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Local Tri-directional Weber Patterns: A New Descriptor for Texture and Face Image Retrieval

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***Abstract*— Pattern based image retrieval algorithms gained popularity in recent times due to their high discriminative nature and competence to obtain local information structure. This paper presents a novel Local tri-directional weber patterns (LTriWPs) for content based image retrieval. The renowned pattern based algorithms like Local binary pattern (LBP) and Weber local descriptor (WLD) bring out the gray scale relationship of centre pixel with its neighbourhood pixels. In the proposed method, mutual relationship of the current pixel with its adjacent neighbourhood pixels in three significant directions is used. Further, the relationship among neighbourhood pixels is encoded based on the magnitude of differential excitation. Differential excitation reveals that the current pixel belongs to an edge or a spot. The proposed method is tested on two databases namely Brodatz texture database and ORL face image database. The experimental results show a significant improvement in terms of average precision rate and average recall rate as compared to LBP, Local Ternary pattern(LTP) and other existing techniques**.

***Keywords*— Image retrieval, Texture, Pattern recognition, Local binary pattern, Weber local descriptor.**

I. INTRODUCTION

Content based image retrieval is aimed at finding and collecting images which are relevant to the visual queries from the available database. Since, content is characterized by several parameters such as colour, texture, shape, position, region of interest, etc, quantification of these parameters become difficult for analysis. Several image types like satellite images, natural images and medical images have their own distinct features. Humans have the inherent ability of solving such seemingly complex problem with ease. Several researchers have proposed many feature descriptors based upon low level features like colour, texture and shape. A versatile image feature descriptor is the need of the hour as the available literature points to the fact that there is no single method available to deal with such a diverse set of image types. A broad review of content based image retrieval methods has been reported in [1].

Recently, Pattern based texture feature extraction methods attracted wide attention of the researchers. The dawn of Local binary pattern (LBP) proposed by Ojala et al. changed the course of texture image retrieval[2].The local binary pattern became a versatile feature descriptor because of its ability to code fine details, resistance to lighting changes and low computational complexity [2, 3]. Many variations of LBP have been reported in [4], [5], and [18]. S.A.Orjuela Vargas et al proposed a family of local textural descriptors called Geometric local textural patterns (GLTP) techniques. The GLTP exploit the intensity variations based on oriented neighbourhood contrary to close neighbourhoods, but they are sensitive to fine texture variations [6]. Mural et al proposed pattern based techniques for biomedical image retrieval based on the directional binary wavelets [7].A method to extract local information based on the distribution of edges in an image instead of local difference of pixels called local maximum edge binary patterns presented in [8], [19], Further, Mural et al proposed local tetra patterns [9], local ternary co-occurrence patterns [11] and modified colour motif co-occurrence matrix for image indexing and retrieval [12]. Manisha et al proposed center symmetric local binary co-occurrence pattern for biomedical and texture images using the gray level co-occurrence matrix (GLCM). GLCM is used to obtain co-occurrence of local pattern map in different directions and distances [13], [17]. Integration of colour and local derivative pattern features are presented in [13]. Anu et al proposed a pattern to extract the structure of image based on Texton XOR patterns [14].Jie Chen et al proposed, Weber local descriptor which accounts for the original intensity of the stimulus resembling to human perception [15]. A feature descriptor based on intensity variations in three directions called Local tri-directional pattern is presented in [16].

Weber local descriptor and Local binary patterns explore the local information structure by encoding the difference of center pixel with its neighbours. In the proposed method, the directional information of the center pixel with its neighbouring pixels is considered in different directions. In the proposed method, the mutual relationships of current pixel with its adjacent neighbours and the center pixel are encoded in binary form based on the magnitude of differential excitation. The histogram of pattern map is used to form the feature vector. The proposed method is tested on Brodatz texture database, ORL face image databases and compared with other existing methods. The paper is systematized as follows: Section 1 presents motivation, related work of the problem and main contribution of the proposed method. Section 2 describes the local patterns and the proposed method. The proposed framework and similarity measure concepts are presented in section 3. Further, the experimental results and discussion to support the algorithm are presented in section4.The conclusion and summary of the work is presented in section5.

