LARGE-SCALE-INVARIANT TEXTURE RECOGNITION

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Abstract: This paper addresses the problem of texture recognition across large scale variations. Most of the existing methods for texture recognition handle only small-scale variations in test images. We propose using microscopic-scale textures to classify texture images at any coarser scale without prior knowledge of the relative scale. In particular, given a test camera image, we compute the average error of approximating the test texture with patches of the microscopic texture for certain category and scaling factor. Recognition is made by selecting the category with the minimum average error over all categories and scaling factors. Experiments on camera and low-magnification microscopic images show the validity of the proposed method.

1 INTRODUCTION

This paper explores the problem of classifying texture across large scale variations. In particular, using high-magnification microscopic textures, we aim to classify textures at any coarser scale. The difficulty of the problem stems from several facts. First, images of the same material with large variations of the imaging scale may appear so different even for a human observer (Figure 1). Second, accurate and fast techniques need to be developed to relate the material appearances at different scales. Although a lot of work has been done in the area of texture recognition (Davies, 2008), (Varma and Zisserman, 2009), little attention has been made to the effect of large scale variations. The CUReT database (Dana and Koenderink, 1999) captures texture images for 61 categories where each category is represented by 205 images of different viewing and illumination conditions. However, this database lacks examples of scale variation except for 4 materials that have slightly scaled images. Varma and Zisserman (Varma and Zisserman, 2009) claim that their MRF texture model is not adversely affected by scale changes. However, their experiments were done on the aforementioned scaled CUReT images which have only a small scale factor of 2. Kang (Kang and Nagahashi, 2005) developed a framework for scale-invariant texture analysis using multi-scale local autocorrelation features. Nevertheless, the experiments were limited to small changes in scale ranging from 0.7 to 1.3. Leung and Peterson (Leung and Peterson, 1992) used moment-invariant and log-polar features to classify texture. However, scale variations in their experiments were limited to 0.5, 0.67, and 1.0.

Our contribution in this paper is threefold. Firstly, we introduce a new approach for classifying texture across large scale variations. In particular, we show how an approximation of a test image using microscopic textures can be used to recognize textures at any scale. Secondly, we employ our approach to estimate the relative scale of a test image with respect to microscopic texture. Thirdly, we provide a dataset of multi-scale textures that can be used to assess the robustness of texture classifiers to scale changes.

2 COLLECTING MULTISCALE TEXTURES

Many texture databases are freely available including the CUReT database (Dana and Koenderink, 1999) and the UIUC database (Lazebnik and Ponce, 2005). While these databases sample reasonably the variations in illumination and viewing points, none of them properly captures scale variations of the textured materials. To fill this gap, we started collecting multi-scale texture data. In this paper, we show experiments on five categories of materials that have challenging textural patterns: cloth, loofa, marble, sponge, and granite plaster (Figure 1). For every category, we captured images using two imaging devices. Firstly, camera texture images were collected using a high-resolution 8-MB digital camera. Twenty images were taken at different distances, angles and illumination

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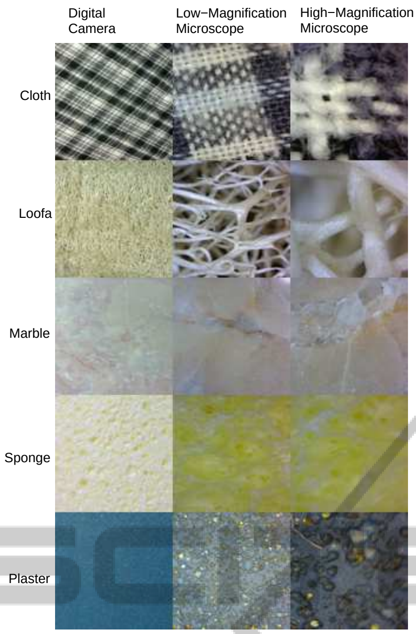

Figure 1: Multi-scale texture samples. Columns represent images taken by a digital camera, a microscope at low and high magnification, respectively. Each row shows images for one type of texture.

conditions. Secondly, microscopic texture images were collected using a low-cost hand-held digital microscope. The microscope has a magnification power of up to 230X. However, sharp microscopic images can be realized at magnification powers of about 60X and 220X. For each category, we collected at least 10 images at the low-magnification level and 20 images at the high-magnification level.

