A New Statistical Approach for Texture Analysis

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ABSTRACT: This paper describes a new statistical method for texture analysis. First, we propose the concept of a *Texture Unit*, which may be considered as the smallest complete unit that best characterizes the local texture in the eight directions from a given pixel. Then, we show how a texture image can be broken down into a set of *Texture Units*, and characterized by the distribution of Texture Units within the image, resulting in the *Texture Spectrum*. The method has been evaluated with some of Brodatz' natural images and several examples of air-borne Synthetic Aperture Radar (SAR) imagery. Processing has included classification, filtering, and texture characterization. Promising results are obtained and are presented in this paper.

INTRODUCTION

TEXTURE IS THE TERM USED to characterize the tonal or grey level variation in an image. It is an important feature for identifying objects or regions of interest in an image, whether the image is a photomicrograph, an aerial photograph, or a satellite image. Texture analysis is playing an increasingly important role in digital image processing and interpretation, principally motivated by the fact that it can provide independent supplementary information about image properties. Such textural information is sometimes the only way to characterize an image. A good understanding or interpretation of an image includes the description of both spectral and textural aspects of the image, such as in the interpretation of remotely sensed data, or biomedical or microscopic images.

Methods of texture analysis can be broadly divided into two major categories (Haralick, 1979). The first is the *structural method*, where texture is considered to be a repetition of basic primitive patterns with a certain rule of placement. An image of a brick wall is an excellent example suited to this approach. Traditional Fourier spectrum analysis is often used to determine the primitives and the placement rule. Several authors have applied this method in texture classification and texture characterization, with a certain degree of success (He *et al.*, 1987; Matsuyama *et al.*, 1980; D'Astous and Jernigan, 1984). However, problems may be encountered in practice when identifying the primitives in natural images such as sand and cork, or in remotely sensed images. Even if one is able to extract primitives, the description of a placement rule for a natural image may be extremely complicated (Chellappa and Kashyap, 1985).

The second major approach in texture analysis is the *statistical method*. The aim of this method is to characterize the stochastic properties of the spatial distribution of grey levels in an image. The grey level co-occurrence matrix is frequently used in this method. The element $S(i,j,\mathbf{v})$ of the co-occurrence matrix is the estimated probability of going from grey level i to j, given the displacement vector $\mathbf{v} = (\Delta x, \Delta y)$. This type of second-order grey level co-occurrence matrix has been shown to be a valid measure of the spatial distribution of grey levels within the image (Haralick, 1986; Julesz *et al.*, 1973; Gagalowicz, 1980). A set of textural features derived from the co-occurrence matrix has been widely used in practice to extract the textural information (Haralick *et al.*, 1973; Conners, 1979; He *et al.*, 1987). At the present time, there are two major obstacles to this approach in practice. The first is that the co-occurrence matrix depends not only on the spatial relationships of grey-levels but also on regional intensity background variation within the image. The second obstacle is that the co-occurrence matrix characterizes the spatial relationships between pixels for a given displacement vector $\mathbf{v} = (\Delta x, \Delta y)$, so the choice of this vector is somewhat problematic. For this reason, the features derived from the co-occurrence matrix approach are often averaged over several displacement vectors. However, this requires much more additional calculation time on the one hand, and may reduce the sensibility of the co-occurrence matrix to different textures on the other hand.

The purpose of this paper is to present a new statistical method of texture analysis. We focus our attention on texture characterization and discrimination. First, the concept of *Texture Unit* is proposed, which may be considered as the smallest complete unit which best characterizes the local texture aspect in all the eight directions from a given central pixel. Then, we show that a texture image can be decomposed into a set of Texture Units and characterized by its *Texture Spectrum*, which is the occurrence distribution of Texture Units within the image. Experimental results show that the Texture Spectrum has promising discriminating performance and therefore has potential usefulness in texture characterization and classification.

The next section describes the methodology of the proposed approach, including the concepts of Texture Unit and Texture Spectrum. Results obtained by applying the method to some Brodatz' natural images (Brodatz, 1968) and several samples of airborne SAR imagery are then presented. The paper finishes with some conclusions and a discussion.