II.LOCAL DESCRIPTORS

A. Weber Local Descriptor

Influenced by Weber's law, Jin Chen et al [15] proposed a local feature descriptor termed as Weber Local Descriptor (WLD). According to Ernst Weber [15], the relationship between the smallest changes in stimulus to the original stimulus is constant. Mathematically,

$$\frac{\Delta p}{p} = E \qquad (1)$$

Where Δp represents the change in stimulus, p represents the original stimulus and E stands for the fact that the ratio of change in stimulus to the original stimulus is constant although variations exist in p term. The fraction $\frac{\Delta p}{p}$ is known as the Weber fraction.

Weber local descriptor can be described for an image in two steps. First, the relative difference of center pixel with its neighbourhood pixels called differential excitation (Z) and the other one, gradient orientation (G_O) of the center pixel. Feature vector is obtained by concatenating the histograms of differential excitation and gradient orientation. Jin Chen et al showed that the WLD performed well compared to the classical descriptors like Gabor etc.

Differential excitation (Z) of center pixel with p ($p = 8$) neighbourhood is defined as

$$Z(x_c) = \arctan\left[\sum_{i=1}^{p-1} \frac{(x_i - x_c)}{x_c}\right] \qquad (2)$$

Where x_c -center pixel, x_i -neighbourhood pixels.

Z may take positive or negative values. Whether a pixel belongs to an edge or a spot can be determined based on the magnitude of differential excitation. If Z is positive, it implies that the intensity of the center pixel is lighter than its surrounding pixels and if Z is negative, it indicate that the intensity of center pixel is darker compared to surrounding pixels [15].

Gradient orientation (G_O) is defined as

$$G_O(x_c) = median(G_{Oi}) \text{ , where } i = 0,1,2,.....\frac{p}{2}-1 \qquad (3)$$

Where G_{Oi} is the angle of a gradient difference

$$G_{Oi} = \arctan\left(\frac{x_{R(i+4)} - x_i}{x_{R(i+6)} - x_{R(i+2)}}\right) \qquad (4)$$

Where $x_i, (i = 0,1,2,....\frac{p}{2}-1)$ are neighbours of a current pixel, $R(x)$ is obtained using modulus operation i.e., $R(x) = \mathrm{mod}(x, p)$ where p is the number of neighbours. The $WLD(Z, G_O)$ form the descriptor.

B. Local Binary Patterns

The local binary pattern for texture images is introduced by Ojala et al. The local binary pattern (LBP) operator finds a wide variety of applications in image classification, object tracking and facial expressions etc.

$LBP_{q,d}$ for q neighbourhood and d radius is defined as

$$LBP_{q,d} = \sum_{m=0}^{q-1} 2^m \times S(x_m - x_c) \qquad (5)$$

$$S(y) = \begin{cases} 0, y < 0 \\ 1, y \geq 0 \end{cases} \qquad (6)$$

Where x_c -center pixel, x_m -neighbourhood pixel intensities. Histogram of LBP map is obtained using the equation (7) as

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

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

$$S_1(i, j) = \begin{cases} 1, i = j \\ 0, else \end{cases} \qquad (7)$$

C. Local Tri-directional Weber Patterns (LTriWP)

Local tri-directional weber pattern is an extension of Weber local descriptor (WLD). The proposed method encodes the differential excitation of the center pixel with its neighbours on different directions. Here, 8 neighbourhood pixels with radius $d = 1$ are considered for the center pixel. The pattern formation is demonstrated as in Fig1 and mathematically explained as follows

Consider a center pixel I_c with eight neighbourhood pixels $(I_1, I_2, I_3.....I_8)$. First, calculate the differential excitation (Z) for each neighbourhood pixel with its two most adjacent neighbourhood pixel and the center pixel.

$$d_i = \frac{(I_{i+1} - I_i)}{I_i} + \frac{(I_{i-1} - I_i)}{I_i} + \frac{(I_c - I_i)}{I_i}, \forall i = 2,3,4,...7 \qquad (8)$$

For $i = 1$

$$d_i = \frac{(I_{i+1} - I_i)}{I_i} + \frac{(I_{i+7} - I_i)}{I_i} + \frac{(I_c - I_i)}{I_i} \qquad (9)$$

