International Journal of Soft Computing 4 (3): 122-126, 2009
ISSN: 1816-9503

Supervised Classification of Images using Textural Features

[1]S.S. Sreejamole and [2]L. Ganesan
[1]GCE, Tirunelveli, Anna University, India
[2]A.C. Tech, Karaikudi, Anna University, India

Abstract: Texture is an important spatial feature, useful for identifying objects or regions of interest in an image. The gray-level co-occurrence matrix 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 study describes the local binary pattern, texture spectrum and entropy approach. In this method, the local texture in formation 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. A preliminary evaluation study demonstrates the potential usefulness of the proposed methods for texture analysis.

Key words: Texture spectrum, local binary pattern operator, entropy operator, images, statistical methods, spatial feature

INTRODUCTION

As the spatial resolution of satellite-image data increases, 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 (He and Wang, 1987; Marceau *et al.*, 1989). 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 (Haralick, 1979; Van Gool *et al.*, 1985). 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 (D'Astous and Jernigan, 1984; He *et al.*, 1988, 1987). Problems may be encountered in practice in identifying 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 gray levels in an image. The gray-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 (He *et al.*, 1987; Haralick *et al.*, 1973; Brodatz, 1968). Sometimes, this kind of second-order gray-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 gray levels but also on the regional intensity background variation within the image. Secondly, the co-occurrence matrix reveals textural information of the image in a given displacement vector V = (Ax, Ay) so that the choice of this vector is somewhat problematic.

The purpose of this study, 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 features like local binary pattern, texture spectrum and entropy, which describe 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 methods in texture analysis.

Corresponding Author: S.S. Sreejamole, GCE, Tirunelveli, Anna University, India

MATERIALS AND METHODS

Local Binary Pattern (LBP): In LBP the signs of the eight differences are recorded into an 8-bit number. The original 3×3 neighborhood is thresholded by the value of the center pixel. The values of the pixels in the thresholded neighborhood are multiplied by the weights given to the corresponding pixels. Finally, the values of the eight pixels are summed to obtain a number for this neighborhood. The LBP histogram computed over a region used for texture description. LBP provides us with knowledge about the spatial structure of the local image texture.

LBP is invariant against any monotonic gray scale transformation. The method is rotation variant like most existing texture measures. LBP does not address the contrast of texture, which is important in the discrimination of some textures. For this purpose, we can combine LBP with a simple contrast measure C also, shown in Fig. 1 and consider joint occurrences of LBP and C. LBP and LBP/C perform well also for small image regions (e.g., 16×16 pixels), which is very important e.g., in segmentation applications.

Texture spectrum: In a square raster digital image each pixel is surrounded by 8 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 9 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 8 elements, $TU = \{E_1, E_2, \ldots E_8\}$, 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, ... 8 and the element E, 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.

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:

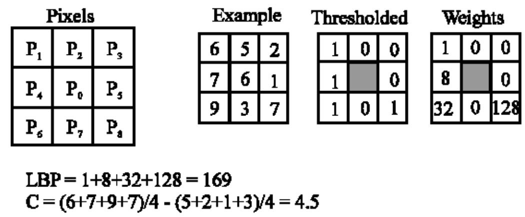

Fig. 1: Computation of LBP and contrast measure C

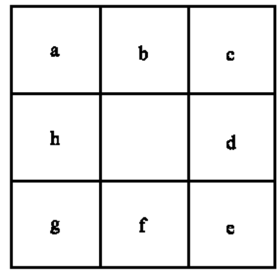

Fig. 2: Eight clockwise, successive ordering ways of the 8 elements of the texture unit

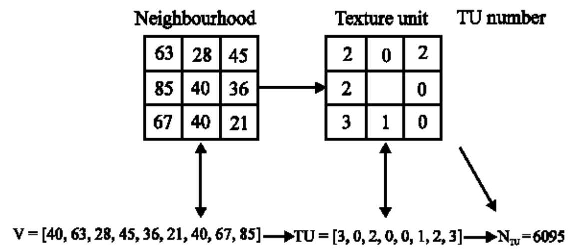

Fig. 3: Transforming a neighborhood to a texture unit with the texture unit number texture-unit number

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

where:

N_{TU} = The texture unit number
E_i = The ith 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. 2, 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. 3 gives an example of transforming a neighborhood to a texture unit with the texture unit number under the ordering way 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 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 2 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 perceived 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 might affect the relative positions of the texture units in the texture spectrum, but will not change their frequency values in the latter. 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.

Entropy: If an image is interpreted as a sample of a "gray level source" that emitted it, we can model that source's symbol probabilities using the gray-level histogram of the observed image and generate an estimate, called the first-order estimate, H, of the source entropy:

$$H = -\sum_{k=1}^{L} p_r(r_k) \log p_r(r_k)$$

$$k = 1, 2, \ldots, L$$

RESULTS AND DISCUSSION

In order to evaluate the performance of the texture spectrum in texture characterization and classification, several experimental studies have been carried out on 9 of Brodatz's natural images (Brodatz, 1968). 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. 4 consists of 256×256 pixels with 64 normalized gray levels.

