Texture Unit, Texture Spectrum, and Texture Analysis

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Abstract—**Texture is an important spatial feature, useful for identifying objects or regions of interest in an image. The grey-level cooccurrence matrix (GLCM) approach is one of the most popular statistical methods used in practice to measure the textural information of images. Based on the proposed concept of *texture unit*, this paper describes a new statistical approach to texture analysis, termed here the *texture spectrum* approach. In this method the "local" texture information for a given pixel and its neighborhood is characterized by the corresponding texture unit, and the global textural aspect of an image is revealed by its texture spectrum. The proposed method extracts the textural information of an image with a more complete respect of texture characteristics (simultaneously in all eight directions instead of only one displacement vector used in the GLCM approach). A preliminary evaluation study demonstates the potential usefulness of the texture spectrum method for texture analysis in remote sensing.**

I. Introduction

As THE spatial resolution of satellite-image data increases (80 m for Landsat–MSS, 30 m for Landsat–TM, and 10 m for Spot–PLA), texture analysis plays a more important role in image processing, image classification, and in the interpretation of remotely sensed data. In remote sensing data with a high spatial resolution (for example, 20 × 20 m or 10 × 10 m), some of the landscape elements are represented by a group of pixels, not by only one pixel. This means that image classification and interpretation based on the analysis of individual pixels will result in a relatively high rate of classification confusion and will no longer be sufficient to satisfy the needs of landscape mapping and cartography [1], [2]. A good understanding or a more satisfactory interpretation of remotely sensed imagery should include descriptions of both the spectral and textural aspects.

Methods of texture analysis are usually divided into two major categories [3], [4]. The first is the structural approach, where texture is considered as a repetition of some primitives, with a certain rule of placement. The traditional Fourier spectrum analysis is often used to determine the primitives and placement rule. Several authors have applied this method to texture classification and texture characterization with a certain degree of success [5]–[7]. Problems may be encountered in practice in indentifying the primitives and the placement rule in natural images, such as for some remotely sensed data.

The second major approach in texture analysis is the statistical method. Its aim is to characterize the stochastic properties of the spatial distribution of grey levels in an image. The grey-tone co-occurrence matrix is frequently used for such characteristics. A set of textural features derived from the co-occurrence matrix has been widely used in practice to extract textural information from digital images [7]–[10]. Sometimes this kind of second-order grey-level co-occurrence matrix produces unsatisfactory results. Some reasons for this are as follows. First, the matrix depends not only on the spatial relationships of grey levels but also on the regional intensity background variation within the image. Secondly, the cooccurrence matrix reveals textural information of the image in a given displacement vector $\vec{V} = (\Delta x, \Delta y)$ so that the choice of this vector is somewhat problematic.

The purpose of this paper is to present a new statistical method of texture analysis which is focused on texture characterization and discrimination. The concept of *texture unit* is proposed first. It may be considered as the smallest complete unit which best characterizes the local texture aspect of a given pixel and its neighborhood in all eight directions of a square raster. Then a texture image is characterized by its *texture spectrum*, which describes the distribution of all the texture units within the image. Some natural images have been used to evaluate the discriminating performance of the texture spectrum. The results obtained here demonstrate the potential usefulness of the proposed method in texture analysis.

II. Methodology

A. Texture Units

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

Given a neighborhood of 3 × 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 $\{i = 1, 2, \ldots 8\}$ is the intensity value of the neighboring pixel i), we define the corresponding texture unit by a set containing eight elements,

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$TU = \{E_1, E_2, \ldots E_8\}$, where E_i ($i = 1, 2, \ldots 8$) is determined by the formula:

$$E_i = \begin{cases} 0, & \text{if } V_i < V_0 \\ 1, & \text{if } V_i = V_0 \\ 2, & \text{if } V_i > V_0 \end{cases}$$

for $i = 1, 2, \ldots 8$, and the element E_i occupies the same position as the pixel i.

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

B. Labeling Texture Units

There is no unique way to label and order the 6561 texture units. In our study, the 6561 texture units are labeled by using the following formula:

$$N_{TU} = \sum_{i=1}^{8} E_i \cdot 3^{i-1}$$

where N_{TU} represents the texture unit number and 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 ordered clockwise as shown in Fig. 1, the first element may take eight possible positions from the top left (a) to the middle left (h), and then the 6561 texture units can be labeled by the above formula under eight different ordering ways (from a to h).