For $i = 8$

$$d_i = \frac{(I_{i-7} - I_i)}{I_i} + \frac{(I_{i-1} - I_i)}{I_i} + \frac{(I_c - I_i)}{I_i} \qquad (10)$$

$$Z(I_i) = \arctan(d_i) \qquad (11)$$

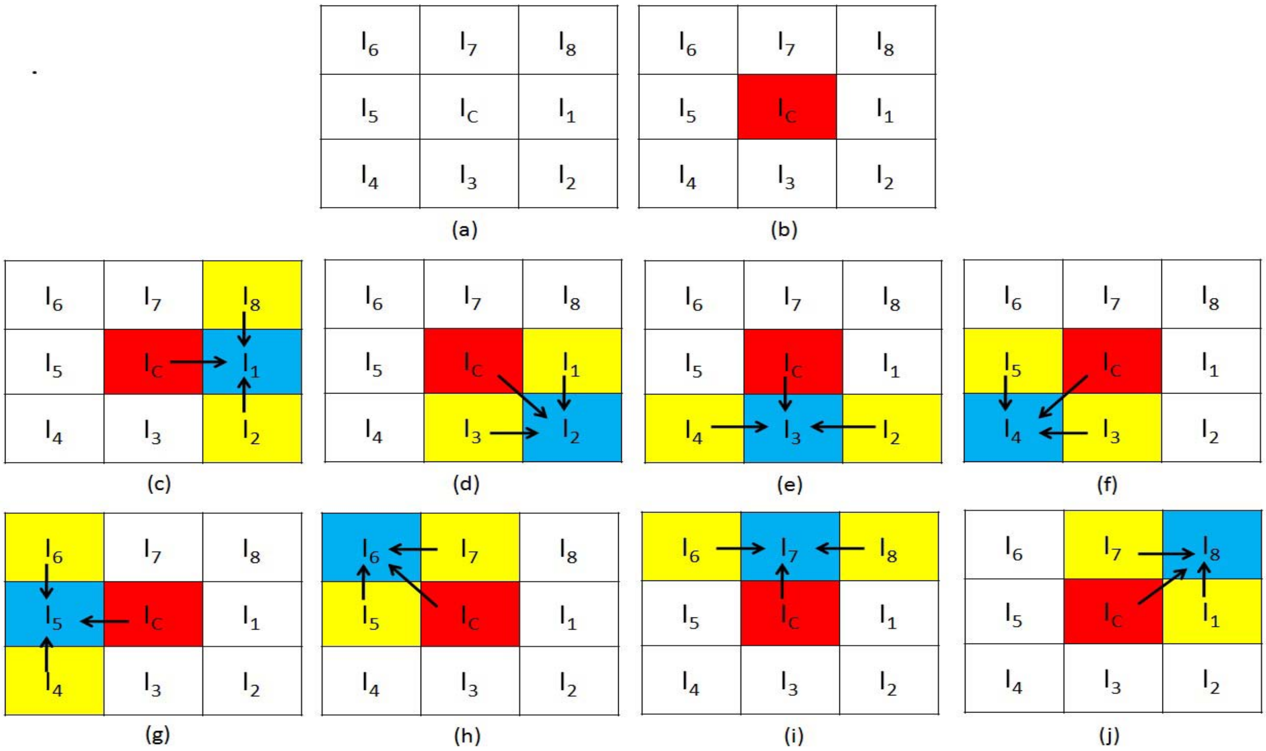

Fig.1. Proposed method sample window example. Fig (a) - (b): Center and neighbouring pixels notations. Fig(c) - (j): Consideration of eight local tri-directional patterns for calculation of differential excitation.

$Z(I_i)$ is the differential excitation of i^{th} neighbourhood pixel. If differential excitation is positive mean that the current pixel I_i is brighter than the surrounding pixels in the given direction i.e. peak stimulus exist. On the other hand if it is negative mean that the current pixel I_i is lighter than the surrounding pixel, a valley exits. A pattern number is assigned based on the magnitude of differential excitation. For $Z(I_i) > 0$, $f(Z(I_i))$ is assigned with a pattern value 1 called as peak pattern . If $Z(I_i) \le 0$, $f(Z(I_i))$ is assigned with a pattern value of zero and the pattern is called as valley pattern. The given sample window, the local tri-directional pattern for peak stimulus $(Z(I_i) > 0)$ is calculated using equations (8)-(11) as

