CHAPTER 2

TEXTURE CLASSIFICATION METHODS GRAY LEVEL CO-OCCURRENCE MATRIX AND TEXTURE UNIT

2.1 BRIEF OUTLINE

The classification of digital imagery is to extract useful thematic information which is one of the main objectives of environmental remote sensing, industrial inspection, document segmentation, medical imaging, etc., and accurate classification is often essential for the effective use of natural images contained in VisTex, OuTex, Granite and Brodatz databases. A variety of classification algorithms/models are available to analyze for image classification namely Sklansky [87], He D.C. and Wang L. [31]. Among them, the *'Gray Level Co-occurrence Matrix' (GLCM), 'Texture Spectrum' (TS),* 'Run Length Matrix' (RLM) and *'Local Binary Patterns'* (LBP) are popular. These models are typically validated through comparisons with performance. A good model is one that matches the performance of human observers, either in terms of absolute performance or in terms of performance trends.

From the literature survey, the present study found the *'Gray Level Co-occurrence Matrix' (GLCM) is a benchmark method for extracting* Haralick features such as [30] (angular second moment, contrast, correlation, variance, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measures of correlation and maximal correlation coefficient), or Conners' features [17] (inertia, cluster shade, cluster prominence, local homogeneity, energy and entropy). These features have been widely used in the analysis, classification and interpretation of remotely sensed data. Its aim is to characterize the stochastic properties of the spatial distribution of grey levels in an image.

He and Wang have proposed the texture spectrum approach for image/texture analysis [22, 107, 108, 109]. In this method, the local texture information for a given pixel and its neighborhood is represented by the corresponding texture unit, and the global texture of an image is characterized by its texture spectrum. But a major inconvenience of this method is the large range of its possible values (i.e., 6561) and at the same time these values are not correlated. Apart from these drawbacks, it is useful and necessary to extract textural image features from the texture spectrum, which will then be more easily used for image analysis, instead of using the row texture spectrum.

2.2 GRAY LEVEL CO-OCCURRENCE MATRIX

One of the other most popular statistical methods used to measure the textural information of images is the *'Gray Level Co-occurrence Matrix'* (GLCM). The GLCM method gives reasonable texture information of an image that can be obtained only from two pixels. Grey level co-occurrence matrices introduced by Haralick [30] attempt to describe texture by statistically sampling how certain grey levels occur in relation to other grey levels. Suppose an image to be analyzed is rectangular and has N_x rows and N_y columns. Assume that the gray level appearing at each pixel is quantized to N_g levels. Let $L_x = \{1,2,...,N_x\}$ be the horizontal spatial domain, $L_y = \{1,2,...,N_y\}$ be the vertical spatial domain, and $G = \{0,1,2,...,N_g-1\}$ be the set of N_g quantized gray levels. The set $L_x \times L_y$ is the set of pixels of the image ordered by their row-column designations. Then the image I can be represented as a function of co-occurrence matrix that assigns some gray level in $L_x \times L_y$; $I: L_x \times L_y \rightarrow G$. The gray level transitions are calculated based on the parameters, displacement (d) and angular orientation (θ). By using a distance of one pixel and angles quantized to 45^0 intervals, four matrices of horizontal, first diagonal, vertical, and second diagonal (0, 45, 90 and 135 degrees) are used. Then the un-normalized frequency in the four principal directions is defined by Equation (2.1).

$$p(i,j,d,\theta) = \# \left\{ \begin{array}{c} ((k,l),(m,n)\epsilon\left|(L_x \times L_y) \times (L_x \times L_y)\right| \\ (k-m=0, |l-n|=d) \ or \ (k-m=d, l-n=-d) \\ or \ (k-m=-d, l-n=d) or \ (|k-m|=d, l-n=0), \\ or \ (k-m=d, l-n=d) or \ (k-m=-d, l-n=-d), \\ I(k,l)=i, \qquad I(m,n)=j \end{array} \right. \tag{2.1}$$

where # is the number of elements in the set, (k, l) the coordinates with gray level i, (m, n) the coordinates with gray level j. The following Figure 2.1 illustrates the above definitions of a co-occurrence matrix ($d=1$, $\theta = 0^0$):

3	3	3
1	3	3
1	3	2

(a)

0^0	1	2	3
1	0	0	2
2	0	0	0
3	0	1	3

(b)

45^0	1	2	3
1	0	0	2
2	0	0	0
3	0	0	2

(c)

90^0	1	2	3
1	1	0	1
2	0	0	1
3	0	0	3

(d)

135^0	1	2	3
1	0	0	0
2	0	0	1
3	0	0	2

(e)

Figure 2.1: An example of Gray level co-occurrence matrix.

