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Local Tri-directional Weber Rhombus Co-occurrence Pattern: A New Texture Descriptor for Brodatz Texture Image Retrieval

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***Abstract*— A new feature extraction method called Local Tri-directional Weber Rhombus Co-occurrence Pattern (LTriWRCoP) for texture image retrieval is presented in the paper. Most of the local binary pattern (LBP) variants extract the local information based on difference of current pixel with its neighborhood pixels but they ignore the original intensity of the stimulus. The proposed LTriWRCoP not only explores the inter relationship among the neighborhood pixels but also considers the original intensity of stimulus for extracting the local information structure. Further, gray level co occurrence matrix (GLCM) is used to get the co occurrences of pixel pairs in local pattern map as it is more robust than the frequency of patterns obtained using histogram. The proposed method also examine the co-occurrence of pixel pairs in various directions and distances. The experimental results on the Brodatz texture database reveals the superiority of the proposed method to the other methods in terms of average precision and recall rates**

Index Terms*—GLCM, Image retrieval, Local binary pattern , Pattern recognition ,Texture

I. Introduction

Enhancements in multimedia technology lead to exponential growth in the size of image repositories. Managing and archiving these databases became a herculean task. Texture is an important low level feature of an image. Repetitive blocks or a similar pattern in an image indicates the presence of texture. Local binary patterns (LBP) proposed by Ojala et al [1] showed promising results in texture feature extraction and object tracking. For texture feature extraction several methods have been used including local binary patterns, local ternary patterns, discrete wavelet transform, Gabor filters etc.

The concept of gray level co occurrence matrix (GLCM) is introduced by Haralick et.al to extract statistical features for texture image classification [2]. The literature points the fact that the GLCM provides the spatial co-relation of pixels in the image and it is useful in texture feature extraction. The GLCM is used for better feature description in texture descriptors. Further, local tetra patterns, local ternary co-occurrence patterns and modified colour motif co-occurrence matrix for image indexing and retrieval are proposed by Mural et al [3-8]. center symmetric local binary co-occurrence pattern for biomedical and texture images using GLCM is proposed by Manisha et al. A local tri-directional pattern for image retrieval is presented in [9]. The combination of histogram of colour and local Rhombus pattern for object tracking is presented in [10].

Most of the pattern based techniques like LBP, Local ternary patterns (LTP), Center symmetric local binary patterns (CSLBP) encodes the difference of pixels to obtain local information structure but ignores the original stimulus intensity[11-16]. Weber local descriptor proposed by Jie Chen et al accounts for the original intensity of the stimulus resembling to human perception and uses the histogram to extract the frequency information of local pattern map[17]. The center symmetric local binary co-occurrence pattern(CSLBCoP) proposed by Manisha et al encodes the difference of pixel in symmetric neighbourhood for local pattern map and obtains the co-occurrence pixel pair in local pattern map for better feature extraction but omits the original intensity stimulus.

The proposed Local tri-directional Weber Rhombus co-occurrence pattern not only considers the original intensity stimulus but also exploits the co-occurrences of pixel pairs in local pattern map with GLCM. The experiments conducted on Brodatz texture image database shows the efficiency of proposed method compared CSLBP, CSLBCoP in terms of average precision rate and average recall rate.

II. Related Work

A. Weber Local Descriptor

Jin Chen et al proposed weber local descriptor as function of differential excitation and gradient orientation. The differential excitation (χ) of a pixel with eight neighbourhoods (p=8) is defined as in [17]

$$\chi(y_c) = \arctan\left[\sum_{i=1}^{p-1} \frac{(y_i - y_c)}{y_c}\right] \tag{1}$$

Where y_i is neighbourhood pixel and y_c is center pixel

Gradient orientation (G) is defined as

$$G\,(y_c) = median(G_i)\text{, where } \quad i = 0,1,2,\ldots.\frac{P}{2}-1 \tag{2}$$

Where G_i represents the angle of a gradient difference

$$G_i = \arctan\left(\frac{y_{R(i+4)} - y_i}{y_{R(i+6)} - y_{R(i+2)}}\right) \quad (3)$$

Where $y_i, (i = 0,1,2,....\frac{p}{2}-1)$ are neighbours of a current pixel, $R(y)$ is obtained using modulus operation i.e., $R(y) = \mathrm{mod}(y, p)$ where p is the number of neighbours. The Weber local descriptor is given by $WLD(\chi, G)$.

