Performance evaluation of cross-diagonal texture matrix method of texture analysis

Abdulrahman Al-Janobi*

Department of Agricultural Engineering, College of Agriculture, King Saud University, P.O. Box 2460, Riyadh 11451, Saudi Arabia

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Abstract

This paper presents a new texture analysis method incorporating with the properties of both the gray-level co-occurrence matrix (GLCM) and texture spectrum (TS) methods. The co-occurrence features extracted from the cross-diagonal texture matrix provide complete texture information about an image. The performance of these features in discriminating the texture aspects of pictorial images has been evaluated. The textural features from the GLCM and TS have been used for comparison in discriminating some of Brodatz’s natural texture images. The classification error was 2.4% with features from the cross-diagonal texture matrix, whereas the errors were 18.9 and 38.7% with features from the GLCM and TS, respectively. © 2000 Pattern Recognition Society. Published by Elsevier Science Ltd. All rights reserved.

Keywords: Textural features; Co-occurrence matrix; Texture spectrum; Cross-diagonal texture matrix; Texture classification

1. Introduction

Feature extraction is the procedure of generating descriptions of an object in terms of measurable parameters. The extracted features represent the relevant properties of the object, and may be used with a classifier to assign the object to a class or grade. The general task of texture measurement and evaluation has long been the topic of intense research in the image processing community. It is commonly agreed that textural features play a fundamental role in classifying objects and outlining the significant regions of a gray-level image.

Texture analysis is important in several image segmentation and classification problems. It is a well-developed technology and has been used for the analysis of all types of images. These range from microscopic images in the biomedical area to satellite images of the earth’s surface. In texture segmentation, the pixels are grouped together to form regions of uniform texture, whereas in texture classification, the problem is to classify an instance of a textured region in an image as one of a set of classes.

Several approaches to texture analysis have been developed over the past 20 years. Researchers have attempted to compare different methods and used in various applications. A more accurate classification method would result, if the attributes describing color are included in texture analysis.

There are several methods for defining the textural features. Each method has its own way to define the features that are used in the classification problem. In practice, structural and statistical approaches are the two major methods for extracting textural features. In the structural method, texture is considered as the repetition of some basic primitive patterns with a certain rule of placement. The well-known Fourier spectrum analysis is often used to determine the primitives and the displacement rule. In the statistical method, the stochastic properties of the spatial distribution of gray levels in an image are characterized. Surveys on many of these methods can be found in literature [1-5].

Many textural features proposed by researchers have been reported in the literature and have been widely used in texture analysis. The most common features used in
practice are those derived from the GLCM [6-8]. Features extracted from Markov random fields (MRFs) are descriptive and generative and have been found to be very useful for texture classification, image segmentation, and other applications [9,10]. General class of two-dimensional (2-D) auto-regressive (AR) models has been applied for describing textures and for subsequent recognition and classification [11,12]. Features derived from a set of Gabor filters have been widely used in texture analysis for texture segmentation and surface quality inspection [13,14]. Fractal models of surfaces have been employed in image analysis where the objects are rough, irregular, and multi-scale such as clouds, trees, and natural textures [15-19]. Textural features extracted from TS have been used in texture description and discrimination [20,21]. Baheerathan et al. [22] proposed a set of textural features based on complexity curve for texture classification and to estimate the texture directionality and periodicity. By using multilevel dominant eigenvector estimation algorithm and the Battacharyya distance measure for feature extraction. Tang [23] demonstrated that textural features extracted from a new run-length matrix can produce great classification results over traditional run-length techniques. Chen et al. [24,25] proposed a set of statistical geometrical features based on the statistics of geometrical properties of connected regions in a sequence of binary images. And in their further work [26] they demonstrated that the combination of these features with a new generating-shrinking algorithm is one of the best texture classification systems considered. Wavelet transform method of feature extraction has been applied to the problems of texture classification and segmentation [27-29].