METHODOLOGY

TEXTURE UNITS

Considering a digital image stored in a grid form, each pixel is surrounded by eight neighboring pixels. The local texture information for a pixel can be extracted from a neighborhood of 3 by 3 pixels, which represents the smallest complete unit (in the sense of having eight directions surrounding the pixel).

Given a neighborhood of 3 by 3 pixels, which will be denoted by a set containing nine elements $V = \{V_0, V_1, \ldots V_8\}$, where V_0 represents the intensity value of the central pixel and V_i is the intensity value of the neighbouring pixel i, we define the corresponding *Texture Unit* as a set containing eight elements TU $= \{E_1, E_2, \ldots, E_8\}$, where E_i is determined by the formula

$$E_i = \begin{cases} 0 \text{ if } V_i < V_o \\ 1 \text{ if } V_i = V_o \\ 2 \text{ if } V_i > V_o \end{cases}$$

$$\text{for } i = 1,2, \ldots, 8$$

and the element E_i occupies the same position as the pixel i.

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As each element of TU has one of three possible values, the combination of all the eight elements results in $3^8 = 6561$ possible Texture Units in total.

Labeling Texture Units

There is no unique way to label and order the 6561 different Texture Units. In our study, the Texture Unit Number (N_{TU}) is found by using the following formula:

$$N_{TU} = \sum_{i=1}^{8} 3^{i-1} E_i, \quad N_{TU} \in \{0,1,2,\ldots,6560\}$$

where E_i is the i^{th} element of Texture Unit set TU = $\{E_1, E_2, \ldots, E_8\}$.

In addition, the eight elements may be ordered differently. If the eight elements are clockwise ordered, the first element may take eight possible positions from top-left (a) to middle-left (h) (see Figure 1). So, the 6561 Texture Units can be labeled by the above formula under eight different ordering ways (from a to h).

Figure 2 gives an example of transforming an image neighborhood to a Texture Unit with the Texture Unit number under the ordering method a.

Texture Spectrum

The previously defined set of 6561 Texture Units describes the local texture aspect of a given pixel, that is, the relative grey level relationships between the central pixel and its eight neighbors. Thus, the statistics on occurence frequency of all the Texture Units over a whole image should reveal texture information of the image to be analyzed. We will call the occurrence frequency function of all the Texture Units the *Texture Spectrum*, with the abscissa indicating Texture Unit number N_{TU} and the ordinate representing its occurrence frequency.

a	b	c
h		d
g	f	e

FIG. 1. Eight clockwise successive ordering ways of the eight elements of Texture Unit: the first element E_1 may take eight possible positions from a to h.

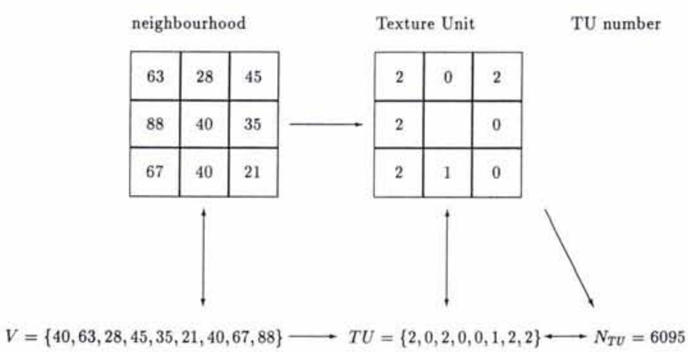

FIG. 2. Example of transforming a neighborhood to Texture Unit with texture unit number.

In practice, a real image is usually composed of two parts: texture elements and random noise or background. The greater the proportion of texture components to background, the better that the texture may be perceived by human vision. In the Texture Spectrum, an increase in percentage of texture components in an image will result in a tendency to form a particular distribution of peaks. In addition, different textures are composed of particular Texture Units with different distributions in their Texture Spectra. In this way, the global texture of an image can be characterized by its Texture Spectrum.

It should be noted that the labeling method chosen may affect the relative positions of Texture Units in the Texture Spectrum, but does not change their frequency values in the Texture Spectrum.

EVALUATION AND APPLICATION

In order to evaluate the performance of the Texture Spectrum in texture characterization and classification, several experimental studies have been carried out on some of Brodatz' natural texture images (Brodatz, 1968) and airborne SAR imagery. The methods and results are presented as follows.

