STRUCTURAL FAULT DETECTION IN RANDOM MACRO TEXTURES

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ABSTRACT

In this paper, we present a scheme based on iterative morphology for highlighting defects in random textures. The idea is to identify abnormally sized structures in the texture by determining their persistence when iterative morphological erosion is applied. We present some results from a large testbed database of images of granite and ceramic tiles.

1 INTRODUCTION

Texture is generally divided into two main types: micro and macro textures. Many methodologies have been developed to describe and model them and detailed surveys can be found in [3, 2]. Many existing texture descriptors are based on the view that texture is a regular pattern composed of repeated primitive elements. Automatic inspection of such regularly-textured surfaces is simplified by the inherent regularity in the placement of the texture primitives. Thus, deviations from the texture primitives should be easily identifiable and, more importantly, measurable. Unfortunately, most natural images do not generally show such regularity, although, in most cases, human vision can immediately identify different textured areas. Some prototypical examples of irregular textures, which are known as *random macro textures*, are ceramic, marble and granite images, which are of particular concern in this paper. The placement of the primitives within these is purely random and highly irregular. The abnormalities that may occur in such textures can be divided into two basic categories, blob-like and thin structures (i.e. cracks). In this paper, we deal with the processing of macro-textures and concentrate on the problem of blob-like defect detection.

Almost no work of direct relevance to the detection of purely random textures exists in the vision literature. In most cases, either the texture is not truly random or features that are sought within textures are not necessarily useful to analyse random textures. For example, Panjwani and Healey [5] present an unsupervised segmentation technique based on Markov Random Fields which clusters a "random" colour image in RGB space. They apply their technique to a natural scene which consists effectively of random shapes, i.e. very large and uniform areas, such as a scene consisting of sea, sky and hills. Thus, the technique has been demonstrated for images containing large uniformed colour patches, but not for images which depict colour texture. Caelli & Reye [1] describe a technique to estimate colour texture features from three spectral channels by using multiscale isotropic filters. This technique relies on the use of texture local orientation which is not relevant to our problem as our granite and ceramic textures tend to be rather isotropic. The detection of surface defects on ceramic materials has been attempted by Mueller and Nickolay [4] using morphological processing. However, their techniques are designed to detect defects on plain, non-textured surfaces of grayscale images.

An algorithm was proposed recently [6, 7] aimed at the simultaneous identification of colour and structural defects in highly random granite and ceramic textures. In Section 2 we shall review this chromato-structural approach and discuss its disadvantages and shortcomings in Section 3. Then we shall introduce in Section 4 a new technique based on iterative morphology, designed for replacing the structural analysis of the approach in [6] and [7]. We present some results to demonstrate how the new approach works.

2 RANDOM TEXTURE DEFECT DETECTION

For the inspection of complex colour texture images, one has to find ways of representing not only the chromatic properties of the image, but also the way each perceived chromatic class is distributed. Song et al [6, 7] presented an algorithm appropriate for the analysis of such textures with the purpose of identifying colour defects as well as structural defects. As the proposed algorithm was aimed at the inspection of granite slabs which has to comply with the human standards, the chromatic classes identified by the system had to reflect the classes perceived by a human observer. To achieve that, Song et al [6, 7] proposed a two-tier colour clustering technique according to which the image pixels are segregated in a large number of colour clusters in the RGB space (where the noise can easily be assumed to be homogeneous), and the clusters created this way are subsequently associated to form super-clusters according to the proximity they have in the Luv space (which is assumed to be perceptually uniform, but with inhomogeneous noise). This way each super-cluster created represents pixels that according to the human vision system belong to the same chromatic class. When testing a new image, pixels that cannot be associated with any one of these classes are classified as faulty. The pixels of each chromatic class are then flagged to create a binary array. This way the originally complex coloured image is analyzed into a stack of binary images, one per perceived chromatic class. Each binary image consists of a set of blob-like objects. Song et al [6, 7] proposed the structural analysis of each such image to represent the structural and distributional characteristics of each chromatic class in the image so that deviations from these characteristics will identify faults in a test image. In particular, they defined four parameters which represented the shape and the density of the blobs in each of the binary images and assumed that these parameters are normally distributed. Defects were identified in a test image if at least one of the corresponding parameters was falling far from the assumed distributions, using thresholds specified during the training phase of the process.