B. Local Binary Patterns

The local binary pattern for p neighbourhood and d radius is defined as in Ojala et al

$$LBP_{p,d} = \sum_{n=0}^{p-1} 2^n \times S(y_n - y_c)$$

(4)

$$S(x) = \begin{cases} 0, x < 0 \\ 1, x \geq 0 \end{cases}$$

(5)

Where y_c -center pixel, y_m -neighbourhood pixel intensities. Histogram of LBP map is obtained using the equation as

$$H(L)\big|_{pattern} = \sum_{x_1=1}^{m}\sum_{x_2=1}^{n} S_1\left(pattern(y_1, y_2), L\right),$$

Where $L \in \left[0, (2^P - 1)\right]$

(6)

$$S_1(i, j) = \begin{cases} 1, i = j \\ 0, else \end{cases}$$

(7)

III. Proposed Method

In WLD, histogram that express the frequency of each pattern is considered but mutual occurrences of pattern is ignored. Whereas, CSLBCoP considers the mutual occurrences of pattern and ignores the original stimulus of intensity. The proposed method combines the best of both the methods by considering the mutual occurrence of pattern to represent the image features and the original stimulus intensity.

Consider a sub image having center pixel y_c with p=8 neighbourhood pixels as shown in the Fig1.

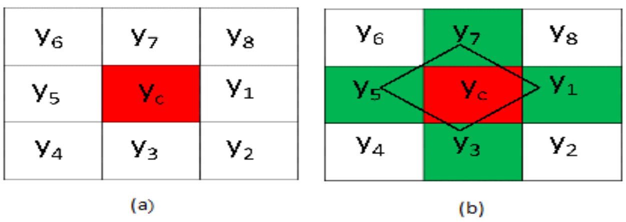

Fig1 (a): Example sub image (b): Local Rhombus pattern example window

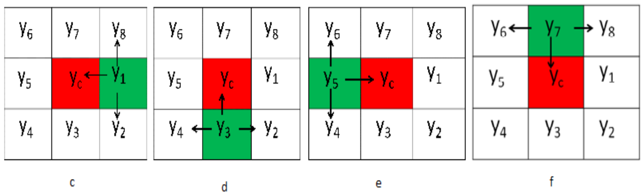

Fig1(c)-(f) shows the consideration of tri-directional pixels in a Rhombus pattern for a given sample window

First, calculate the differential excitation of pixels y_1, y_3, y_4, and y_5 using the formulae given below

$$d_i = \frac{(y_{i+1} - y_i)}{y_i} + \frac{(y_{i-1} - y_i)}{y_i} + \frac{(y_c - y_i)}{y_i}, \forall i = 3,5,7 \quad (8)$$

$$d_i = \frac{(y_{i+1} - y_i)}{y_i} + \frac{(y_{i+7} - y_i)}{y_i} + \frac{(y_c - y_i)}{y_i}, \forall i = 1 \quad (9)$$

$$\chi(y_i) = \arctan(d_i)$$

(10)

$\chi(y_i)$ is the differential excitation of i^{th} neighbourhood pixel. If $\chi(y_i) > 0$ means that the current pixel y_i is brighter than the surrounding pixels in the given direction otherwise y_i is lighter than the surrounding pixel. The pattern map $LTriWRP$ is defined for a given 3x3 window as

$$f(\chi(y_i)) = \begin{cases} 1, \chi(y_i) > 0 \\ 0, \chi(y_i) \leq 0 \end{cases}$$

(11)

$$LTriW(y_C) = \left[\chi(y_1), \chi(y_3), \chi(y_5), \chi(y_7)\right] \quad (12)$$

$$LTriWRP(y_c) = \begin{cases} 2^0 \times f\left(\chi(y_1)\right) + 2^1 \times f\left(\chi(y_3)\right) + \\ 2^2 \times f\left(\chi(y_5)\right) + 2^3 \times f\left(\chi(y_7)\right) \end{cases} \quad (13)$$

The Patterns obtained from LTriWRP, ranged from 0 to15. The tri-directional weber rhombus pattern is obtained for the given input image. Eight neighbourhood pixels with a radius r=1 are considered for the pattern. After pattern map, the range of intensity in the pattern varies from 0 to 15.

Gray level co-occurrence matrix is used to obtain the occurrence of pixels pairs in the LTriWRP pattern mapped image. The GLCM can be extracted in various directions and distances for the given image. In the proposed method, four combinations of GLCM are demonstrated as follows

Combination1: Four GLCM of distance 1 with angles $0^0, 45^0, 90^0$ and 135^0 are extracted.