Texture Spectrum and Image Classification

Different texture images should have correspondingly different spectra, if the Texture Spectrum has discriminating performance for different textures. Four of Brodatz' natural texture images have been used for this evaluation. Figure 3 shows these textures. They are, respectively, the image of (A) beach sand, (B) water, (C) pressed cork, and (D) fur hide of an unborn calf. We have chosen these images because they are broadly similar to one another, and are similar to parts of digital images usually encountered in practice, for example, to landscape scenes provided by Earth observation satellites. Each image is represented by 256 by 256 pixels with 64 normalized grey levels.

Texture Spectra have been calculated for the four images with

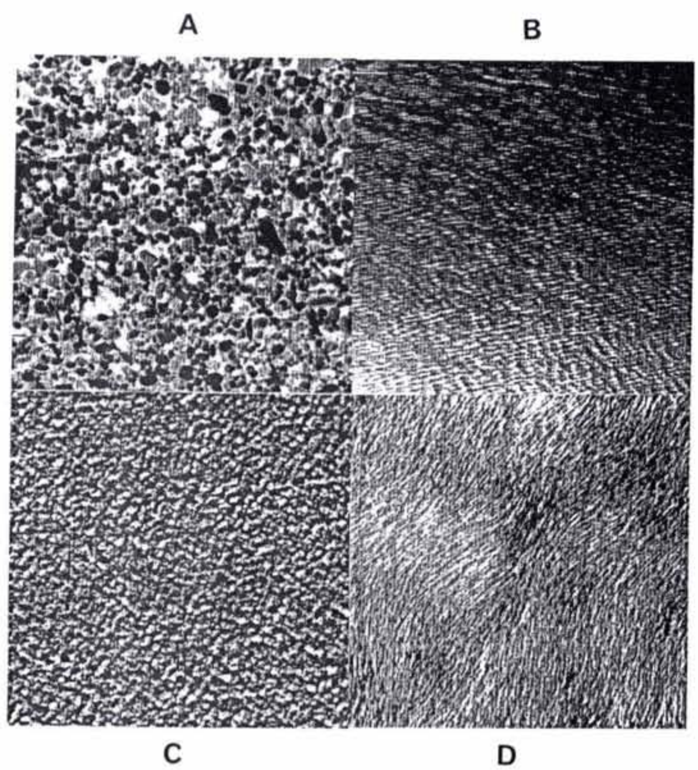

FIG. 3. Four of Brodatz' texture images: (A) beach sand, (B) water, (C) pressed cork, and (D) fur hide of an unborn calf.

the eight ways of ordering (from a to h). The result shows that different textures have correspondingly different spectra. Figure 4 illustrates the four spectra under the ordering method a. We note that the Spectra are different in terms of the number, position, width, and height of their principal peaks, demonstrating the discriminating performance of the Texture Spectrum.

A further quantitative evaluation of discrimination ability was performed using a supervised classification over the four texture images of Figure 3. A sample subimage of 30 by 30 pixels was randomly selected over each texture. Using a window of 30 by 30 pixels together with a step of two pixels in the row and column, the full image of Figure 3 has been processed and each central pixel of the window was assigned to one of the four texture classes, where the minimum distance decision rule was employed and the integrated absolute difference between two Texture Spectra has been taken as the distance. The result, illustrated in Figure 5, shows 98.5 percent correct classification for texture image A, 96.4 percent for texture B, 98.9 percent for texture C, and 95.9 percent for texture D, resulting in an average classification accuracy of 97.5 percent.

It should be noted that the above correct classification rates are calculated over all the pixels, including the regions near the boundaries of the four textures. If we remove these pixels from the counter, the correct classification rate will be 100 percent for textures A, B, and C, and 98.4 percent for D, representing an average recognition rate of 99.6 percent.

Textural Filtering

Digital filtering constitutes an important type of image transformation and is widely used in image processing for edge detection, noise suppression, smoothing, recognition, and enhancement of images. Based on traditional Fourier analysis, the low-pass, high-pass, and band-pass are the three basic classical linear filters (Gonzalez and Wintz, 1987; Pratt, 1982; Rosenfeld and Kak, 1982). The combination of these filters can form a wide variety of more complicated filters and are frequently used in practice. For example, the noise suppression, edge detection, and image enhancement techniques are useful for the interpretation of remotely sensed data.