3 ALGORITHM

Our goal is to build a system that uses microscopic textures to correctly classify textures at any coarser scale even without prior knowledge of the relative scale between a test image and the microscopic textures. The steps of our algorithm are as follows. First, we create downsized versions of the microscopic images that have sizes ranging from 10×10 pixels up to 200×200 pixels (the standard size of test images in our experiments). Second, for each of these downsized versions, we calculate Haralick texture features for each of the red, green, and blue color planes as will be explained in Section 4. Then, we store the calculated features of the high-magnification microscopic images. Third, given a test texture image, we subdivide the image into patches of sizes corresponding to those used with the microscopic images. For each patch size selection and each candidate category, we compute the Haralick texture features for the test patches and find the average Euclidean distance from the feature vector of each test patch to those of the downsized microscopic images of the candidate category. After that, we sum the average distance over all the test patches. Finally, the output class for the given test image is chosen to be the one that has the minimum total average distance. The minimum is taken over all categories and all scaling factors since that the relative scaling factor between the test image and the microscopic images is generally unknown.

4 GRAY-LEVEL CO-OCCURRENCE MATRICES

Interactions of neighbour pixels in texture can be described by second-order features that are derived from the Gray-Level Co-occurrence Matrices (GLCM) (Haralick, 1979). These matrices are defined as follows. Given a position operator $P(i,j)$, let A be an $n \times n$ matrix whose element $A(i,j)$ is the number of times that points with gray level (intensity) g_i occur, in the position specified by P, relative to points with gray level g_j. Let C be the $n \times n$ matrix that is produced by dividing A with the total number of point pairs that satisfy P. The element $C(i,j)$ is a measure of the joint probability that a pair of points satisfying P will have the values g_i, g_j, respectively. C is called a *co-occurrence matrix* defined by P. Features derived from such matrices exhibit high distinctive power and relative invariance under large scale variations. We use three of these features:

$$Contrast = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} |i-j|^2 C(i,j) \tag{1}$$

$$Energy = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} C(i,j)^2 \tag{2}$$

$$Homogeneity = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{C(i,j)}{1+|i-j|} \tag{3}$$

5 EXPERIMENTS AND RESULTS

5.1 Classifying Camera Images with Fixed Scales

First, we ran the algorithm with a fixed scale. Specifically, all of the high-magnification microscopic images were downsized to one fixed size and compared with patches from the test camera image of the same size. The recognition results for fixed sizes ranging from 20×20 to 50×50 pixels are shown in Figure 2. The best recognition rate of 82 % occurred at a patch size of 40×40. However, the per-category performance curves show that each material is better recognized at a different scale. This suggests that we vary the scale and let the test images *choose* their right relative scale.

5.2 Classifying Camera Images with Variable Scales

As we suggested in Subsection 5.1, we ran the algorithm for a range of patch sizes 10, 20, 30, 40, and 50 concurrently. The results are shown in Table 1. The recognition rate is 82%. Despite this rate is no improvement over the one achieved with a fixed patch size of 40×40, we still have an important advantage here. In most cases, we don't know the relative scale difference between the test camera image and the microscopic textures. Using our algorithm with a variable scale will return an estimate of this scale along with the category of the test image. For example, of all of the 18 images of the loofa texture that were correctly classified: 7 images were assigned a scale of 4:1 (patch size 50×50), 8 images were assigned a scale of 5:1 (patch size 40×40), and 3 image were assigned a scale of 6.67:1 (patch size 30×30). These estimated scales closely match the actual image scales.