$$LTriWP(I_C) = \left[Z(I_1), Z(I_2), Z(I_3), ...Z(I_8)\right] \tag{12}$$

$$LTriWP_1(Ic) = \sum_{k=0}^{7} 2^k \times S_2\left(Z(I_{k+1})\right) \tag{13}$$

$$S_2(x) = \begin{cases} 1, x < 0 \\ 0, x > 0 \end{cases} \tag{14}$$

For valley pattern $(Z(I_i) \le 0)$

$$LTriWP_2(Ic) = \sum_{k=0}^{7} 2^k \times S_3\left(Z(I_{k+1})\right) \tag{15}$$

$$S_3(x) = \begin{cases} 1, x < 0 \\ 0, x > 0 \end{cases} \tag{16}$$

The peak and valley patterns for given center pixel are mapped for a given image. The histograms of peak and valley pattern are concatenated to form the feature vector as given below

$$Hist = \left[Hist\big|_{LTriWP_1}, Hist\big|_{LTriWP_2} \right] \tag{17}$$

Sample pattern map for LTriWPs are shown in Fig2.

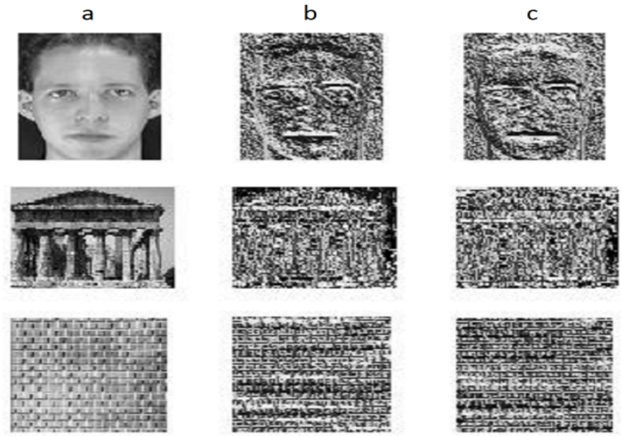

Fig2. Column a: original sample images from three databases, Column b: LTriWP pattern map for peaks of given image, Column c: LTriWP pattern map for valley of given image

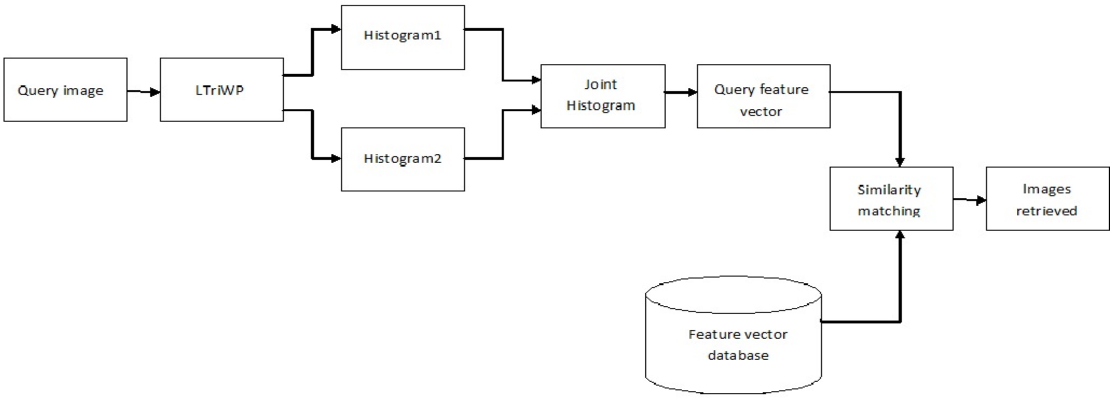

Fig3. Block diagram of proposed system frame work

III. PROPOSED SYSTEM FRAME WORK

Fig3. Shows the proposed frame work block diagram. The algorithm for the proposed work is presented in two parts, first part explains about the feature extraction and the second explains about the image retrieval part.

Part 1: Feature vector construction
Input: image
Output: feature vector

1. Upload each image in the database and convert it into greyscale if it is a RGB image.
2. Compute the local tri-directional Weber patterns and construct the histogram for peak and valley separately.
3. Concatenate both the histograms of peak and valley pattern to form the feature vector of length 1×512 as $f_Q = (f_1, f_2, f_3, ...f_{512})$

Part 2: Image retrieval
Input: Query image
Output: Retrieved similar images

1. Load the database of feature vectors
2. Enter the query image and construct the feature vector as in part 1
3. Compute the similarity index of query image feature vector with every database image feature vector.
4. Sort similarity indices and produce images corresponding to minimum distance indices as result.