Fig. 2 gives an example of transforming a neighborhood to a texture unit with the texture unit number under the ordering way a.

C. 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 neighbors. Thus the statistics of the frequency of occurrence of all the texture units over a large region of an image should reveal texture information. We termed the texture spectrum the frequency distribution of all the texture units, with the abscissa indicating the texture unit number N_{TU} and the ordinate representing its occurrence frequency.

In practice, a real texture image is usually composed of two parts: Texture elements and random noise or background. The greater the proportion of texture components compared to the background, the better that texture can be preceived by human vision. In the texture spectrum the 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 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 the texture units in the texture spectrum, but will not change their frequency values in the latter.

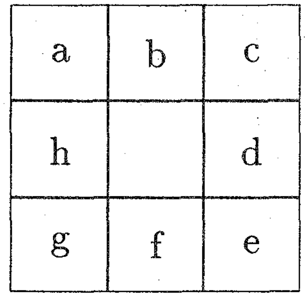

Fig. 1. Eight clockwise, successive ordering ways of the eight elements of the texture unit. The first element E_1 may take eight possible positions from a to h.

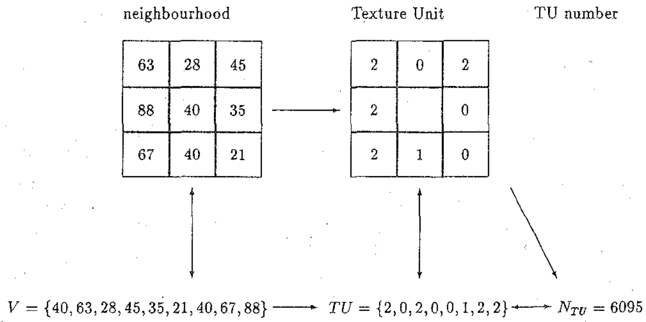

Fig. 2. Example of transforming a neighborhood to a texture unit with the texture-unit number.

It should be also noted that the local texture for a given pixel and its neighborhood is characterized by the corresponding texture unit, while the texture aspect for a uniform texture image is revealed by its texture spectrum calculated within an appropriate window. The size of the window depends on the nature of the texture image.

III. Evaluation

In order to evaluate the performance of the texture spectrum in texture characterization and classification, several experimental studies have been carried out on four of Brodatz's natural images [11]. These images were selected because they are broadly similar to one another and also that they resemble parts of remotely sensed images. Each image shown in Fig. 3 consists of 256 × 256 pixels with 64 normalized grey levels.

A. Texture Spectra

If the texture spectrum has discriminating performance for different textures, different texture images should have correspondingly different spectra. This leads up to calculating the texture spectra for the four images of Fig. 3 with eight ways of ordering (from a to h). The size of the window used for calculating the texture spectrum was 256 × 256 pixels; i.e., the size of a uniform texture image. The results are illustrated in Fig. 4. We note that different textures have correspondingly different spectra when comparing the number, position, width, and height of their

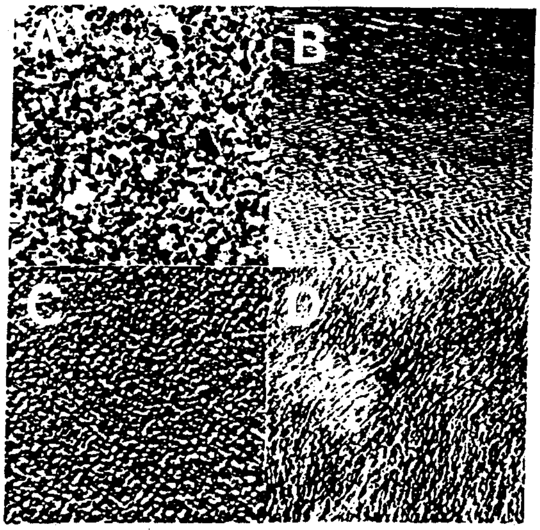

Fig. 3. Four natural texture images (from reference [11]).