One of the most important advantages of the Texture Spectrum is that it characterizes textural aspects of an image in the form of a spectrum, making it possible to consider digital filtering from the point of view of texture analysis, called *textural filtering*. An example of a noise suppression filter was designed in our studies, where the aim was to remove both spectral and textural noises (regional intensity background variation), and thereby enhance the image's texture.

The basic idea of such a filter is that the noise can be eliminated by some averaging operations over a large region, and that the texture of the processed image can be conserved by keeping the Texture Spectrum unchanged. In other words, an image will be filtered by averaging operations in such way that the output image has the same Texture Spectrum as that of the input image.

In practice, the filtering operation is achieved by the following steps:

(1) Calculation of the Texture Spectrum of the image to be filtered. This operation gives $S(N_{TU})$, the occurence frequency of the Texture Unit numbered N_{TU}, $N_{TU} = 0,1,2,\ldots, 6560$.

(2) For each Texture Unit, calculation of nine averaging values over all the neighbors of 3 by 3 pixels (V_j) belonging to the same Texture Unit. Thus, we obtain an averaged standard sample of 3 by 3 pixels for each texture unit. We note $M_j(N_{TU})$ the average value of the j^{th} element for Texture Unit numbered N_{TU}, $N_{TU} = 0,1,2,\ldots, 6560$ and $j = 0,1,2,\ldots, 8$.

$$M_j(N_{TU}) = \frac{1}{S(N_{TU})} \sum_{i \in N_{TU}} V_j(i)$$

(3) Transformation of the original image so that each pixel will be replaced by the averaged standard value with respect to texture unit number. For a given pixel considered, it represents a different

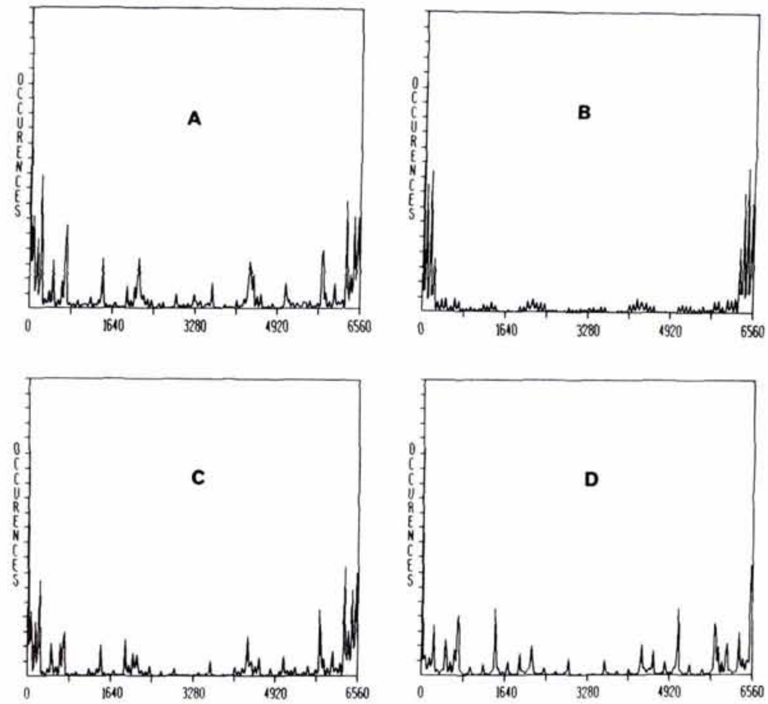

Fig. 4. Texture Spectra of the four test images of Figure 3 under the ordering method *a*. The abscissa indicates Texture Unit Number.