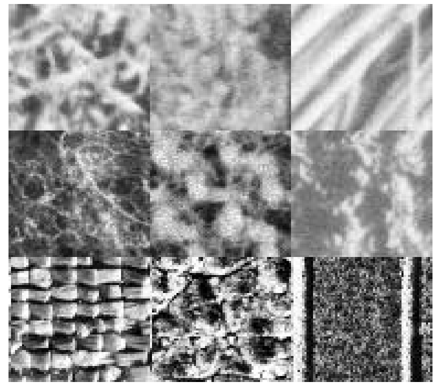

Fig. 4: Nine natural Brodatz's text images

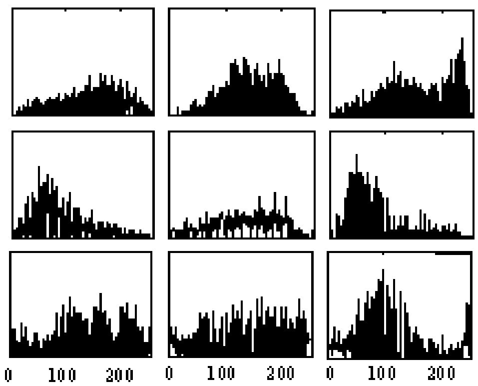

Fig. 5: Histogram of 9 images using LBP operator

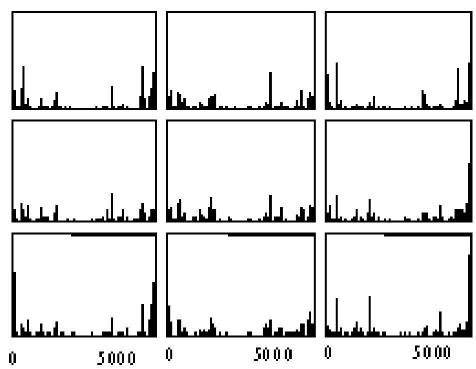

Fig. 6: Histogram of 9 images using texture spectrum

In addition to the visual evaluation a quantitative study was performed using a supervised classification over the nine texture images of Fig. 4. A sample sub image 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. 4 was processed and each central pixel of the window was assigned to one of the four texture classes.

Table 1: Classification percentage

Method	LBP	TSO	Entropy
Image 1	95.41	84.65	96.22
Image 2	95.9	92.51	82.14
Image 3	87.82	99.82	93.99
Image 4	96.25	90.61	97.59
Image 5	96.37	92.56	82.68
Image 6	97.24	93.93	81.88
Image 7	86.67	93.81	88.08
Image 8	96.51	93.69	81.57
Image 9	81.46	70.49	78.09

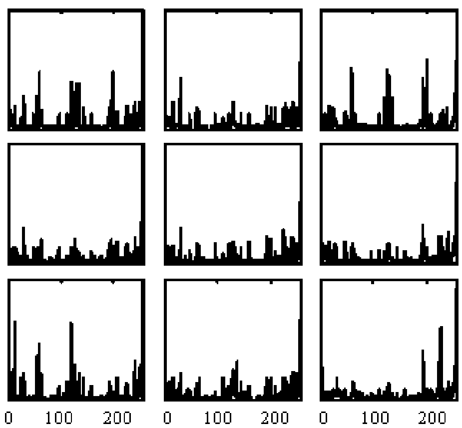

Fig. 7: Histogram of 9 images using entropy operator

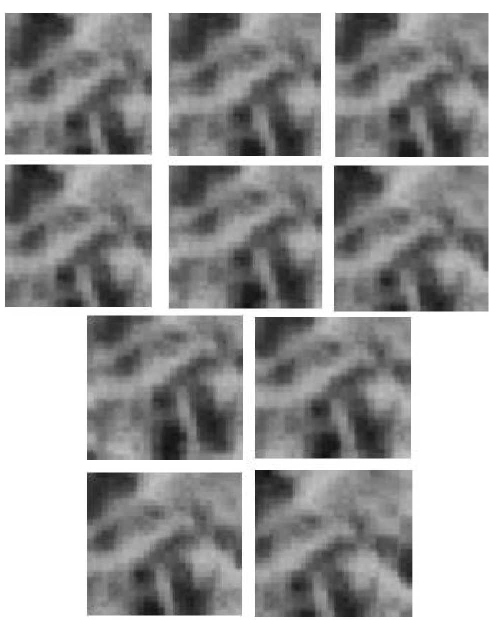

Fig. 8: Supervised classification using LBP operator

Here, the texture spectrum was calculated within a window of 30×30 pixels. Histogram of nine images using LBP Operator, Texture spectrum Operator and entropy Operator are shown in Fig. 5-7. The minimum-distance decision rule was used and the integrated absolute difference between two texture spectra was considered as the distance between them. The supervised classification result of the image using LBP Operator, Texture Spectrum Operator and Entropy Operator are shown in Fig. 8 and 9. The classification results are shown in Table 1.