Researchers have also attempted to carry out comparative studies to evaluate the performance of textural features. Weszka et al. [30] compared features derived from GLCMs on terrain images and found that the co-occurrence features were best among those studied. Ohanian and Dubes [31] compared and evaluated in a quantitative manner textural features derived from GLCMs, discrete MRFs, Gabor multi-channel filters, and fractal geometry and found that the co-occurrence features performed best followed by the fractal features. He and Wang [21] compared the features derived from the TS with the features from the GLCM on airborne synthetic aperture radar (SAR) images and found that the features from TS showed better discriminating performance than the co-occurrence features. Baheerathan et al. [22] compared the textural features from the complexity curve with the GLCM features on Brodatz textures [32] and found that the classification rate achieved by the features from the complexity curve was substantially higher than the best combination of three GLCM features. Tang [23] demonstrated that textural features extracted from run-length matrices performed comparably well with the co-occurrence features and better than the wavelet features.

The objectives of this research were (1) to develop a new texture analysis method namely cross-diagonal texture matrix (CDTM) that contains the advantages of both the GLCM and TS of texture analysis and (2) to compare the performance of it with the GLCM and TS methods by testing some of natural texture images extracted from the Brodatz album [32].

2. Background

GLCM and TS methods of texture analysis are briefly described here. Techniques of both methods are utilized in the development of the new method.

2.1. Gray-level co-occurrence matrix (GLCM)

A set of textural features derived from the GLCM has been used to extract the textural information. These co-occurrence textural features are descriptive and easily computable features based on gray-level spatial dependencies. Suppose an image I to be analyzed is rectangular and has N resolution pixels in the horizontal direction, N resolution pixels in the vertical direction, and the gray levels appearing in resolution pixels are quantized to N levels. Haralick et al. [6] defined a matrix of relative frequencies, \( P(i,j) \) with which two neighboring pixels separated by distance, \( d \) at a specified angle, \( \theta \) occur on the image, one with gray level, \( i \) and the other with gray level, \( j \). Such GLCMs depend on the angular relationship between neighboring pixels as well as on the distance between them. By using a distance of one pixel and angles quantized to 45° intervals, four matrices of horizontal, first diagonal, vertical, and second diagonal (0, 45, 90 and 135°) are used. Then the unnormalized frequency in the four principal directions is defined by

\[
P(i,j, d, 0) = \#
\]

where \# is the number of elements in the set, \((k, l), (m, n)\) with gray level \(i\), \( (m, n) \) the coordinate with gray level \(j\), \( L \) the horizontal spatial domain, \((1, 2, ..., N)\), \( L \) the vertical spatial domain, \((1, 2, ..., N)\), and \((L x L)\) are set of resolution cells ordered by their row-column designations.

The GLCMs were normalized by dividing each entry of the matrix by a normalizing constant \( R \), as
where \( p(i,j) \) is the \( (ij) \)th entry in a normalized GLCM, \( P(i,j) \) the \( (ij) \)th entry in an unnormalized GLCM, and \( R \) the normalizing constant.

For a square or a rectangular image, the normalizing constant \( R \) was defined as

\[
R = \left[ 2N(N - 1) + 2N(N - 1) \right] + 4(N - 1)(1) \quad (3)
\]

It is assumed that the texture information is contained in the four matrices in the four principal directions. Haralick et al. [6] suggested a possible set of 28 textural features that could be extracted from these GLCMs. The co-occurrence features used in this study are given in Appendix A.

Because of the descriptive and easily computable nature, the co-occurrence features have been widely used in most of the texture analysis problems. The GLCM of second order gives valid measure of spatial distribution of gray levels within the image. The computational time complexity for extraction of textural features from the GLCM depends on the gray-level value of an image. Decrease in maximum gray-level value reduces the size of the GLCM and that in turn decreases the computational time complexity. The computational time is very crucial in most of the applications. Hence, one may accept small reductions in classification accuracy for reduced computational time. The drawback to co-occurrence features is the large number of potential features and the lack of theory to support any set of features.

2.2. Texture spectrum (TS)

The TS approach has been introduced and described in detail by Wang and He [20]. The basic concept is that a texture image can be decomposed into a set of essential small units called texture units. A texture unit is represented by eight elements, each of which has one of three possible values \((0, 1, 2)\) obtained from a neighborhood of 3 x 3 pixels.