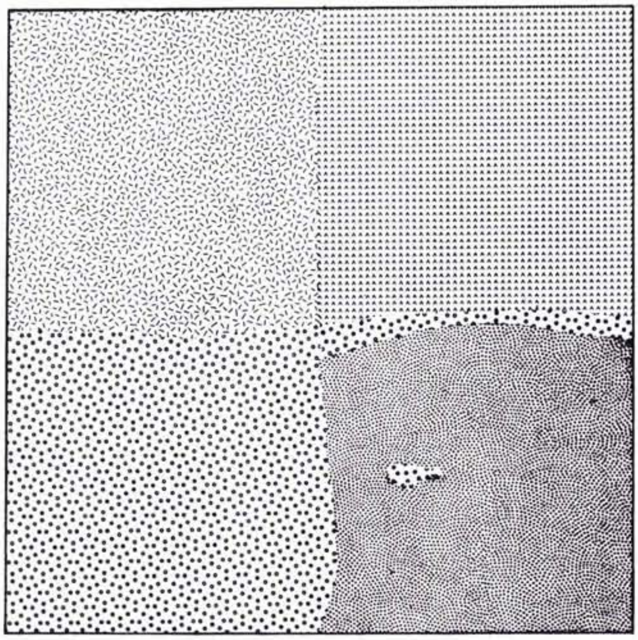

FIG. 5. Classification result of Figure 3.

element of nine neighborhoods of nine texture units around it. In this way, its final intensity value will be the average of the standard values of the nine elements $M_j(N_{TU})$.

We stress that, in this filtering procedure, all the operations are performed with respect to the Texture Unit number, resulting in the Texture Spectrum of the image unchanged on the whole. The noise and regional background variation will be reduced or eliminated by performing averaging operations twice.

Figure 6 shows an example of such textural filtering. The left column presents the four original Brodatz' images, and the right column contains the filtered images. We note that, by removing the spectral and textural noises from the original images, the filtering operation enhances the perception of texture within the images, especially for the second and fourth images. These two images have a relatively large variation in background intensity. After filtering, this variation is attenuated considerably.

TEXTURAL FEATURES

The Texture Spectrum reveals textural information of an image in a primitive form. It is useful and necessary to extract textural features from the Texture Spectrum. These features will then be more easily used in practice for texture characterization and image classification. In this section, we give several examples of features to demonstrate their ability in texture description and discrimination.

(1) Black-White Symmetry (BWS)

For a given Texture Spectrum, if we note $S(i)$ the occurrence frequency of the Texture Unit numbered $i, i = 0,1,2,\ldots,6560$, we define the Black-White Symmetry (BWS) by the following formula:

$$BWS = \left[1 - \frac{\sum_{i=0}^{3279} |S(i) - S(3281 + i)|}{\sum_{i=0}^{6560} S(i)} \right] \times 100$$

BWS values are normalized from 0 to 100, and measure the symmetry between the left-half (0 to 3279) and the right-half (3281 to 6560) in the Texture Spectrum. A high BWS value can be understood by noting that, if we invert the intensity values of the original image (equivalent to exchanging the value 0 with 2 in Texture Units set), the Texture Spectrum of the new image will remain approximately the same.