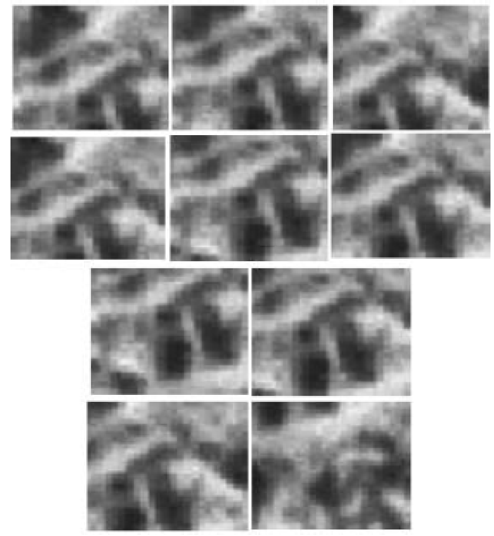

Fig. 9: Supervised classification using TSO

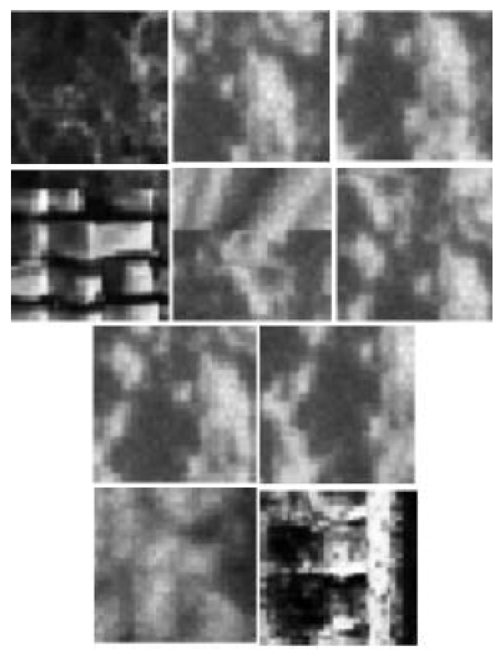

Fig. 10: Supervised classification using entropy

CONCLUSION

Based on the concept of Local Binary Pattern (LBP), texture spectrum operator and entropy measure, texture analysis has been presented. 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.

REFERENCES

Brodatz, P., 1968. Texture-A Photographic Album for Artists and Designers Dover Publications Inc. New York: Reinhold, citeseer.comp.nus.edu.sg/context/ 94954/o,623235.

D'Astous, F. and M.E. Jernigan, 1984. Texture discrimination based on detailed measures of power spectmm, 7ICPR(84) in Proc. IEEE Comput. Soc. Con5 on Pattern Recogn. Image Process., pp: 83-86. www.visionbib.com.

Haralick, R.M., 1979. Statistical and structural approaches to texture. In Proc. IEEE, 67 (5): 786-804. EHO232-9/85/0000/03044$01.00$1979,IEEE.ISSSN.0018-9219.Citeseer.comp.nus.edu.sg/context.

Haralick, R.M., K. Shanmugan and I. Dinstein, 1973. Textural features for image classification. IEEE Trans. Syst. Man, Cybern., SMC-3 (6): 610-621. www.wipo.int/pctdb/en/wo.jsp.IA-US2006003197P.

He, D.C. and L. Wang, 1987. Classification automatique, assitCe par analyse de texture, des paysages de la pointed'ArGay par dea donn Ces Thermatic Mapper. Int. J. Remote Sensing, 8 (2): 129-135. ieeeexplore.org/ie11/36/2143/00572934. DOI: 10.1080/01431168708948621.

He, D.C., L. Wang and J. Guibert, 1988. Texture discrimination based on an optimal utilization of texture features. Pattern Recogn., 2: 141-146. EEE comput soceit.conf.on pattern recognition and image processing.

He, D.C., L. Wang and J. Guibert, 1987. Texture features extraction. Pattern Recogn. Lett., 6: 269-273. www.informaworld.com/index/777859391.pdf.

Marceau, D., P.J. Howarth and J.M. Dubois, 1989. Automated texture extraction from high spatial resolution satellite imagery for land-cover classification: Concepts and application. In Proc. IGARSS'89/12th Can. Symp. Remote Sensing (Vancouver, BC, Canada), 5 (14): 2765-2768.

Van Gool, L., P. Dewaele and A. Oosterlinck, 1985. Survey-texture analysis Anno. Comput. Vision, Graphics and Image Process., 29: 336-357. portal.acm.org.id 258034.