A. 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 feature 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

$$d(Q, DB) = \sum_{i=1}^{L} \left| \frac{f_{DB_i} - f_Q}{1 + f_{DB_i} + f_Q} \right| \tag{18}$$

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

IV. EXPERIMENTAL RESULTS AND DISCUSSION

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 are 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.

$$P_i(N) = \frac{N_R}{N_T} \tag{19}$$

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

$$R_i(N) = \frac{N_R}{N_D} \tag{20}$$

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 formulae

$$AP_N(j) = \frac{1}{N_1} \sum_{i=1}^{N_1} P_i(N) \tag{21}$$

$$AR_N(j) = \frac{1}{N_1} \sum_{i=1}^{N_1} R_i(N) \tag{22}$$

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

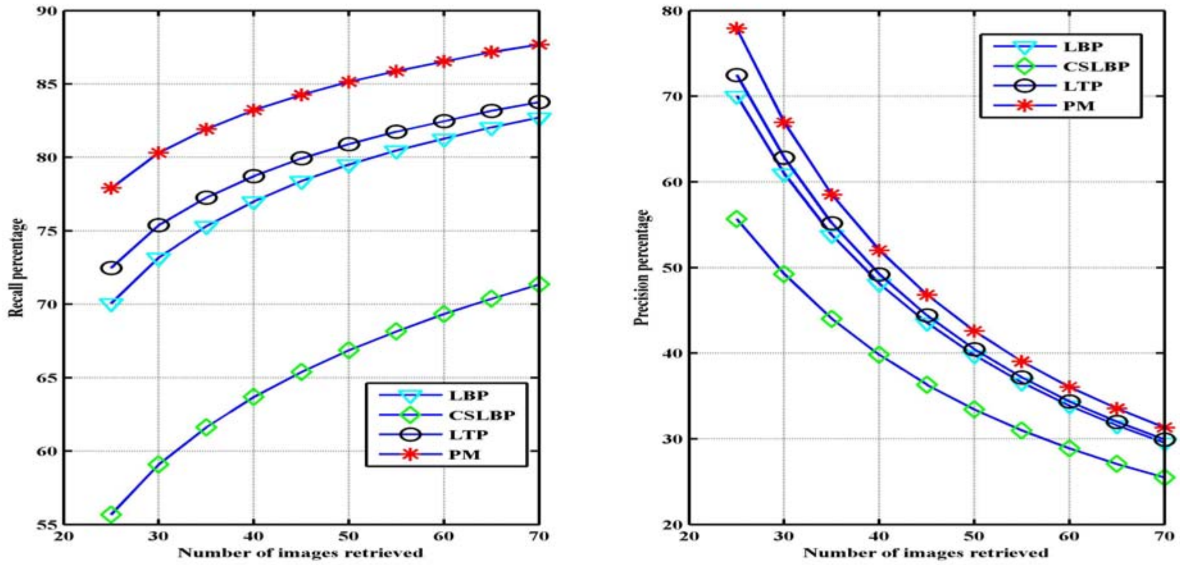

Fig4. Average precision percentage, average recall percentage curve for experiment-I- Brodatz texture database

$$APR_N = \frac{1}{N_2}\sum_{i=1}^{N_2} AP_N(i) \qquad (23)$$

$$ARR_N = \frac{1}{N_2}\sum_{i=1}^{N_2} AR_N(i) \qquad (24)$$

A. *Experiment –I*

Brodatz texture database [22] 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 performance evaluation. Each image in the database is given as query image. The average precision, average recall is computed and plotted as shown in Fig4. From Fig4, it is evident that the proposed method (LTriWP) outperformed the other three existing techniques in terms of ARR, ARP. Fig5 and Fig6 show the sample images and query image retrieval example respectively.