Given a neighborhood of 3 x 3 pixels denoted by a set containing nine elements: \( V = (V_1, V_2, \ldots, V_9) \), where \( V_1 \) represents the intensity value of the central pixel and \( V_i \) the intensity values of the neighboring pixels. Then the corresponding texture unit can be represented as a set containing the elements, \( TU = (E_1, E_2, \ldots, E_8) \). The following formula can be used to determine the elements, \( E_i \) of the texture unit:

\[
E_i = \begin{cases} 
0 & \text{if } V_i < V \\
1 & \text{if } V_i = V \\
2 & \text{if } V_i > V 
\end{cases}
\quad (4)
\]

and the element \( E_1 \) occupies the same position as the pixel \( i \).

As each element of texture unit has one of three values, the combination of all eight elements results in \( 3^8 = 6561 \) possible texture units in total. These texture units are labeled by using the formula

\[
iV = \sum_{i=1}^{8} E_i \quad (5)
\]

where \( N \) is the texture unit number, and \( E_i \) the \( i \)th element of texture unit set \( TU = (E_1, E_2, \ldots, E_8) \).

The eight elements may be ordered differently. If the eight elements are ordered clockwise around the central pixel, the first element may take eight possible positions from the top left corner to the left middle, then the 6561 texture units can be labeled by the above formula under eight different ordering ways. The occurrence distribution of texture units is called the TS. He and Wang [21] reported several textural features based on the concept of TS. The features used in this study are given in Appendix B.

As the texture unit represents the local texture information of a given pixel and its neighborhood, the statistics of all the texture units in an image reveal its global texture aspects. The TS has promising discriminating performance and hence it can be used for texture characterization and classification. The computational time complexity depends on the number of texture units in a texture image rather than the maximum gray-level value.

3. Cross-diagonal texture matrix

Most of the texture analysis methods reported in literature have focused only on the neighboring pixels to obtain the texture information. The GLCM method of texture analysis characterizes the spatial relationship between a pixel and a neighboring pixel at a given specific distance and angle. It has been noted that a reasonable texture information of an image can be obtained between two pixels. The TS method of texture analysis gives the texture information using the eight neighboring pixels around the central pixel. The level of this information depends on the ordering of the neighboring pixels. Until now, no work has been reported in literature to produce a strong texture information of an image by separating the neighboring pixels into groups and form a relationship between them. In this work, an attempt has been made to develop a new method of texture analysis in characterizing the texture information by separating the eight neighboring pixels around a central pixel in a neighborhood of 3 x 3 pixels. Properties of both the GLCM and TS were utilized in the development of the new method.

In this new method of texture analysis, called cross-diagonal texture matrix (CDTM), the eight elements in
the texture unit obtained from a neighborhood of 3 x 3 pixels are divided into two groups, each with four elements as shown in Fig. 1. The texture information can be obtained from the mathematical model representing the two groups. The diagonal elements are arranged in one group, whereas the other group contains the other elements in the texture unit. Each element in the two groups has one of three possible values from patterns 0, 1, and 2. It has a value 0 if the intensity value of that element is less than the value of the central pixel, 1 if they are equal, and 2 if the intensity value is greater than the central pixel value. The properties of the combination of all four elements in each group results in 81 (3⁴) texture units in total. These two new texture units are called cross-texture unit (CTU) and diagonal-texture unit (DTU), respectively. The elements in them are located in places in the cross and diagonal directions with respect to the reference central pixel. Both the texture units are labeled by using the following formula

\[ \text{NDTU} = E_D \cdot J \cdot Y \cdot D \]  

(6)

\[ \text{ED} \cdot E_D \cdot J \cdot Y \cdot D \]  

(7)

where \( J \), \( TU \) is the cross-texture unit number, \( D \), \( TU \) the diagonal-texture unit number, \( E \), \( i \) the \( i \)th element of cross-texture unit set \( \{ E_1, E_2, E_3, E_4 \} \), and \( E \), \( i \) the \( i \)th element of diagonal-texture unit set \( \{ E_D, E_D, E_D, E_D \} \).

