TEXTURE CLASSIFICATION USING MORPHOLOGICAL GRADIENT TEXTURE SPECTRUM

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ABSTRACT

In this paper, a new notion called Morphological Gradient Texture Spectrum (MGTS) is proposed for texture analysis and classification. The Morphological Gradient Texture Spectrum is used as a discriminating tool in texture analysis and classification. To evaluate the performance of the proposed method in the discrimination of textures, we perform a supervised classification procedure to classify texture images extracted from Brodatz's album. A simple measure is defined to determine the distance between two MGTS. Promising results indicate that our method is efficient in texture classification. We also evaluate two basic texture features, namely, coarseness and directionality from the MGTS for visual-perceptual feature extraction.

Keywords: morphological gradient texture spectrum, texture classification, coarseness, directionality

1. INTRODUCTION

Texture analysis is one of the important techniques in image processing. The major problem of texture analysis is the extraction of texture features. In the previous works, many texture features have been proposed for different application purposes. Techniques on feature extraction can be broadly divided into two major components: structural and statistical approaches.[1] Structural approaches rely on finding an elementary pattern that is replicated to generate the texture pattern. Grammatical models are then used to describe the replication pattern of these primitives throughout the texture pattern.[2] Contrarily, statistical approaches commonly use the autocorrelation function,[3] modeling texture by random fields,[4] co-occurrence matrix[5] and measures of self similarity such as fractal dimension (FD).[6,7]

Recently, spatial texture spectrum concept introduced by He and Wang was successfully applied in texture classification,[8] texture edge detection,[9] and for some geological applications using remotely sensed data.[10] In that method, a texture image is decomposed into a set of 3×3 texture unit. Each non-central pixel in a texture unit is assigned with one of the three values 0,1,2 resulted from a comparison with the central pixel. Thus, there are totally 3^8=6561 standard texture units. The occurrence distribution of texture units in a texture image, called texture spectrum, is used as a discriminating tool in classifying textures. However, that method is time consuming when we applied it to texture classification. The main reason is that the length of texture spectrum is too long and a great amount of computation is required when we compare different texture spectra of images.

In this paper, we use *morphological gradient*[11] to replace the texture unit. The corresponding texture spectrum, called the Gradient Texture Spectrum, is used as a new feature in texture analysis and classification. The morphological gradient for a small texture block can be regarded as a local texture roughness information. Thus, a texture image can be characterized as the occurrence distribution of texture gradients in that texture image.

To evaluate the performance of the feature extraction method, we apply it to the classification of four texture mosaics each contains four natural textures. A simple measure is defined to determine the distance between two MGTS. Experimental results show that up to 98% classification accuracy rates are obtained by the proposed method. For visual-perceptual feature extraction, two basic texture features, namely coarseness, and directionality are evaluated from MGTS. From the experimental results, we conclud that the MGTS is a good tool for texture analysis and classification.

2. MOPHOLOGICAL TEXTURE GRADIENT SPECTRUM

Let f be a gray scale image, the $s \times s$ *neighborhood* for each point $p(i,j)$ in f is defined as

$$N(i,j) = \{(x,y),(i-s/2) \le x \le (i+s/2) \text{ and } (j-s/2) \le y \le (j+s/2)\}.$$

The *morhological gradient* with $s \times s$ *neighborhood* for each point $p(i,j)$ in f is defined as

$$g(i,j) = \max\{f(x,y),(x,y) \in N(i,j)\} - \min\{f(x,y),(x,y) \in N(i,j)\}$$

Fig. 1 gives an example of the transformed gradients of the centered nine points with 3×3 neighborhood in a 5×5 image block. In total, we have 256 different gradients, from 0 to 255, in a texture image with 256 gray levels. Such gradient defined for a point is considered as a local roughness feature within its $s \times s$ neighborhood.

12	20	89	80	28
26	26	54	48	64
45	38	43	27	36
42	72	76	33	76
65	23	28	48	53

$\longrightarrow$

77	69	62
50	50	49
53	53	49

Fig. 1: An example to transform a 5×5 image block into the corresponding gradients of the central nine pixels.