3 IDENTIFYING THE SHORTCOMINGS

Extensive experimentation showed that although the former part of the above algorithm seemed to be sound, the latter part was liable to some pitfalls. We tested four different series of images of granite of the same type, totaling sixty images. For each type of granite the various thresholds were set during the training phase. However, for some test images the faults were not detected unless the thresholds were manually adjusted for the particular image. This is not desirable for a fully automated inspection system. We achieved 100% good performance when we modified the method to perform the structural analysis of each binary image not only for the flagged blobs that belong to the same chromatic class, but for both the *foreground* and the *background* components of each binary image. Although this performance was highly satisfactory, from the way the results were obtained and the thresholds were set, it was felt that the algorithm was not robust enough, and the 100% success rate might not be maintained if the test image database was enlarged. This was because some chromatic classes consisted of very few blobs and the statistics performed on the corresponding binary image could not have been that robust and reliable. More than that, the distributions of the structural parameters of these blobs were not always normal.

4 NEW APPROACH

For the above reasons, we decided to abandon entirely the parametric representation of the structural characteristics of the image and replace it by morphological filtering. Initially we perform the iterative morphological processing on a perfect training image and record information such as the number of iterations required before each binary cluster image is exhausted, and the residual pixel count at each stage. Each binary image is morphologically filtered twice: once the blobs are subject to iterative erosion until they disappear, and once to iterative dilation until the structure in the image disappears completely. In the testing phase, we perform the same tasks and images that require a larger number of iterations of the corresponding morphological operations before they become blank are identified as faulty with the persisting structures as the faults. The residual pixel count can be a useful indicator as to how the erosion is progressing in comparison to the corresponding stage in the training phase.

Thus for each test image, following chromatic classification and using initial binary image A_i^0 for cluster i, we perform iterative morphological erosion/dilation for each colour cluster. For the erosion operation, this may be formalised as such:

$$\begin{aligned} A_i^{n+1} &= A_i^n \ominus B \\ &= \left\{ d \in E^2 : d + b \in A_i^n \quad \forall b \in B \right\} \end{aligned} \tag{1}$$

where B is the structuring element and E^2 represents images in the 2-dimensional Euclidean space. The dilation operation can be stated in a similar way.

Let us consider that we have an image with a defective blob, which although has the right colour characteristics, it is larger than the other blobs of the same chromatic class. By performing iterative erosion on each cluster (binary image), the cluster containing the defective blob will require a greater number of iterations for the blob to disappear completely, in comparison to its corresponding counterpart cluster from the training stage. Since information on each blob in each cluster is available, we can backtrack to determine the exact location of the defective blob(s) in the corresponding cluster(s). In the reverse situation when the defect is smaller than the general texture features, iterative dilation will detect the fault. In practice, on each binary image we perform two iterative erosions, one with a white and one with a black structuring element and note each time the parameters before the eroded pattern disappears entirely.

This new version of the algorithm had 100% success rate in fault detection tested on all 60 images that were available, while at the same time was not too sensitive to the choice of the various thresholds.

5 RESULTS

Figure 1 is used to demonstrate the results of the iterative morphology technique for two different images of the same kind of granite. Using a perfect training image, our initial clustering and chromatic classification result in five binary images. For this particular texture we then test six new images in this series. For each image in the series we carry out clustering as before. For each image we perform iterative erosion using Equation 1 on the set of binary images obtained corresponding to each class. These results are shown in Figure 2 as number of iterations against the log of normalised pixel counts at each iteration for four of the six images. There were two faulty images in this series which are shown in Figure 1. The structural fault in the top image is highlighted by the first and third graphs in Figure 2 where it is detected in two different clusters. The second graph of Figure 2 demonstrates the larger defect in the second granite image in Figure 1. Thus, the graph shows that a great number of iterations were required for the constituent pixels of the associated cluster to erode away. Of course, this erosion is also performed on 2-channels of information obtained from the binary images: background and foreground. The process of defect detection for each image under inspection is approximately 60 seconds on a Sun Sparc 10 Dual Processor for 400×300 images. In this application we use a flat 3×3 structuring element for B.

6 CONCLUSIONS

Automatic visual inspection of random textures plays a crucial role in machine vision applications. The iterative morphology scheme described in this paper provides an efficient mechanism for detecting blobs of abnormal sizes in randomly-textured images. Although the structural analysis proposed in [6, 7] was more powerful, designed to be able to detect many more structural defects, it was proved to be too sensitive to the thresholds and unnecessarily complicated, as most of the types of defects it could detect appeared either very rarely or never in the granite images. Even though the algorithm proposed here is restricted to the detection of over or under-sized blobs, it proved adequate for the application in automatic inspection of granite images. It had 100% success rate in fault detection when tested on our database of 60 images, while at the same time was not too sensitive to the choice of the various thresholds. We believe it is suitable for random textures with defects that have an acceptable colour, thus they pass the first stage of the chromato-structural algorithm concerned with the colour analysis of each image, but have sizes greater or smaller than the sizes of similar blobs in the general underlying texture. This approach is much faster than that in [6, 7] and we expect to reduce the computational time further when the system is implemented on a parallel processing architecture.