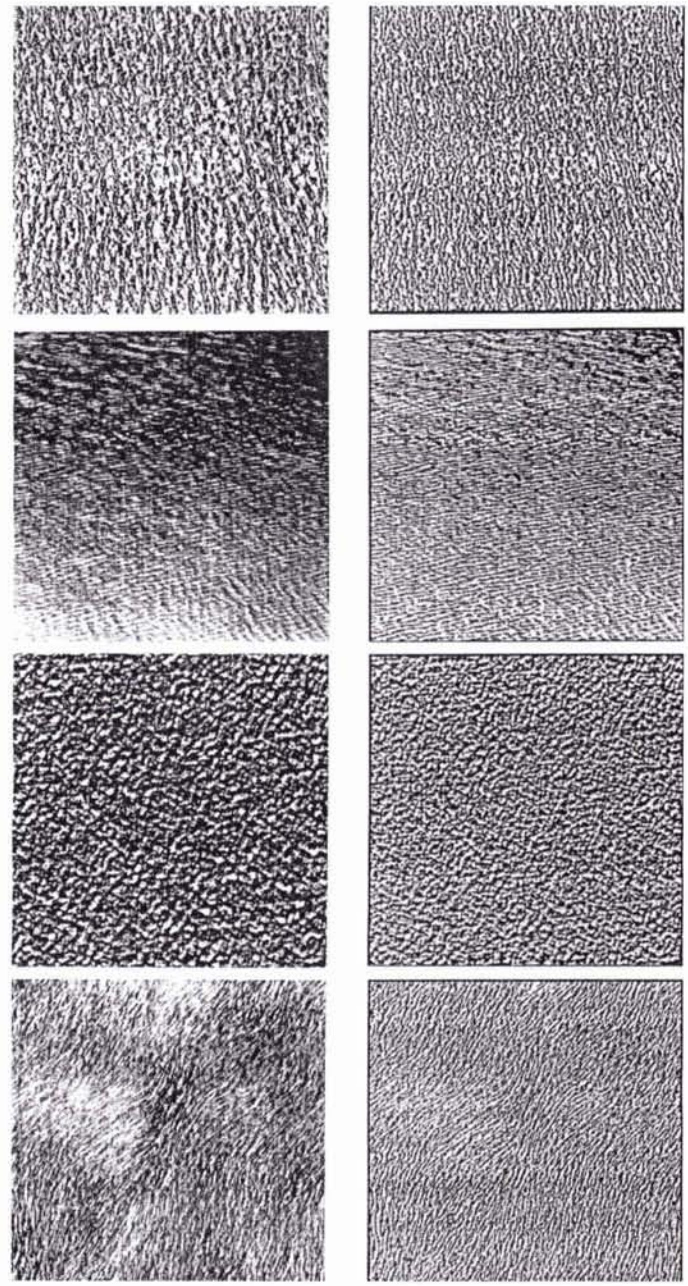

FIG. 6. Four of Brodatz' texture images (left-column) and the result of textural filtering (right-column).

(2) Geometric Symmetry (GS)

Let $S_j(i)$ be the occurrence frequency of the Texture Unit numbered i in the Texture Spectrum under the ordering way j, where $i = 0,1,2,\ldots,6560$, and $j = 1,2,3,\ldots,8$ (the ordering ways $a,b,c,\ldots,h$ are, respectively, represented by $j = 1,2,3,\ldots,8$), we define the Geometric Symmetry (GS) for a given image by the following formula:

$$GS = \left[1 - \frac{1}{4} \sum_{j=1}^{4} \frac{\sum_{i=0}^{6560} |S_j(i) - S_{j+4}(i)|}{2 \times \sum_{i=0}^{6560} S_j(i)} \right] \times 100$$

GS values are normalized from 0 to 100, and measure the symmetry between the spectra under the ordering ways a and e, b and f, c and g, and d and h for a given image. A high GS value indicates that, if we rotate the image 180 degrees, the Texture Spectrum will be approximately the same. In fact, the GS feature reveals information about the shape regularity of images.

(3) Degree of Direction (DD)

If we keep the same notation as in the GS definition, we define the Degree of Direction (DD) for a given image by the following formula:

$$DD = \left[1 - \frac{1}{6} \sum_{m=1}^{3} \sum_{n=m+1}^{4} \frac{\sum_{i=0}^{6560} |S_m(i) - S_n(i)|}{2 \times \sum_{i=0}^{6560} S_m(i)} \right] \times 100$$

DD values are also normalized from 0 to 100, and measure the degree of linear structure within an image. A high DD value indicates the Texture Spectrum is sensitive to the orientation of the image. In other words, that there are some linear structures of fundamental elements within the image. So the DD feature may reveal information about the orientation characteristics of images.

In order to evaluate the performance of the proposed features on natural scenes, a set of sample subimages was extracted from an airborne Synthetic Aperture Radar (SAR) image used for a geological study of an integrated data set of multi-sensor imagery. Nine subimages are shown in Figure 7 that describe areas occupied by three different rock units (Roscoe, 1984): (1) Proterozoic Western River Formation: quartzite,argillite, siltstone, and dolomite; (2) Archean massive to foliated granitic rocks; and (3) Archean metasedimentary rocks. Three subimages were chosen for each rock unit, and each sample was represented by 40 by 40 pixels.