As the gradient with $s \times s$ neighborhood for a point p represents the local aspect, the statistics of gradients in an image should reveal its texture information. The occurrence distribution of gradients will be called the Morphological Gradient Texture Spectrum (MGTS), with the abscissa indicating the gradient value and the ordinate representing its occurrence frequency.

Fig. 2 and Fig. 3 show the MGTS for the four images of Fig. 4 to Fig. 7 with 3×3 and 5×5 neighborhood respectively. In Fig. 2, we can find that the MGTS are distinguishable from each other. Thus, we can use them as a discriminating tool in texture classification. In addition, we can obtain the information about the size of basic texture unit in test images from the texture spectra. For instance, an abrupt peak appears in the spectrum shown in Fig. 3a which indicates the size of the constituting texture unit in Fig. 4a is near to the size of neighborhood used in creating the MGTS.

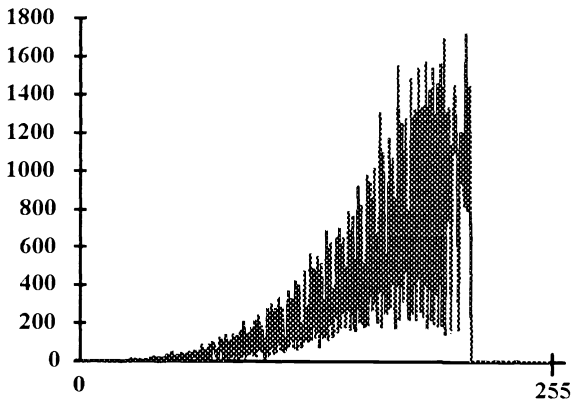


Fig. 2a

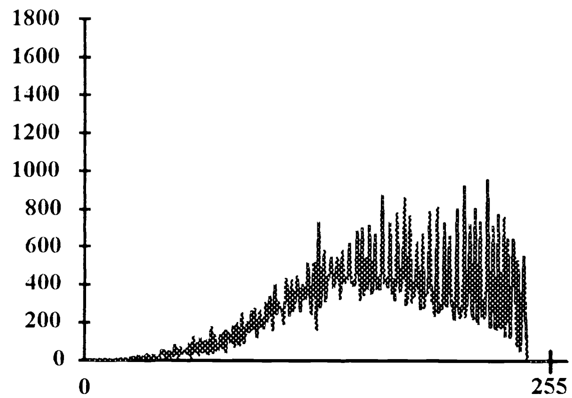


Fig. 2b

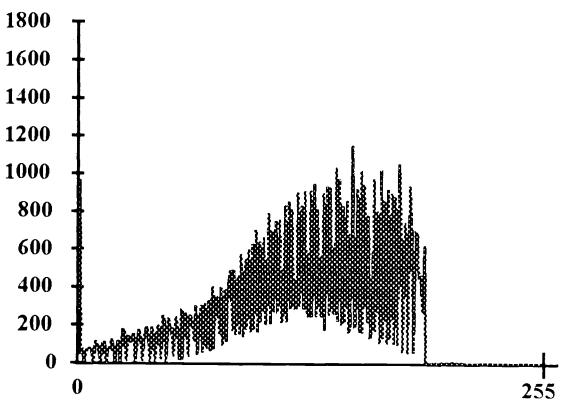


Fig. 2c

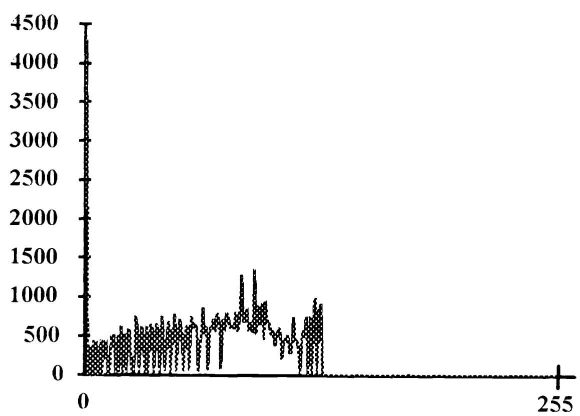


Fig. 2d

Fig. 2a-2d: Four MGTS for the four images shown in Fig. 4a-4d , respectively, using 3×3 neighborhood for each point.

