MORPHOLOGICAL ANALYSIS OF TEXTURED IMAGES FOR IDENTIFICATION OF THIN STRUCTURES

Davide Corso, Roberto Fioravanti and Stefano Fioravanti

DIBE - University of Genova, Italy
Via Opera Pia 11/A, Genova I-16145
ITALY

ABSTRACT

The paper addresses the problem of a real time approach for thin structures identification. The proposed method make use of adaptive morphological operators in which the normal textural properties are brought to bear on the filter design in order to enhance the output related to anomalous structures. We discuss how the introduction of adaptivity criteria is useful to reduce the sensitivity of morphological filtering to local variations typical of textures and to noise. In addition, theoretical investigations related to the problem of the optimization algorithm are presented and discussed. Experimental results have been carried out both on classical natural textures and on ceramic tile images and prove the efficiency of the proposed approach in many practical applications.

1. INTRODUCTION

Texture has received considerable attention in the image analysis literature. A number of distinct approaches have been suggested for texture representation falling to two major classes: those based on the spatial statistics of the textured image, and those based on its spectral properties. From the methods that operate in the spatial domain, the most restrictive in terms of assumptions pertaining to the textural properties they can characterize are structural methods [3] which are based on the view that texture is a regular pattern generated by a repeated placement of well defined textural primitives. Early psychophysical studies [5] motivated the development of methods exploiting second order image statistics exemplified by the co-occurrence matrix representation [4]. The generative methods attempt to represent texture by models which can reproduce statistically similar textural characteristics [2] [1]. The last category of methods in this class is based on rank order statistics or mathematical morphology [8].

In this paper we explore these approaches In particular, the rank order based approach is developed where for crack detection we focus on an adaptive rank order filtering scheme. The problem we consider is that of detecting hair-like cracks on complex textural backgrounds. The experimental comparisons will be carried out on Brodatz textures with cracks superimposed on them and on ceramic tile textures with natural cracks.

2. IDENTIFICATION OF THIN DISCONTINUITIES

The class of rank-order filters and morphological operators presents several advantages in terms of computational complexity, low dependency on texture statistics, and robustness to noise.

Lets consider a generic Rank Order Filter (ROF) [6] with rank r and mask M, defined as follows:

$$y_i = E_{r,M}[x_i] = \underset{(N-1)r+1}{Rank}\left\{x_{i-j} \mid j \in M\right\} \qquad (1)$$

where the operator Rank{X} extracts the n-th element of the array X previously ordered in ascending sequence. It can be observed that common filters like minimum, maximum and median are obtained from Eq. 1 by imposing the value of r equal to 0, 1, or 0.5 respectively.

Given the formal definition of ROF, we can introduce the dual filter, defined as a filter with rank $(1-r)$ mirrored with respect to the mask center. Called D the dual of E, the following equation holds:

$$D_{r,M}[x_i] = E_{1-r,M^*}[x_i] = \underset{(N-1)(1-r)+1}{Rank}\left\{x_{i+j} \mid j \in M\right\} \qquad (2)$$

On the basis of Eq. 2, a formal definition of a generic Rank Order Based Filter (ROBF) with rank r and mask M is expressed by the following

$$R_{r,M}[x_i] = D_{r,M}\left[E_{r,M}[x_i]\right] \qquad (3)$$

It can be noticed that simply imposing the value of r in Eq. 3 it is possible to generate some interesting filters like Opening (r=0) and Closing (r=1) with a generic mask M. Such filters, usually called morphological filters, have been extensively used to solve the problem of thin discontinuities addressed in this section and are the subject of the following pages.

3. MORPHOLOGICAL FILTERING

Among the various types of morphological filters [8], the operator that has been selected as the best candidate for the identification of thin discontinuities is the *(Close-Open)* one [9], denoted in the following *CO*, which can be defined as follows:

$$\begin{aligned} CO(I) &= Close(I) - Open(I) = \\ &= Erosion(Dilation(I)) - Dilation(Erosion(I)) \end{aligned} \qquad (4)$$

The effect of such operation can be better clarified by the simple example of Fig 1: at the top, a 3x3 *CO* is applied to two round shaped objects, while at the bottom, the same operation is performed on two thread-like elements. It is evident that, while in the former case the effect of the filtering is minimal since the erosion does not eliminate completely the object, in the latter case the *CO* enhance the thin structures. It is to be pointed out that the result would not change if the objects were dark on a light background where the thin structure disappear in the Closing operation, or light on a dark background, with the thin structure eliminated by the Opening operation.