Even though Haralick [30] extracted 24 parameters from co-occurrence matrix, only seven are commonly used such as energy, entropy, contrast, local homogeneity, correlation, cluster shade and cluster prominence as given in Equations (2.2) to (2.8) and is stored in feature database. In addition, the first order statistical features (i.e., mean and standard deviation (StdDev) are used to describe the characteristics of image as shown in Equations (2.9) to (2.10) respectively. The first and second order statistical features are shown below:

$$\text{Entropy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij})P_{ij} \tag{2.2}$$

Entropy measures the randomness of intensity distribution, low values for smooth images than for a coarse image.

$$\text{Energy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij})^2 \tag{2.3}$$

Energy measures the number of repeated pairs and also measures uniformity of the normalized matrix.

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij}\,(i-j)^2 \tag{2.4}$$

The contrast feature is a difference moment of the P matrix and is a standard measurement of the amount of local variations present in an image. The higher the value of contrast are, the sharper the structural variations in the image.

$$\text{Local Homogenity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1 + (i-j)^2} \tag{2.5}$$

It measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. The converse of homogeneity results in the statement of contrast.

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{2.6}$$

where P_{ij} is the pixel value in position (i,j) of the texture image, N is the number of gray levels in the image, μ is $\mu = \sum_{i,j=0}^{N-1} iP_{ij}$ mean of the texture image and σ^2 is $\sigma^2 = \sum_{i,j=0}^{N-1} P_{ij} (i-\mu)^2$ variance of the texture image. Correlation is the measure of similarity between two images in comparison.

$$\text{Cluster Shade} = \sum_{i,j=0}^{N-1} P_{ij} \left(i - M_x + j - M_y\right)^3 \tag{2.7}$$

$$\text{Cluster Prominence} = \sum_{i,j=0}^{N-1} P_{ij} \left(i - M_x + j - M_y\right)^4 \tag{2.8}$$

where $M_x = \sum_{i,j=0}^{N-1} iP_{ij}$ and $M_y = \sum_{i,j=0}^{N-1} jP_{ij}$

$$\text{mean}(m) = \sum_{i=0}^{L-1} z_i p(z_i) \tag{2.9}$$

The measures mean (m), which represents the average intensity.

$$\text{standard deviation } (\sigma^2) = \sum_{i=0}^{L-1} (z_i - m)^2 p(z_i) \tag{2.10}$$

where σ^2 is the standard deviation, it indicates the intensity contrast.

2.3 TEXTURE UNIT

Texture can also be characterized based on local texture aspects. Local texture aspects contain information regarding texture behavior. Texture is an important spatial feature useful for identifying objects or regions of interest in an image. The texture image can be decomposed into a set of essential small primitive units, called *'Texture Units'* (TU) which characterizes the local texture information for a given pixel and its neighborhood. As the TU represents the local texture aspect, the statistics of TU in an image should reveal its texture information. The occurrence distribution of TUs is called as *'Texture Spectrum'* (TS), with the 'abscissa' indicating the type of TPU and the 'ordinate' representing its occurrence frequency. The TU is introduced and described in detail by He D.C. and Li Wang [22, 107, 108, 109].

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). A 3×3 neighborhood pixels 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, where $i = \{1,2,\ldots,8\}$, is the intensity value of the neighboring pixel i. A general representation of texture elements are shown in Figure 2.2. Based on this, the corresponding TU is defined by a set containing eight elements i.e., $TU = \{E_1, E_2 \ldots E_8\}$ are formed with a ternary value i.e. 0 or 1 or 2 by comparing V_0 with V_i. Where E_i (i=1, 2....8) is determined by the formula

[C7] given in Equation (2.9) and the element E_i occupies the same position as the pixel i.