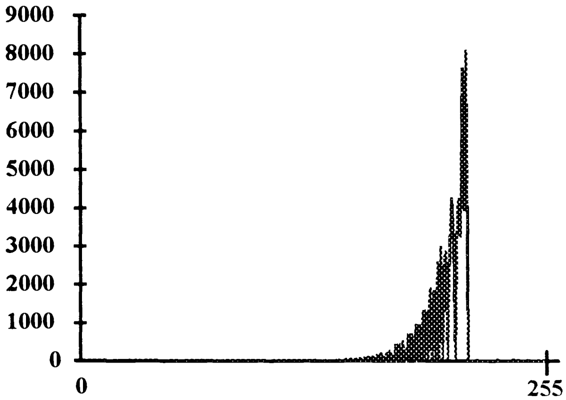


Fig. 3a

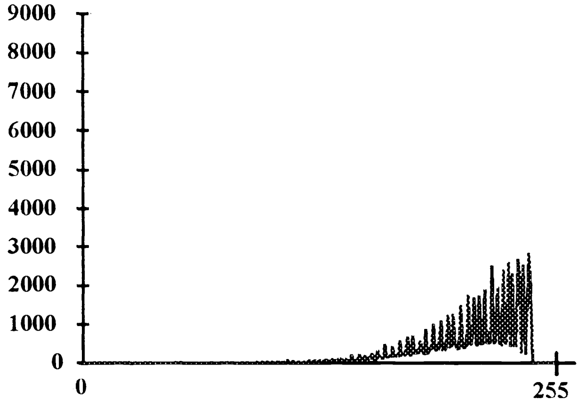


Fig. 3b

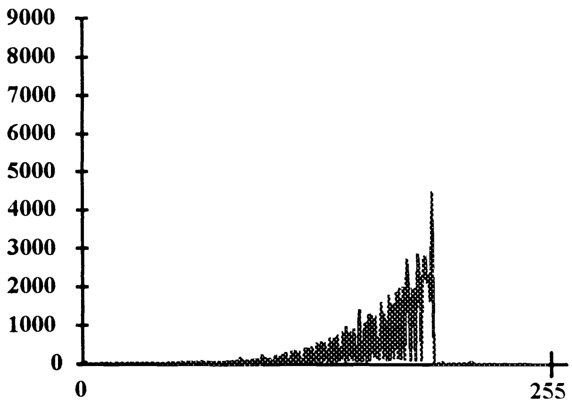


Fig. 3c

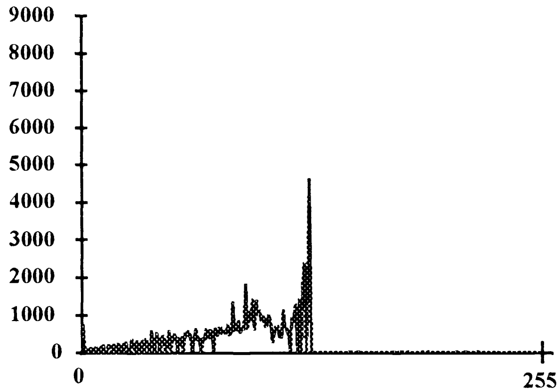


Fig. 3d

Fig. 3a-3d: Four MGTS for the four images shown in Fig. 4a-4d , respectively, using 5×5 neighborhood for each point.

3. TEXTURE CLASSIFICATION

To demonstrate the discrimination performance of the MGTS, we use a supervised classification with minimum distance rule to classify nature images extracted from Brodatz's album.[12] These natural images are of size 256×256 with 256 gray levels. In our experiments, four different mosaics each contains four texture images are used and illustrated in Fig. 4 to Fig. 7. For each test mosaic, the following algorithm is performed to classify the mosaic into one of the four classes.

step 1: Randomly select a 30×30 sample subimage from each texture image;

step 2: Calculate MGTS for each sample subimage using $s \times s$ neighborhood. The four spectra are denoted as $S(i,j)$, where i= 1 to 4 and $S(i,j)$ represents the occurrence frequency of gradient value j in the MGTS of the sample subimage i.

step 3: Scan the four textures in the test mosaic by moving a 30×30 window across the textures overlay. Calculate the MGTS of image masked by each window and denoted as $W(j)$, j=0 to 255.