It is quite difficult for the human eye to distinguish differences between the textures of either the same rock units or the different ones. The three features BWS, GS, and DD were calculated for each sample subimage and the result is shown in Figures 8 to 10. It can be seen that the three rock units can easily be distinguished by any one of the three proposed features derived from their Texture Spectra, demonstrating strong discriminating performance. For example, the Directional Degree in Figure 10 enables one to separate clearly the more "dotty" pattern of the metasedimentary rocks. The Geometrical Symmetry diagram in Figure 9 reveals a complementary texture attribute for the same unit. A similar interpretation can be made for the diagram in Figure 8.

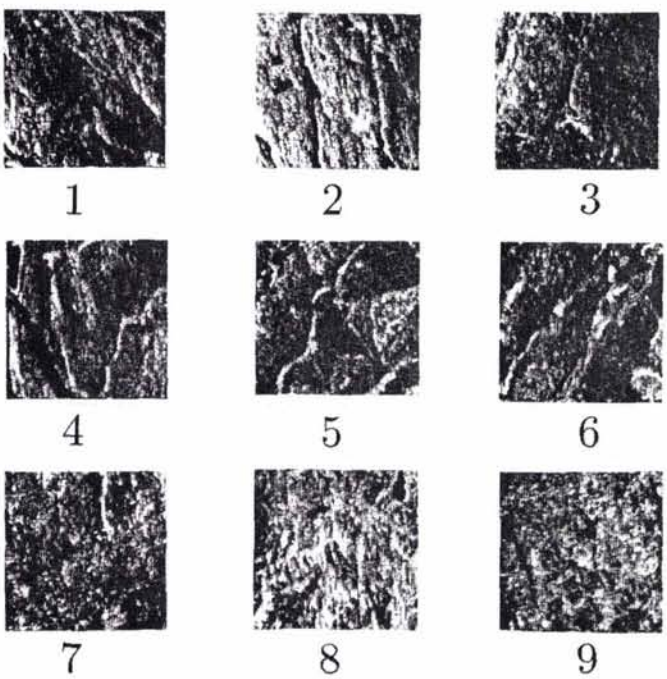

FIG. 7. Nine subimages-extracted from an airborne SAR imagery. Samples 1 to 3: Western River Formation (quartzite, argillite, siltstone, dolomite); Samples 4 to 6: Archean metasedimentary rocks; Samples 7 to 9: Archean massive to foliated granitic rocks.

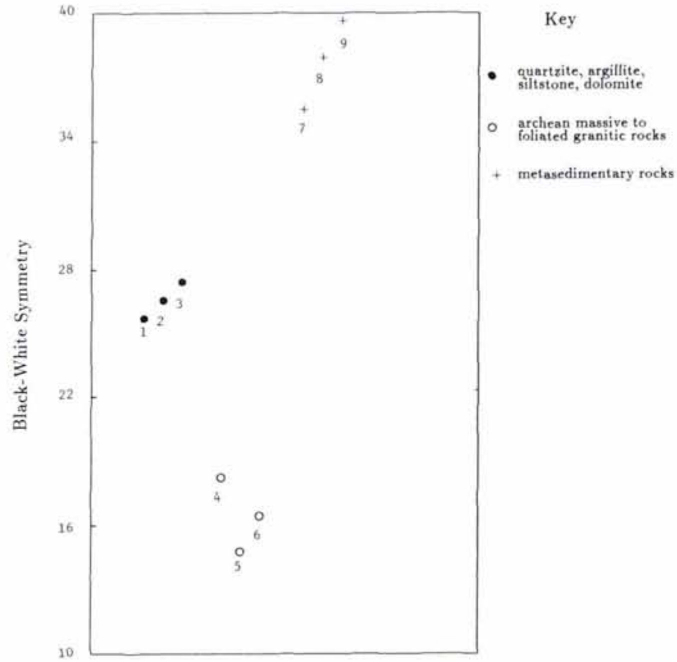

FIG. 8. Black-White Symmetry of nine sample subimages.