Combination2: Four GLCM of distance 2 with angles $0^0, 45^0, 90^0$ and 135^0 are extracted.

Combination3: Two GLCM of distance 1 with angles $0^0, 45^0$ and two GLCM of distance 2 with angles $0^0, 45^0$

Combination4: Two GLCM of distance 1 with angles $0^0, 90^0$ and two GLCM of distance 2 with angles $0^0, 90^0$

As the intensity values vary from 0 to 15(Total 16 intensities) in the pattern map, the length of GLCM matrix is

16 x 16 and each combination has four such GLCMS. Therefore, the feature vector length will be 4x16x16=1024.

IV. PROPOSED SYSTEM FRAMEWORK

A. Feature extraction

The algorithm to extract features from a given image as follows

Input: Image

Output: Feature vector

Step1: Input the gray scale image or convert the image to into gray scale if it is RGB image

Step2: Apply Local tri-directional Weber Rhombus Pattern to get the pattern of the given image.

Step3: Apply any one combination of GLCM as explained in the previous section at various distances and angles.

Step4: convert the four 16x16 matrices into vectors obtained from previous step

Step5: concatenate all four vectors obtained in step4 into a single vector to form the feature vector.

B. Similarity measure

The query image feature vector is represented by $f_Q = (f_1, f_2, f_3, ... f_L)$. Where, L is the length of the feature vector obtained after feature extraction. The features vectors in the database are represented by $f_{DB_i} = (f_{DB_1}, f_{DB_2}, ... f_{DB_N})$, N represent the number of images in the data base. The goal of similarity measure is to retrieve n top matches for the given query image from the feature database by measuring the distance between query image features and image features in the database.

For similarity measure, d_1 distance metric is used and it is computed as follows

$$d(Q, DB) = \sum_{i=1}^{L} \left| \frac{f_{DB_i} - f_Q}{1 + f_{DB_i} + f_Q} \right|$$

(14)

Where f_{DB_i} feature vector of ith image in the database is f_Q is feature vector of query image. $d(Q, DB)$ - distance function.

V. EXPERIMENTAL RESULTS

The performance of the proposed method is compared to the existing methods in terms of average precision rate (APR) and average recall rate (ARR).The formulae for precision and recall as follows

The precision and recall for i^{th} image in the database is given by $P_i(N)$ and $R_i(N)$ respectively with N number of images retrieved for each query image.

$$P_i(N) = \frac{N_R}{N_T}$$

(15)

Where N_R is number of relevant images retrieved, N_T is total number of images retrieved

$$R_i(N) = \frac{N_R}{N_D}$$

(16)

Where N_R is number of relevant images retrieved, N_D is total number of images in the database.

The average precision (AP_N) and average recall AR_N for j^{th} category with N_1 number of images are determined by using the formula.

$$AP_N(j) = \frac{1}{N_1} \sum_{i=1}^{N_1} P_i(N) \quad (17)$$

$$AR_N(j) = \frac{1}{N_1} \sum_{i=1}^{N_1} R_i(N) \quad (18)$$

Average precision rate (APR) and average recall rate (ARR) for a given database with N_2 categories are obtained by using the formulae.

$$APR_N = \frac{1}{N_2} \sum_{i=1}^{N_2} AP_N(i) \quad (19)$$

$$ARR_N = \frac{1}{N_2} \sum_{i=1}^{N_2} AR_N(i) \quad (20)$$

A. Experiment#1

Brodatz texture database [18] is considered for the experiment. It consists of 112 images of size 640 × 640. For the experiment, each image is divided into 25 sub images of size 128×128. Therefore 112×25=2800 images are considered for evaluation of performance. Each image in the database is given as query image. The average precision, average recall is computed for different methods using combination1 (GLCM with d=1, angles 0^0,45^0,$90^0$and 135^0) and graphs are plotted as shown in Fig2. From Fig2 it is evident that the proposed method (LTriWRCoP) outperformed the other existing techniques in terms of ARR, ARP.