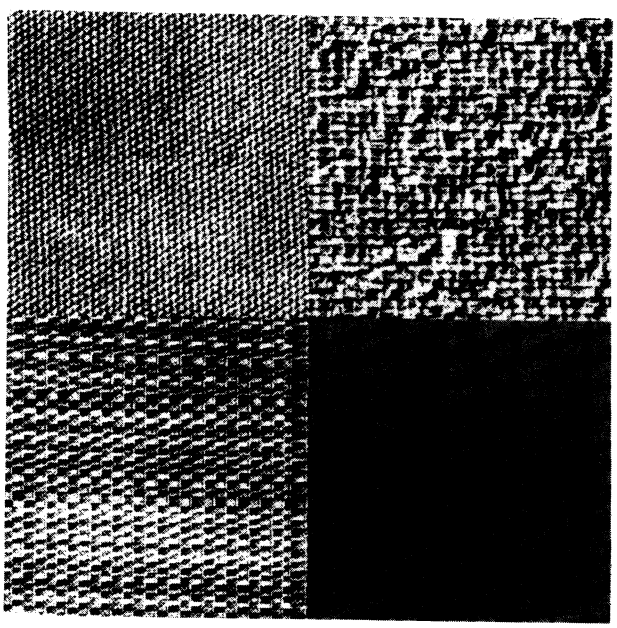
step 4: Calculate the absolute difference between the MGTS of each window and one of each sample:

$$D(i) = \sum_{j=0}^{255} \left| W(j) - S(i,j) \right| \quad i = 1,2,3,4 \tag{1}$$

step 5: The central pixel of window considered will be assigned to class K such that $D(K)$ is minimum among all $D(i)$.

Using the above described method, $232324 = (512-30)^2$ pixels of a test mosaic have been processed and the test mosaic is assigned to one of the four classes. Results of the supervised classification are listed in TABLE 1. An average classification accuracy rate of 98% is obtained using the proposed method. Noted that the misclassification occurs mainly at the texture borders. If we remove these pixels from our consideration, the correct classification rate will be near 100%.

a **b**



c **d**

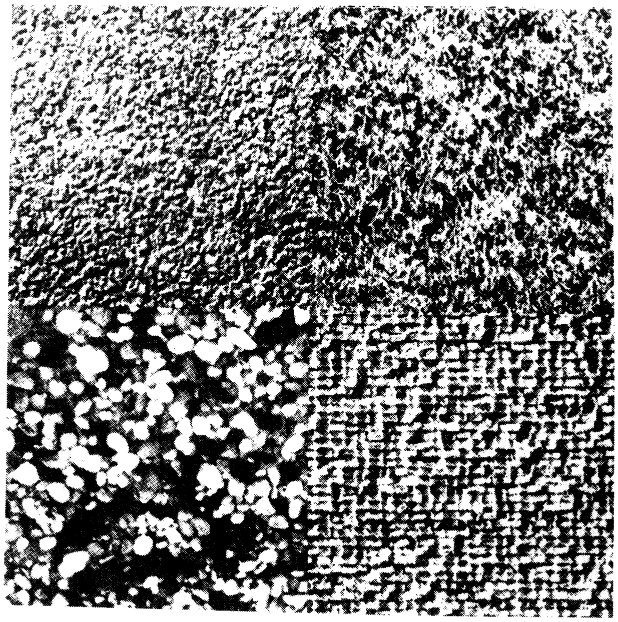
Fig.4.

a **b**

c **d**

Fig.5.