An example of transforming an image neighborhood into CTU and DTU is shown in Fig. 2. The elements in the CTU and DTU may be ordered differently. The first element of each unit may take four possible positions, giving a total of 16 (4 x 4) possible positions for both units. The values of CTU and DTU vary depending on position of elements in the units and can be labeled by using formulae (6) and (7). Fig. 3 shows different values of CTU and DTU by possible positions of elements in them. A CDTM can be obtained from these texture units with CTU number on the x-axis and DTU number on the y-axis as in Fig. 2. This CDTM has elements of relative frequencies in both texture units. From this matrix, a set of Haralick’s features can be extracted to give the texture information about the image.

This new method combines the merits of both GLCM and TS methods of texture analysis and hence it gives the complete texture information about an image. The CDTM has a fixed size of 81 x 81. Also the gray level of the image has no effect on the size of the matrix as in GLCM. In addition, the computational time complexity is reduced considerably because of the reduced size of the matrix.
4. Evaluation of the features

In order to evaluate the performance of the proposed method in texture classification, a set of sample images was extracted from Brodatz's natural texture images [32]. Nine of Brodatz's texture images have been used for this evaluation. They are the images of (1) pressed cork, (2) herringbone weave, (3) water, (4) oriental straw cloth, (5) straw matting, (6) handmade paper, (7) grass lawn, (8) pigskin, and (9) wood grain (Fig. 4). Five texture images, each of resolution 320 x 320 pixels were extracted from each Brodatz's textural image. Then each image was divided into 25 sub-images, each of resolution 64 x 64 pixels. The hundred sub-images from the four images were taken as the training module, whereas the 25 sub-images of the other image were selected as the test module. The features from the CDTM, GLCM, and TS were calculated over each sample sub-image of all the nine texture images of Fig. 4. These textural features were compared using a common statistical classification technique. Bayes minimum risk classifier [33] was used for this purpose. These features were evaluated according to their discriminating power. In the Bayes classifier, the expected loss in assigning random sample $x$ to each class, $i$, is computed. The class that results in the minimum loss is assigned to $x$. A multivariate Gaussian probability density function was assumed for the Bayes classifier, with each density specified by the mean vector and covariance matrix. Loss was minimized by maximizing the decision function

$$d(x) = \ln P(w_i) - \ln |Q| - \ln |m_i| - \frac{1}{2} (x - m_i)^T C_f (x - m_i)$$

(8)

where $d(x)$ is the decision function for class $i$, $x$ the sample feature vector, $Q$ the covariance matrix for class $i$, $m_i$ the mean feature vector for class $i$, and $P(w_i)$ the priori probability of occurrence of class $w_i$.

Among the 34 textural features used in classifying Brodatz's texture images, 13 were GLCM features, 13 were CDTM features, and the remaining eight were TS features. Classification process was carried out in two different ways. First, all the textural features extracted from each method were used for classification and
Fig. 4. Nine of Brodatz’s natural texture images: (a) pressed cork, (b) herringbone weave, (c) water, (d) oriental straw cloth, (e) straw matting, (f) handmade paper, (g) grass lawn, (h) pig skin, and (i) wood grain.

Table 1
Percent classification error with features from the three methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Features</th>
<th>Texture image class</th>
<th>Avg. error (%)</th>
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<tr>
<td></td>
<td></td>
<td>1   2   3   4   5   6   7   8   9</td>
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<td></td>
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<td>Classification   error (%)</td>
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<td></td>
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<td>O W’ 4</td>
<td>1-13</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Total</td>
<td>3</td>
</tr>
</tbody>
</table>

*Gray-level co-occurrence matrix.
Texture spectrum.
*Cross-diagonal texture matrix.
*Ordering way.
the results were compared. Then the individual textural features from each method were used for classification to determine the features giving minimum classification error. These features were used in combination to determine the best combination that would yield the lowest classification error for the nine-class texture image problem. The classification results using the Baye's classifier are summarized in Tables 1 and 2.