V_1	V_2	V_3
V_8	V_0	V_4
V_7	V_6	V_5

E_1	E_2	E_3
E_8		E_4
E_7	E_6	E_5

Figure 2.2: Representation of texture elements.

$$E_i = \begin{cases} 0 & \text{if } V_i < V_0 \\ 1 & \text{if } V_i = V_0 \\ 2 & \text{if } V_i > V_0 \end{cases} \qquad \text{for i= 1, 2, ...,8} \qquad (2.9)$$

As each element of TU has one of the three possible values, the combination of all the eight elements results in $3^8 = 6561$ possible TU's in total. There is no unique way to label and order the 6561 TU's. The 6561 TU's are labeled by [22, 107] using the following Equation (2.10):

$$N_{TU} = \sum_{i=1}^{8} E_i \times 3^{i-1}, \quad N_{TU} \in \{0, 1, 2, \dots, (3^8 - 1)\} \qquad (2.10)$$

Here N_{TU} represents the TU number and E_i is the i^{th} element of TU {E_1, E_2... E_8}. An example of texture unit is represented in Figure 2.3.

83	28	60
76	55	23
90	55	10

2	0	2
2		0
2	1	0

3^0	3^1	3^2
3^7		3^3
3^6	3^5	3^4

$\sum$= 6095

Figure 2.3: Example of transforming a 3×3 neighborhood to a texture unit.

The high range of N_{TU} makes further process on texture unit and texture spectrum very complicated. To overcome this, the texture units are reduced from 0:6560 to 0:255 for classification purpose by assigning binary value 0 or 1 to each element of TU and by this the corresponding N_{TU} ranges from 0 to 255 [Ph.D thesis of Dr.V.Vijayakumar] [105].

The present work adopted VijayaKumar's method of identifying N_{TU} by the following Equation (2.11).

$$E_i = \begin{cases} 0 & \text{if } V_i < V_0 \\ 1 & \text{if } V_i \geq V_0 \end{cases} \qquad \text{for i=1, 2, ..., 8} \qquad (2.11)$$

Here each element of TU has one of the two possible values (o or 1), the combination of all eight elements results in $2^8 = 256$ possible TU's in total. The 256 TU's are labeled by using the following Equation (2.12).

$$N_{TU} = \sum_{i=1}^{8} E_i \times 2^{i-1}, \quad N_{TU} \in \{0, 1, 2, \dots, (2^8 - 1)\} \qquad (2.12)$$

An example of reduced texture unit is also represented in Figure 2.4.

83	28	60
76	55	23
90	55	10

1	0	1
1		0
1	1	0

2^0	2^1	2^2
2^7		2^3
2^6	2^5	2^4

$\sum = 230$

Figure 2.4: Example of transforming a 3×3 neighborhood to a reduced texture unit.

Therefore, the textural aspect of an image is characterized in the form of a texture spectrum.

SUMMARY

The GLCM method analyzes the spatial distribution of gray values, by computing local features at each point in the image, and deriving a set of statistics from the distributions of the local features. The reason behind this is, the spatial distribution of gray values is, one of the defining qualities of texture. The selection of certain image features are based on the statistics of Haralick features. The best statistical features that are used for image analysis are energy, entropy, contrast, local homogeneity, correlation, cluster shade and cluster prominence, mean and standard deviation. The features mean and standard deviation are that first-order statistics estimate properties of individual pixel values, ignoring the spatial interaction between image pixels, whereas second statistics estimate properties of two or more pixel values occurring at specific locations relative to each other. Therefore the statistical approaches yield characterizations of image textures as smooth, coarse, grainy, and so on.

Based on the concept of texture unit and texture spectrum, a statistical method of image analysis had proposed. The texture spectrum method 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 computing only 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. 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.

3. The Texture spectrum method can be easily adapted to the texture or shape analysis of binary images. Other evaluations and applications of TU include texture feature extraction, textural filtering, and texture classification for airborne SAR images.
4. The method described here is currently being applied to an integrated set of VisTex, OuTex, Granite and Brodatz images.