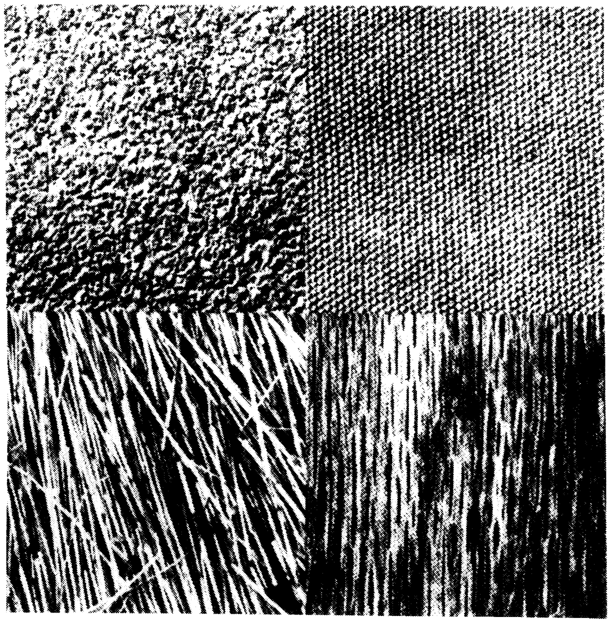
a b



c d

Fig. 6

a b



c d

Fig. 7

Fig. 4 to Fig. 7: Four texture mosaics each contains four Brodatz' texture images.

TABLE 1: Results of classification using the proposed method.

% of correct classification				
	Texture		Mosaic	
	Fig. 4	Fig. 5	Fig. 6	Fig. 7
a	99.7	97.1	98.9	97.8
b	99.5	99.6	97.3	99.5
c	99.4	99.2	99.6	99.7
d	96.8	99.1	97.7	95.5
Average	98.9	98.8	98.4	98.1

4. VISUAL-PERCEPTUAL FEATURES EXTRACTION FROM MGTS

4.1. Texture Coarseness

The textural coarseness of a region is inversely related to the summation of texture gradients per unit area in the region.[13] To extract coarseness feature from a texture, we can estimate the mean brighness of its corresponding MTGS. The larger the mean value, the finer the texture is. Let $\phi(i)$ (i=0,..., 255) be the MGTS of an image and A be the area of the image (the total number of pixels in the image). The occurrence probability of intensity i in the spectrum is computed as

$$p(i) = \phi(i) / A \tag{2}$$

In our study, we define the measurement of coarseness of a texture image as

$$CRS = \frac{c}{\sum_{i=0}^{n-1} i \times p(i)} \tag{3}$$

where c is a normalizing factor. From this definition, a coarser image will have a larger value of *CRS*. Fig. 8 illustrates the measure of coarseness for Brodatz' texture image D54 and the magnified image of D54, respectively. Here, we choose c=512. It can be found that the left image is larger than the other one and gives a larger *CRS*.

CRS=4.53 *CRS*=10.16

Fig. 8. Texture coarseness feature extraction from MTGS.

4.2. Texture Directionality

The directionality is detected from the histogram of texture gradient directions. Let R be a $m \times m$ image square. The texture gradient direction in R can be described by a vector $\vec{v} = \overrightarrow{p_1 p_2}$, where the points p_1 and p_2 own the maximum and minimum gray values of R, respectively. Fig. 9 illustrates all the possible texture direction types using 3×3 image square. An example to transform an image square into the direction type is described in Fig. 10. Then, we can create a texture direction spectrum with the abscissa indicating the direction types and the ordinate representing its occurrence frequency.

Fig. 11 illustrates the direction spectra for Brodatz' texture image D15 and D37, respectively. We can find the most two abrupt peaks of the left spectrum at direction type 45 and 9, respectively. It means that the texture image D15 has high frequent variation in the horizontal directions. Therefore, we can predict that there exists many vertical edges in D15. In contrast, we can also predict the horizontal edge feature for D54 by observing its direction texture spectrum.