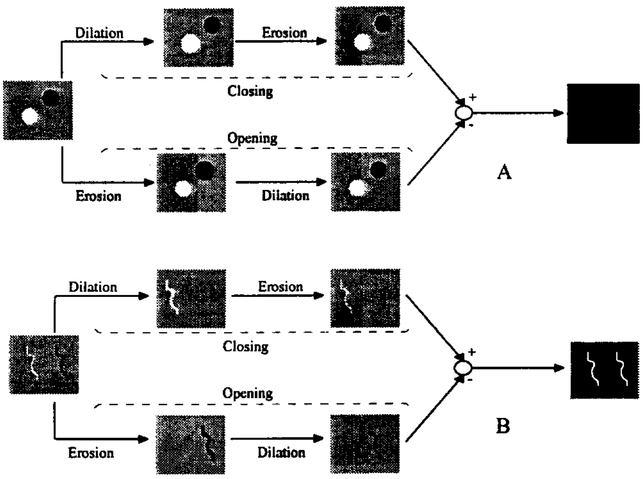

Figure 1 - Result of 3x3-CO operator on bidimensional objects.

In more complex situations, the *CO* operator in its general formulation is not suitable for two reasons: first, it detects not only the anomalous structures, but also the thin configurations that are normally in the texture, and second, it is sensitive to the noise, in the sense that it enhance regular variations of the intensity value. Such problems result in a non-null output even when the filter is applied to a homogeneous texture, as shown in Fig. 2.

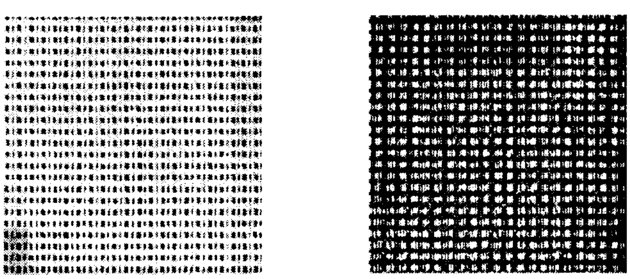

Figure 2 - Result of 3x3 CO operator on a texture by Brodatz (left: original image, right: image filtered and magnified by a factor 2)

4. ADAPTIVE MORPHOLOGICAL FILTERING

In this section we will discuss how the introduction of adaptivity criteria is useful to reduce the sensitivity of morphological filtering to local variations typical of textures and to noise. As the *CO* filter is very simple, there are only two elements that can be considered for achieving a spatial adaptivity: the dimension of the mask and its shape. The former parameter is the easier to modify, but does not produce in general the result needed: in fact, it often happens that the thickness of the irregularities to be identified has a size similar to the acceptable variations of the texture. The latter is more interesting, for it is possible to generate and utilize an optimized structuring element, that is, a *CO* mask that produces a minimum response when applied to an image without irregularities.

In [7] a general solution to the problem of optimum adaptation of the mask in Rank-Order based filtering is proposed. Here, a set of candidates A is fixed a priori, and the fact that the j-th element (pixel) of A belongs or not to the mask is expressed by the sign of a real variable m_j. On the basis of such formulation of the problem, it is possible to define a cost function to be minimized (the goal is to obtain a null response on a regular texture); the method used to perform the optimization is the classical gradient descent algorithm.

Analysing in detail the Salembier solution, some major points of criticism should be expressed; in particular, the definition of the continuous variables m_j simply appears as a mathematical artifice to make the cost function differentiable, but does not change the underlying binary nature of the problem. As a matter of fact, the output of the filter is not sensitive to any variation of the parameter m_j that does not modify the sign: this means that the cost function to be minimized is a step function, and is therefore not suitable for the application of a gradient descent. Fig. 3 shows two examples of cost function in a 2D domain (for higher dimensions the concepts does not change); it is evident that, at each iteration, the direction toward which to move is computed by looking at the partial derivatives in the borders of the current plateau. Consequently, the next step will move to another plateau or remain in the same, depending on the step size, but it is possible to reach only the configurations that have Hamming distance 1. Moreover, due to the high discontinuity of the function, not always the joint use of the two partial derivatives performs well: in Fig. 3 (b) is shown a typical example where this strategy produces the worst possible result.

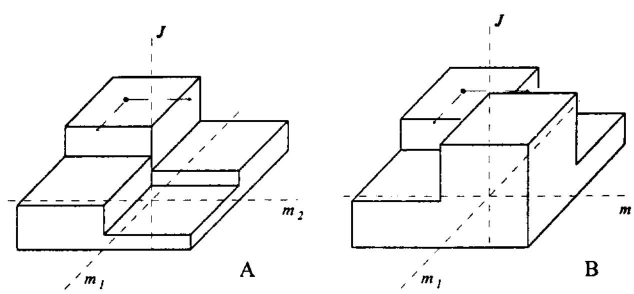

Figure 3 - Example of cost functions in a 2-D domain.