Table 1 shows the percentage classification error in classifying the nine selected Brodatz's texture images with all the textural features from each method. The average errors in classifying the nine texture images with features from the GLCMs in the four principal directions ranged from 16.2 to 20.6%. The GLCMs in the four principal directions were summed up and the 13 Haralick’s features were calculated to feed as inputs to the Baye's classifier. These feature measurements with an average error of 18.9% did not improve the classification accuracy. The features from the TS with an average error of 38.7% showed poor performance among the features from the three methods in classifying the Brodatz’s texture images.

The features from the CDTM performed well in classifying the Brodatz’s texture images with the lowest classification error compared to the other two methods. In this study, to evaluate the textural features only four ordering ways were considered to form the CDTMs. The positions of the elements in the CTU were kept the same, whereas the elements in the DTU were moved in the clockwise direction to obtain the four ordering ways with starting element $E_D$ (Fig. 1). The textural features from these four CDTMs resulted average classification error of the range 2.2-3.6%. However, the textural features calculated from the CDTM formed from the summation of the four CDTMs corresponding to the four ordering ways did not improve the classification accuracy. It gave an average classification error of 2.4%, which was with in the error range of features from the four ordering ways.

Table 2 shows that the average error was reduced considerably with the selective features from the GLCMs and TS. However, the average error for the selective features from the CDTMs was increased compared to the values when all the thirteen features were used together in the classification problem. The comparisons indicate that the textural features extracted from the CDTMs classified pictorial texture images more accurately with minimum misclassification, followed by textural features from the GLCMs, and then the features from TSs.

5. Conclusion

A new texture analysis method called cross-diagonal texture matrix (CDTM) has been developed and tested.
The performance of this method has been compared with GLCM and TS by testing some of Brodatz's natural texture images. The CDTM showed better performance than GLCM and TS. The classification errors with CDTM, GLCM, and TS were 2.4, 18.9, and 38.7%, respectively. Extensive work should be carried out to test the performance of the CDTM in applications such as remote sensing, color imaging, etc.

### Appendix A

The marginal probability, sum and difference matrices, and the textural features used in this study are given in Table 3.

### Appendix B

The textural features based on texture spectrum are given in Table 4.
Table 4

<table>
<thead>
<tr>
<th>Feature Type</th>
<th>Formula</th>
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<tbody>
<tr>
<td>Black-white symmetry</td>
<td>$L = \text{TIS}(0) - S(6560) \times 100$</td>
</tr>
<tr>
<td>Geometric symmetry</td>
<td>$S(j) = \prod_{i=0}^{n} (0 - S(6560) \times 100)$</td>
</tr>
<tr>
<td>Degree of direction</td>
<td>$DD = \sum_{i=0}^{n} (0 - S(6560) \times 100)$</td>
</tr>
<tr>
<td>Orientation features</td>
<td>$MHS = \sum_{i=0}^{n} (0 - S(6560) \times 100)$</td>
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<td></td>
<td>$MVS = \sum_{i=0}^{n} (0 - S(6560) \times 100)$</td>
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<tr>
<td></td>
<td>$MDS1 = \sum_{i=0}^{n} (0 - S(6560) \times 100)$</td>
</tr>
<tr>
<td></td>
<td>$MDS2 = \sum_{i=0}^{n} (0 - S(6560) \times 100)$</td>
</tr>
</tbody>
</table>

where $S(i)$ is the occurrence frequency of the texture unit $i$ in the texture spectrum, where $i = 0, 1, 2, \ldots, 6560$.

References


About the Author—ABDULRAHMAN AL-JANOBI received the B.S. degree in Agricultural Engineering from the King Saud University, Riyadh, in 1986. He joined the King Saud University as an instructor in the department of Agricultural Engineering in 1986. After a year, he joined the Oklahoma State University, Stillwater, USA, for higher studies. He received the M.S. and Ph.D. degrees in Agricultural Engineering in 1990 and 1993, respectively. His studies concentrated mostly on application of machine vision in agriculture field. He returned to the King Saud University, and currently he is an Associate Professor and Head of the Department of Agricultural Engineering. His research interests are texture analysis and machine vision application in grading and sorting agriculture products.