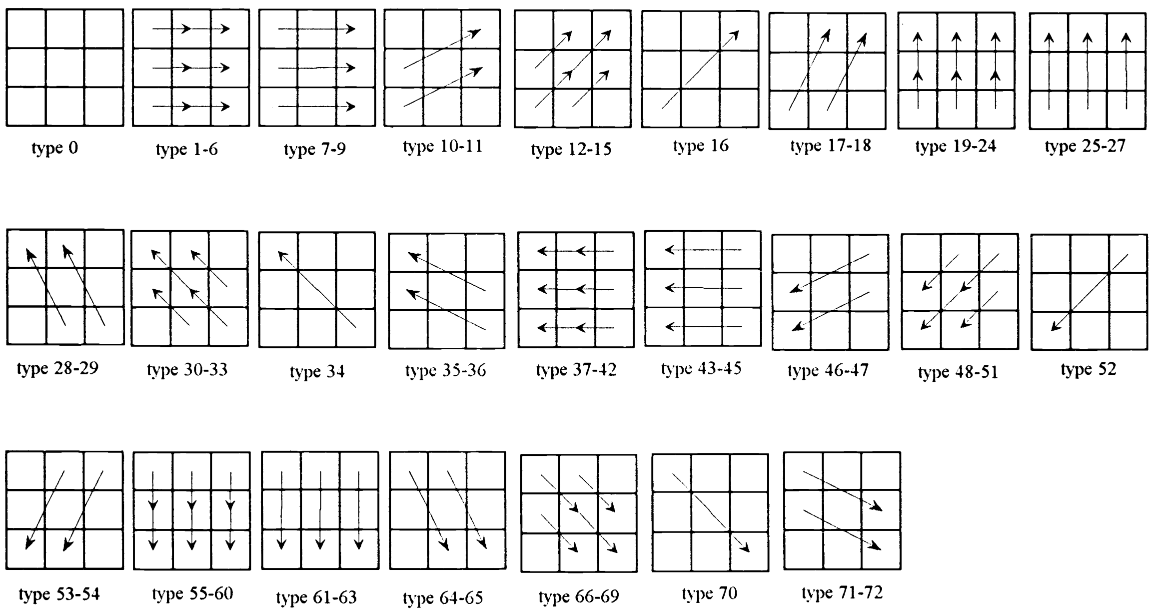


Fig. 9: The total direction types in 3 by 3 region.

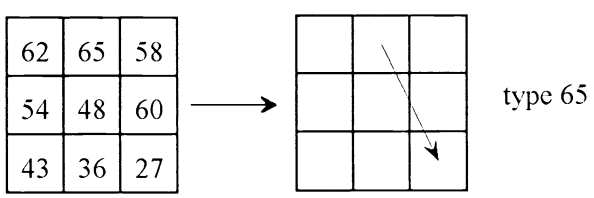


Fig. 10: An example to transform a 3 by 3 image block into the corresponding direction type.

