainly of objects of size 1, 3 , 5 and >13 pixels. Very few 7 pixels sized ogjects appeared, and no 9 and 11 pixels seized were present.



5 CONCLUSION

A method based on a morphological decomposition to segment randomly textured images is related. The decomposition results in a set of component images whose contents depend on the primitives of the texture studied. The objects present in the texture are in fact sorted regarding to their size. The technique is applied to a particular defect detection problem for which the identification of a random texture is necessary. The multiresolution sheme enables a good texture recognition, and the use of dual order filters gives good performance in terms of robustness to noises.

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