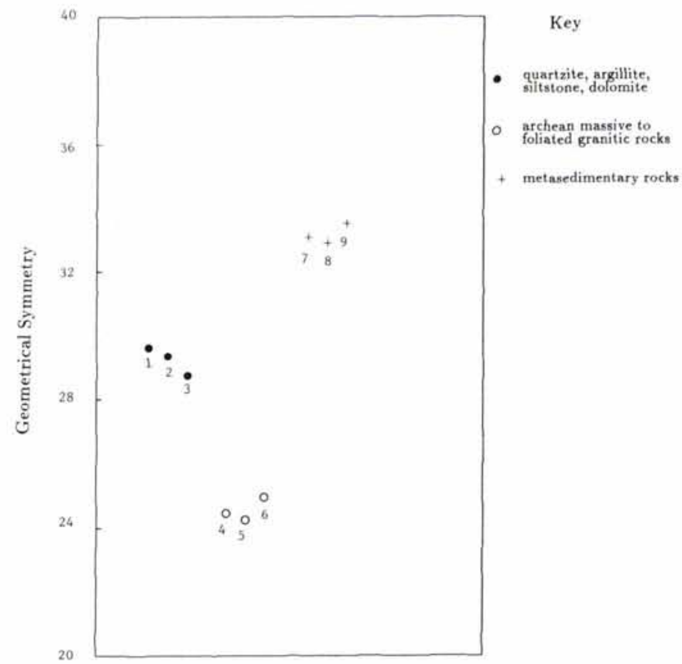

FIG. 9. Geometrical Symmetry of nine sample subimages.

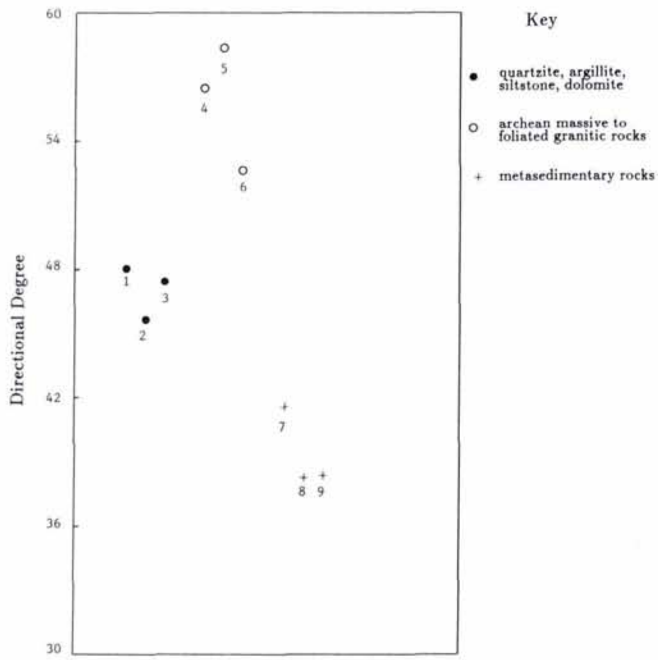

FIG. 10. Degree of Direction of nine sample subimages.

CONCLUSION AND DISCUSSION

As remote sensing technology becomes more mature, the spatial resolution of remotely sensed data becomes greater and greater (80 m for Landsat-MSS, 30 m for Landsat-TM, and 10 m for SPOT-PLA). Image processing and interpretation based on the analysis of individual pixels will no longer be appropriate to the needs of landscape cartography. Texture analysis will play an increasingly important role in image classification and interpretation.

A new statistical approach for texture analysis has been presented in this paper, which is based on the concept of the Texture Unit and Texture Spectrum. Preliminary evaluations presented in the previous section show that the Texture Spectrum is able to reveal texture information about images and has promising discriminating performance for different textures.

The Texture Unit extracts the local textural information for a given pixel from a neighborhood of 3 by 3 pixels, that is, in all the eight directions from the central pixel considered, instead of only one displacement vector used in the grey level co-occurrence matrix. So, the first advantage of the new method is that in this respect it is more complete for the characterization of texture.

Because the definition of the set of 6561 Texture Units is independent of the images to be analyzed, we could expect to describe all forms of texture in a unified way.

Another important advantage of the new approach is that the texture of an image is characterized in the form of a spectrum, making it possible to apply the Texture Spectrum concept to other image processing domain. Textural filtering is an example of such an approach.

The proposed method can be easily adapted to texture analysis of binary images, in which case there will be only $2^8 = 256$ Texture Units. In addition, calculation time will be reduced.

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