The proposed algorithm addresses the optimization problem in a more direct way. Two hypotheses are first made:

i. given a minimum number N_m of non-null elements, every algorithm tends to reach this number in a few steps: it is therefore convenient to keep N_m fixed;
ii. since the optimization involves the global image, the computation of the score to be associated to each candidate is based on the average value of the cost function over the all image.

Given such rules and a generic cost function J that penalizes the higher outputs of the filter, the algorithm proceeds iteratively by searching for the best swap between two candidates of the mask.

In other words, at each step all the pairs of inside-mask and outside-mask elements are exchanged, and the corresponding average cost function is evaluated: If the cost of the current configuration is lower than all the new costs, the algorithm ends, otherwise, the best configuration is chosen and another iteration is started.

The following example better clarifies this procedure. Suppose we have a 2x2 search area (a total of candidate elements $A = 4$) and want to construct a structuring element of two elements ($N_m = 2$); the situation is represented in a 3D space in Fig. 4. The vertices of the hypercube represent all the possible configurations of the mask, with 1, 2, 3 or 4 non-null elements: a 0 in the position i means that the i-th element of the mask is not used, while a 1 in the same position means that it has to be considered in the filtering. In particular, the marked vertices represent the configurations with 2 non-null elements that we are interested in. Starting from the vertex [1010] the algorithm will consider all the four vertices at distance two, produced by the swapping of two elements (i.e., [0110], [0011], [1001], and [1100]) and will compute the minimum of the cost function: if the starting configuration result is the best, then the algorithm is stopped, otherwise, the algorithm is launched again from the new point, and the only remaining configuration (i.e., [0101]) is introduced.

In general, if the search area has a dimension A and the non-null elements are $N_m < A$, then at each iteration it will be necessary to calculate $N_m \times (A-N_m)$ new configurations, and therefore $N_m \times (A-N_m)$ values of the cost function. As this way to proceed is very expensive, a sub-optimal solution yielding good results has been developed, based on a separation of the two operations that compose a swap: in practice, the transition from a mask to another is achieved by first finding the best configuration at distance one from the starting point (raising N_m to N_m+1) and then the best configuration at distance one from the intermediate point. In such a way the cost function has to be calculated only $N_m+(A-N_m)=A$ times.

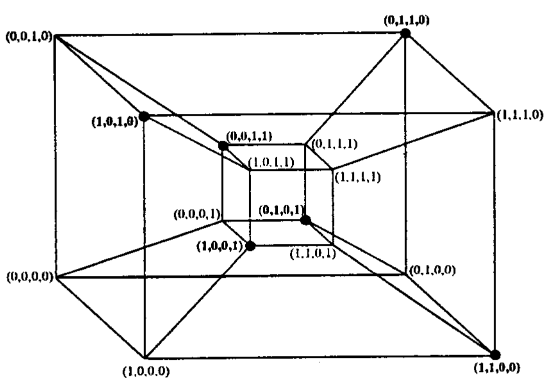

Figure 4 - Cost function domain with possible two-element masks pointed out.

Concerning the choice of the configuration from which the minimization procedure starts, a reasonable choice is to select a symmetrical central block of the desired dimension in the search area: this would not create any a-priori preference in the evolution of the minimization. To experimentally validate this hypothesis, a number of trials have been performed each with the starting point selected randomically: the results obtained confirmed that the best solution is in general achieved by a symmetrical initialization.

5. DECISION CRITERION AND COST FUNCTION

Two major points have still to be defined: the selection of a criterion to detect the presence or not of an anomaly, and consequently the definition of a reliable cost function to be used during the optimization procedure. The choice of an effective decision criterion requires the specification of the main properties that characterise a good decision; by studying the outputs of the filter in different situations, three requirements have been identified:

i. a pixel must be penalized proportionally to its value;
ii. if there is a number of contiguous pixels with non-null value, they must also be penalized proportionally to the number;
iii. as this operation has to be performed several times during the optimization, the number and the complecity of the involved operations must be very low.

The proposed criterion, called Anomaly Presence Degree (ADP) is defined as follows:

$$APD(A)=\sum_{i \in A}(ldg(i))^2 \qquad (5)$$

where A is a square search area with side L and $ldg(i)$ is the output of the filter for the i-th pixel. During the analysis phase the image is subdivided in blocks of dimension $L \times L$, and for each block the ADP parameter is evaluated and compared with a threshold th_{ADP}: if the threshold is exceeded, the block is classified as anomalous, otherwise it is considered regular. Usually the dimension L can be fixed in the range 30 to 60 pixels; in the tests carried out the value L=40 was adopted.