5.3 Classifying Low-magnification Microscopic Textures with Fixed Scales

To examine the ability of our algorithm to deal with different scales, we tested the algorithm with microscopic images taken at the lower magnification power of the microscope. Again, we ran the algorithm with fixed scales. That is, all of the high-magnification microscopic images are downsized to one fixed size and compared with patches from the test low-magnification microscopic image of the same size. The recognition results for fixed sizes ranging from 20×20 to 200×200 pixels are shown in Figure 3. The best rate of 98% occurs at a patch size ranging from 60×60 to 90×90. This result is interesting in two aspects. First, it makes sense to see this improvement over the case of camera images since the low-magnification microscopic images are closer in scale and appearance to the high-magnification microscopic images. Second, if we compare Figures 2

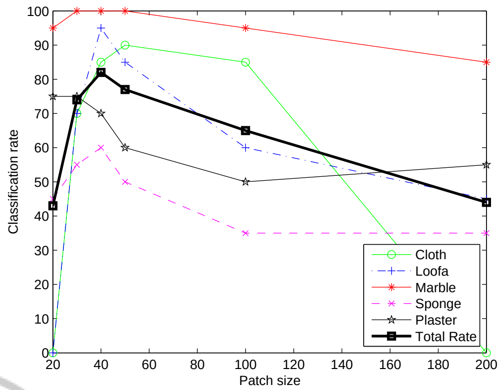

Figure 2: Recognition rate of test camera images as patch size varies. The best overall rate of 82% occurs at a patch size of 40×40.

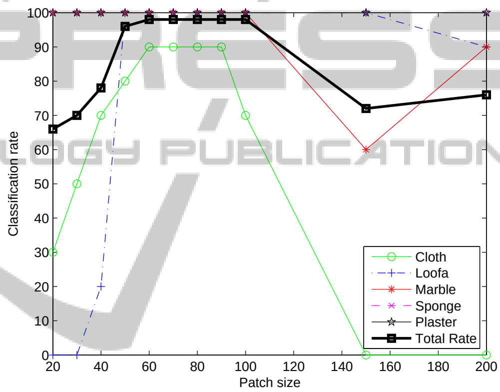

Figure 3: Recognition rate of low-magnification microscopic images as patch size varies. The best overall rate of 98 % occurs for a range of patch sizes between 60×60 and 90×90.

and 3, we will notice an upward shift of the patch size where optimal recognition rate occurs. This indeed agrees with the intuition. Since the low-magnification and high microscopic images are closer in scaling, then the right scale should be smaller (i.e., the patch size should be larger).

5.4 Classifying Low-magnification Microscopic Textures with Variable Scales

We retested our algorithm on the low-magnification microscopic images after allowing the patch size to vary from 60×60 to 90×90 (the optimal patch size range returned by the fixed-scale experiments). The results are shown in Table 2. The overall rate is 98% which is the same as that of the fixed-scaling experiment. Again, we still get the bonus that the right scale is returned for each test image. For example, all

Table 1: Confusion matrix for classifying camera images of Cloth (C), Loofa (L), Marble (M), Sponge (S), and Granite Plaster (P) using high-magnification microscopic images. The overall rate is 82%.

Material	C	L	M	S	P
C	90	10	0	0	0
L	0	90	0	40	0
M	0	0	100	5	25
S	0	0	0	55	0
P	10	0	0	0	75

Table 2: Confusion matrix for classifying low-magnification microscopic images using high-magnification ones. The overall rate is 98%.

Material	C	L	M	S	P
C	90	0	0	0	0
L	10	100	0	0	0
M	0	0	100	0	0
S	0	0	0	100	0
P	0	0	0	0	100

of the 10 images of the loofa texture were correctly classified and additionally their estimated scales were returned: 7 images were assigned a scale of 2.86:1 (patch size 70×70), 2 images were assigned a scale of 2.5:1 (patch size 80×80), and 1 image was assigned a scale of 3.33:1 (patch size 60×60). These estimated scales match roughly the actual ones.

6 CONCLUSIONS AND FUTURE WORK

We showed in this paper how microscopic images can be used to classify texture at coarser scales. In the future, we plan to expand our multi-scale texture dataset to complement the existing texture databases and learn more about the relationship between textures at different scales.

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