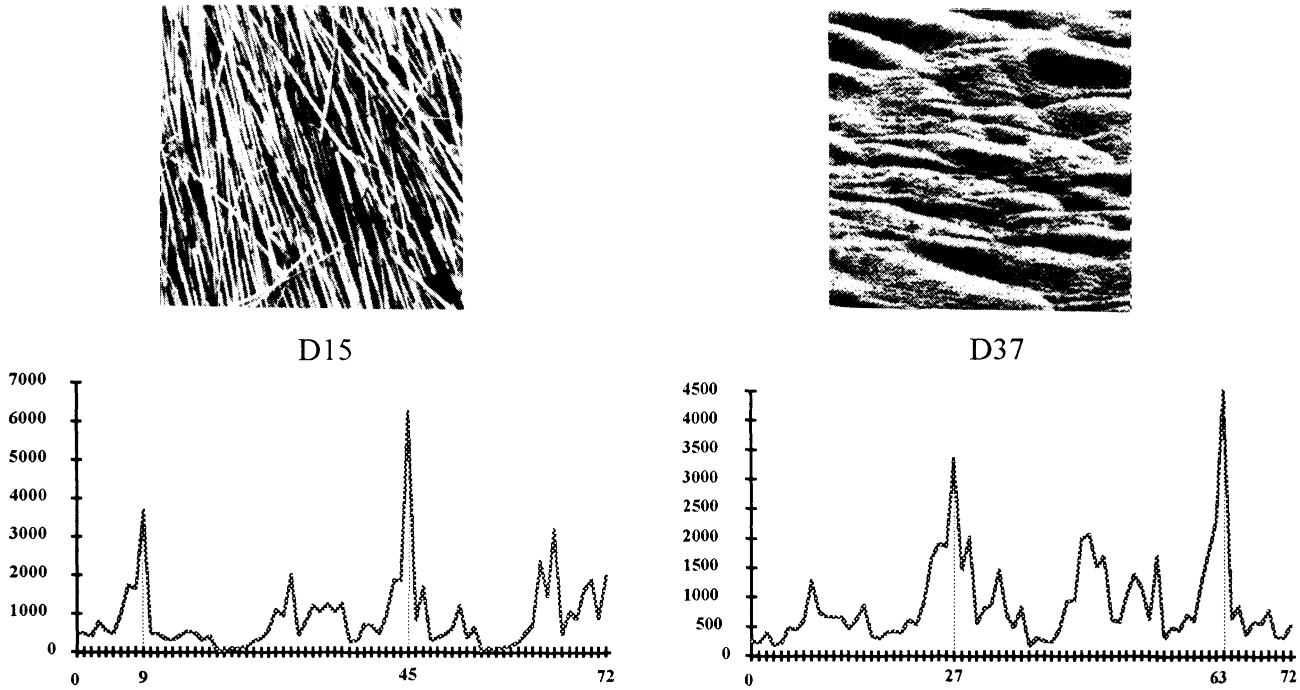


Fig. 11: The texture direction spectra for texture image D15 and d37, respectively.

5. CONCLUSION

The texture spectrum method has been recently proposed for texture analysis. However, the original method which uses texture units is very time consuming in texture classification. In this paper, we extract the gradient feature from an image and create the corresponding texture spectrum for the image. The texture spectrum is then used as a discrimination tool in texture analysis and classification. Experimental results show that our method is efficient in the texture classification. In addition, we extract two visual-perceptual features from MTGS.

From the experimental results, we can conclude that MGTS is an excellent discriminating tool in texture analysis and classification.

6. ACKNOWLEDGMENTS

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7. REFERENCES

1. R. M. Haralick," Statistical and structural approaches to textures," *IEEE Proc.*, **67**, pp. 786-804, 1979.
2. F. Tomita and S. Tsuji, *Computer analysis of visual textures*, Kluwer Academic Publishers, 1990.
3. B. Kartikeyan and A. Sarker," An identification approach for 2-D autoregressive models in describing textures," *CVGIP*, **53**, pp. 121-131, 1991.
4. M. Hassner and J. Sklansky," The use of Markov random fields as models for texture," *Comput. Graphic Image Process.*, **12**, pp. 357-370, 1980.
5. L.S. Davis, S.A. Johns, and J.K. Aggarwal," Texture analysis using generalized co-occurrence matrices," *IEEE Trans. PAMI*, **1**, pp. 251-259, 1979.
6. B.B. Mandelbrot, *The Fractal Geometry of Nature*, San Francisco, CA: Freeman, 1982.
7. S. Peleg, J. Naor, R. Hartley, and D. Avnir," Multiple resolution texture analysis and classification," *IEEE Trans. PAMI*, **6**, pp. 518-523, 1984.
8. D. C. He and L. Wang, " Texture classification using texture spectrum." *Pattern Recognition.* **23**, pp. 905-910, 1990.
9. D. C. He and L. Wang, " Detecting texture edges from images." *Pattern Recognition.* **25**, pp. 595-600, 1992.
10. D. C. He and L. Wang, " Tetxure unit, texture spectrum and texture analysis." *IEEE Trans. on Geosicence and Remote Sensing* **28**, pp. 509-512, 1990.
11. S. Beucher, *Segmentation d'images et morphologi'e mathematique*, Ph.D. thesis, Ecole des Mines de Paris, June, 1990.
12. P. Brodatz, *Textures: A photographic album for artists and designers.* Reinhold, New York, 1968.
13. A. Rosenfeld, " A note on automatic detection on texture gradients " *IEEE Trans. on Computers* **24**, pp. 988-991, 1975.