Acknowledgments

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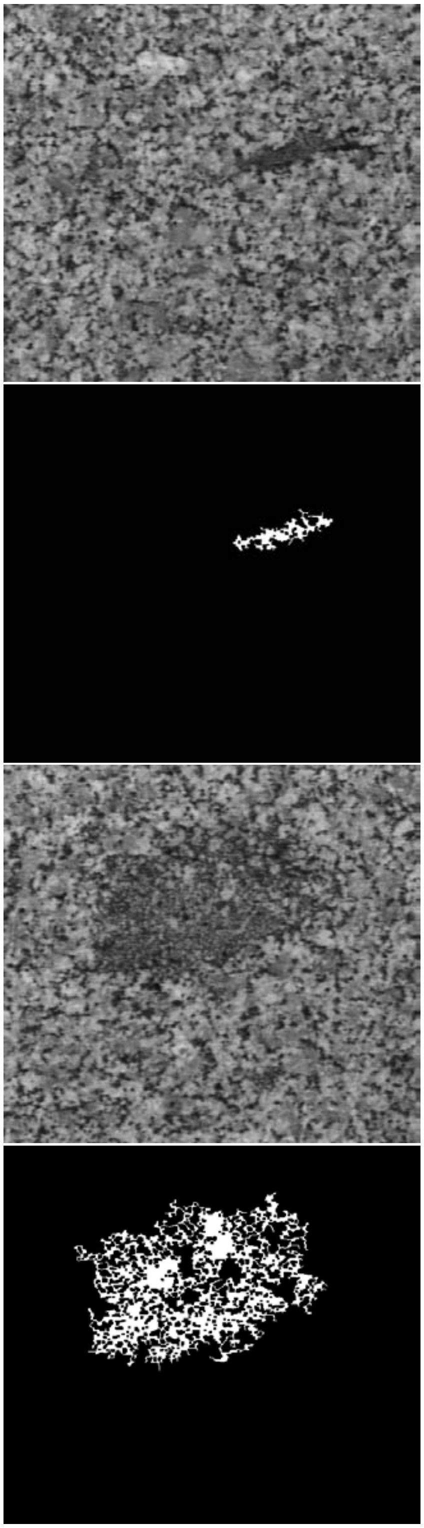

Figure 1: Iterative morphology structural defect detection for two original defective images. Note the more global yet sparse distribution of the fault in the lower image.

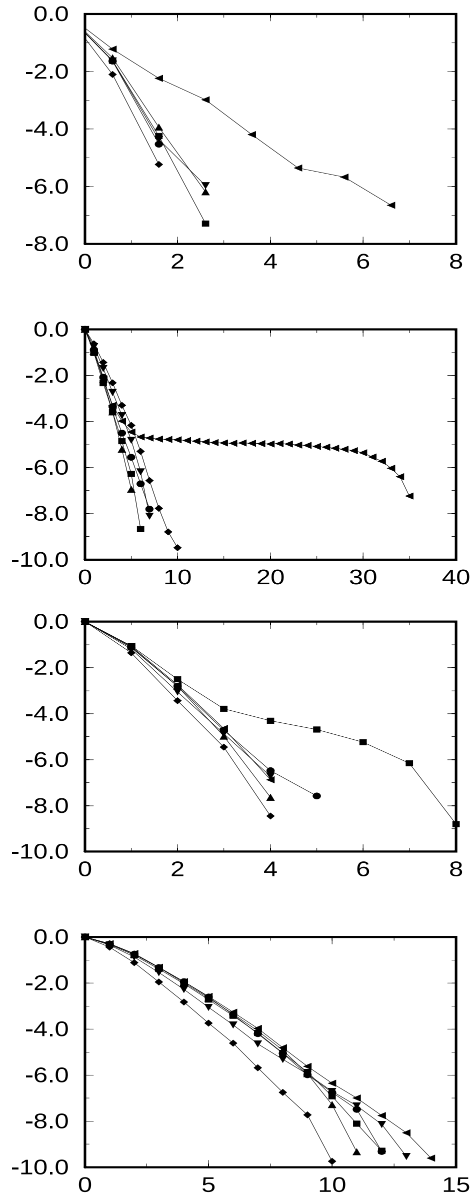

Figure 2: Each panel corresponds to a different chromatic class of a certain type of granite, with the x-axis showing the number of iterations and the y-axis showing the log of normalised pixel counts. Six images are tested. In the chromatic class represented by the bottom panel all images are acceptable. The other 3 panels represent the faults in Figure 1 for different classes.