From Fig3 it is evident that combination4 i.e. Two GLCM of distance 1 with angles 0^0,90^0 and two GLCM of distance 2 with angles 0^0,90^0 resulted in improved recall rates compared other combinations. Whereas, the change in precision is small compared to recall rates for various combinations

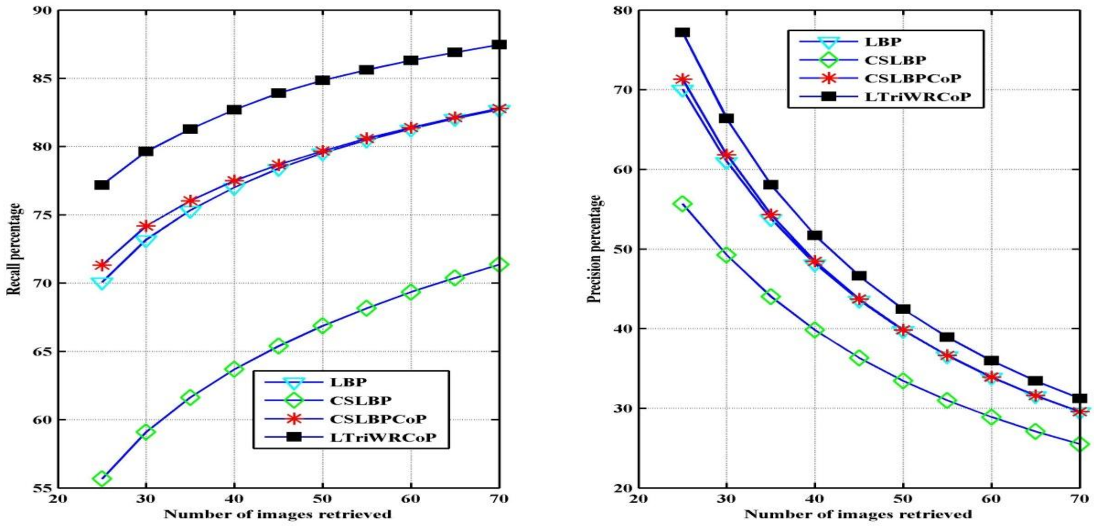

Fig2: *Average recall percentage, average precision percentage curves for Brodatz texture database*

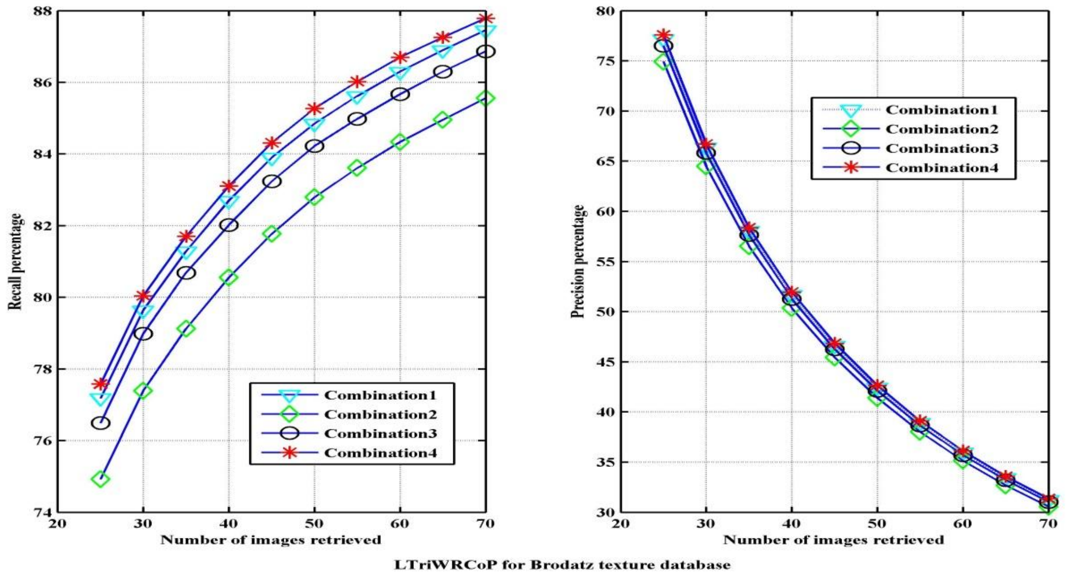

Fig3. LTriWRCoP for Brodatz texture database for various combinations of GLCM with different directions and distances

VI.CONCLUSION

A novel image retrieval algorithm called Local Tri-directional Weber Rhombus Co-occurrence Pattern is proposed in this paper. Each pixel is compared to its most adjacent neighbourhood and center pixel in a three directions for local information extraction. The magnitude of differential excitation is considered to obtain salient features within a local neighbourhood to simulate human being's perception of patterns. Gray level co-occurrence matrix is used to explore the mutual co-occurrence of pattern pairs, which is robust compared to the histogram technique. Experimental results conducted on Brodatz texture database indicate that the proposed method is superior to the existing patterns LBP, CSLBP and CSLBCoP in terms of average precision rate and average recall rate.

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