From what was previously said, it is clear that the goal of the adaptation algorithm, if applied to a normal image used for training, is to minimize the maximum ADP value present in the image: then, the cost function J will be defined as:

$$J=\max_{A \in \Theta}(APD(A)) \qquad (6)$$

where Θ is the set of square blocks into which the image is subdivided. Once the optimization is completed, the minimum value of J can be used to define the value of the threshold th_{ADP}:

$$th_{ADP}=(1+\alpha)J_{\min} \qquad (7)$$

where α is a real positive constant, varying in the range (0,1], to be fixed depending on the characteristics of the image to be analysed. This allows one to define the sensitivity to small variations (the lower the value of α, the higher the sensitivity).

6. RESULTS

The following example show the application of the adaptive Close-Open filtering (ACO) and compares this approach with the non-adaptive filtering. In Fig. 5, the Brodatz texture of Fig. 2 is filtered by using two different masks formed by 9 non-null elements on a 5x5 squared search area: a fixed central mask m_c (left) and an adaptive mask m_a resulting from the optimization algorithm (right).

$$m_c=\begin{bmatrix}0&0&0&0&0\\0&1&1&1&0\\0&1&1&1&0\\0&1&1&1&0\\0&0&0&0&0\end{bmatrix}\quad m_a=\begin{bmatrix}0&0&0&0&0\\0&0&0&0&0\\1&1&1&1&0\\1&1&1&1&1\\0&0&0&0&0\end{bmatrix}$$

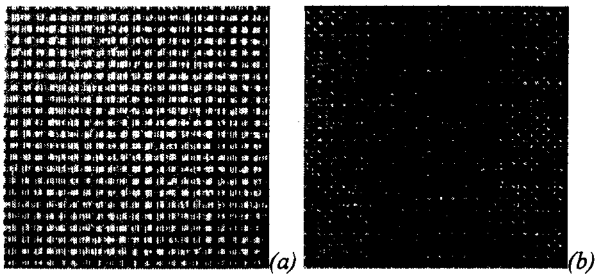

Figure 5 - Outputs of the non-adaptive and adaptive filtering applied to Fig. 2

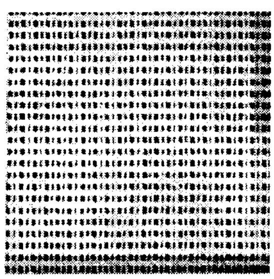

Figure 6 - Texture of Fig. 2 artificially alterated with a thin defect

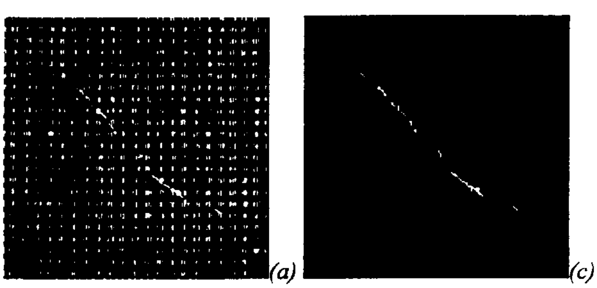

Figure 8 - (a,b) The results of thresholding the outputs of the non-adaptive (a) and adaptive (b) filtering applied to Fig 6

The effect of the adaptation is evident: the mask m_a is less sensitive to the variations of the texture, thus producing a lower response (the output values of Fig. 5 have been magnified for the sake of visibility). In Fig. 6 the same texture was artificially altered by introducing a thin structure, while in Fig. 7 (a) and (b) the response of the *CO* filter applied by respectively using the two mask m_c and m_a is shown. In Fig. 8 (a) and (b) the filtered images are binarized by a simple threshold to emphasize the higher performances of the adaptive method. In (c) the sparse points caused by noise are eliminated by not considering the blocks under the threshold th_{ADP}.

The thresholded outputs of the rank order filters for crack detection on a tile image is shown in Figures 9. The cardinality of the structuring elements was set to 9 with search area of 5*5. The APD criteria was computed for blocks of size 15*15. The Figures shows the output of those blocks with $APD > th_{APD}$ highlighting the crack structures. No post-processing line-filter has been applied, therefore the residual noise could be reduced. The processing time was about 0.4 for cardinality 9 elements, 256*256 images on a HP9000/750 workstation.

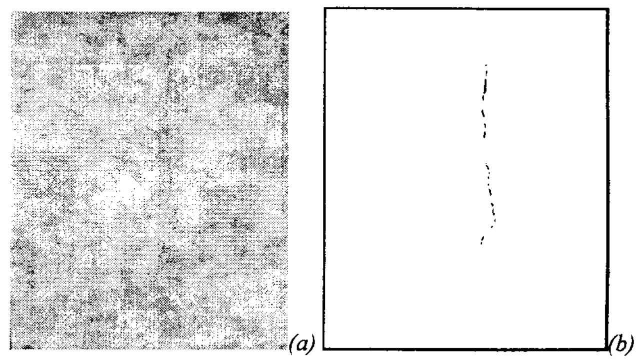

Figure 9 - Image of a tile with a crack (a) and thresholded output of ACO filter (b).

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