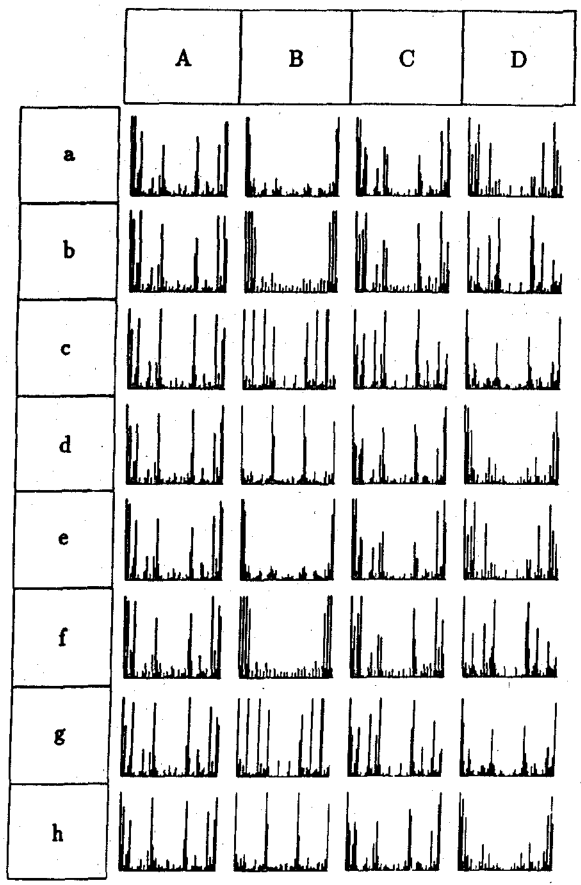

Fig. 4. Texture spectra of four images (from A to D) under eight ordering ways (from a to h). In each spectrum, the abscissa indicates the texture unit number, while the ordinate represents the occurrence frequency.

principal peaks, demonstrating the clear discriminating performance of the texture spectrum.

B. Texture Classification

In addition to the visual evaluation of the texture spectra, a further quantitative study was performed [12] using a supervised classification over the four texture images of Fig. 3. A sample subimage of 30×30 pixels was selected within each texture. Using a window of 30×30 pixels, together with a step of two pixels in the row and column, the full image of Fig. 3 was processed and each central pixel of the window was assigned to one of the four texture classes. Here, the texture spectrum was calculated within a window of 30×30 pixels. The minimum-distance decision rule was used and the integrated absolute difference between two texture spectra was considered as the distance between them. The result represents a 98.5% correct classification for texture image A; 96.4% for texture B; 98.9% for texture C, and 95.9% for texture D, resulting in an average classification accuracy of 97.5%.

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, respectively, 100% for textures A–C, and 98.4% for D, representing an average recognition rate of 99.6%.

It should also be noted that the bin pattern for the texture spectrum, shown in Fig. 4, represents 6561 possible texture units of which only part will be statistically meaningful to characterize a particular texture. A further extension of the method presented here would have to extract the significant bins for each class and the associate bins that represent slightly different patterns. This is equivalent to constructing a structure for the initially arbitrary encoding of so many bins. During classification, for a given window the significant level of bin occupancy will need to be determined and compared with the corresponding bins in the training set.

IV. Discussion

Based on the concept of texture unit and texture spectrum, a new statistical method of texture analysis has been presented. Preliminary evaluations show that the texture spectrum is able to reveal texture information in digital images and that it has promising discriminating performance for different textures. In addition, when compared with the other statistical methods, the proposed method has several advantages:

1) The texture unit method extracts the local texture information for a given pixel from a neighborhood of 3×3 pixels; i.e., simultaneously in all eight directions from the central pixel instead of only computing one displacement vector, as is done for the grey-level co-occurrence matrix. So in this respect the new approach is more complete for the characterization of textural properties.

2) Since the definition of the set of 6561 texture units is independent of the images analyzed, we could expect to describe all the forms of texture in a unified way.

3) The textural aspect of an image is characterized in the form of a spectrum, making it possible to apply the texture spectrum concept to other problems of image processing, such as in designing *digital filters*.

4) The proposed method can be easily adapted to the texture or shape analysis of binary images. There are only two possible values (0 and 1) for each element of the texture unit. The total number of texture units becomes, $2^8 = 256$. The statistics and calculation time will be reduced.

Other evaluations and applications have been conducted, including texture feature extraction, textural filtering, and texture classification for airborne SAR images [12]–[14]. The method described here is currently being applied to an integrated set of airborne SAR, SPOT, Seasat, and Landsat-MSS images for the mineral exploration described in [15].

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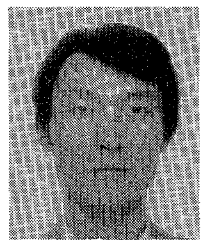

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