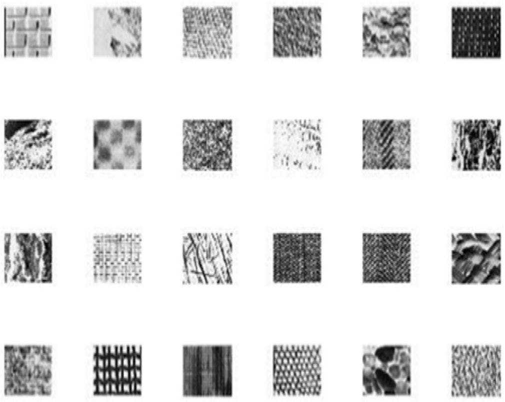

Fig5. Sample 24 texture images of Brodatz texture database

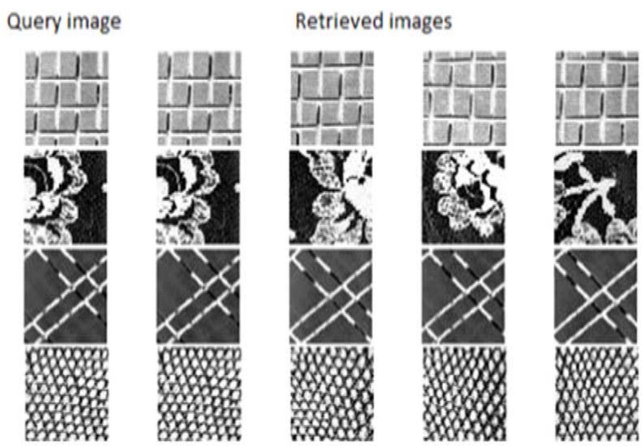

Fig6. Query image and retrieval results of proposed method on Brodatz texture image database

B. Experiment- II

ORL face image database [20] is used for the experiment-II. The database consists of 40 categories with 10 images per category. Each category contain 10 images of the same person with different facial expressions, different light exposure, and at different times with spectacles or without spectacles. Each image size in the database is 92×112.Fig7 shows the performance of proposed method compared to the existing techniques. Fig8 shows one image per category, as sample face images of ORL face image database.Fig9 shows the example query image retrieval.Fig10 shows query image retrieval for different techniques. It is clear from Fig10 that all retrieved images belong to same category for the proposed method (PM) where as some false images are retrieved by the other methods.

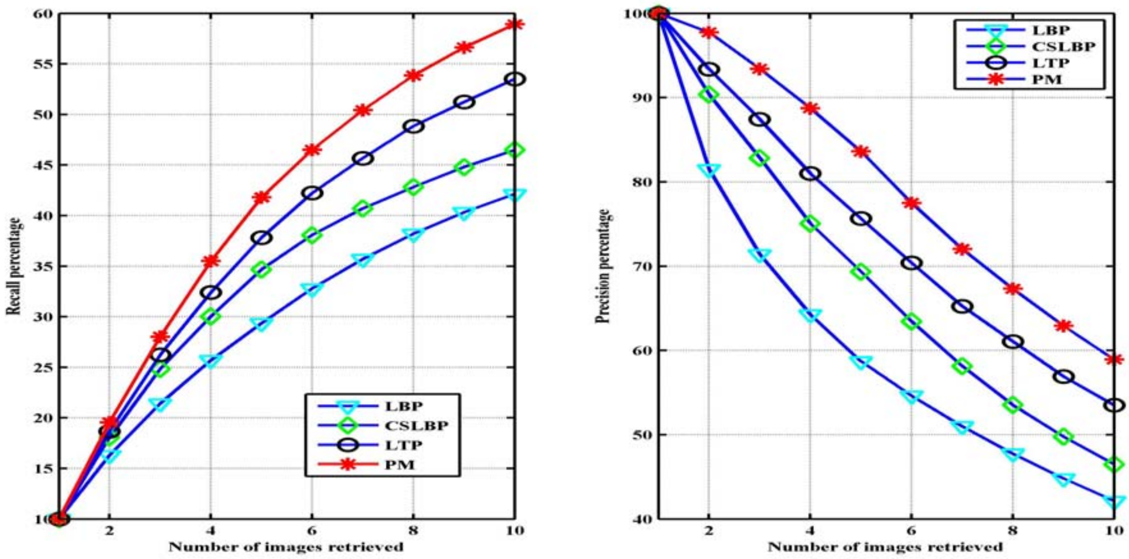

Fig7. Average precision percentage, average recall percentage curve for experiment-II- ORL face image database

Fig8.Sample face images of ORL face image database (one image per category)

Fig10. Query image retrieval for LBP, CSLBP, LTP and Proposed method (PM) in ORL face image database

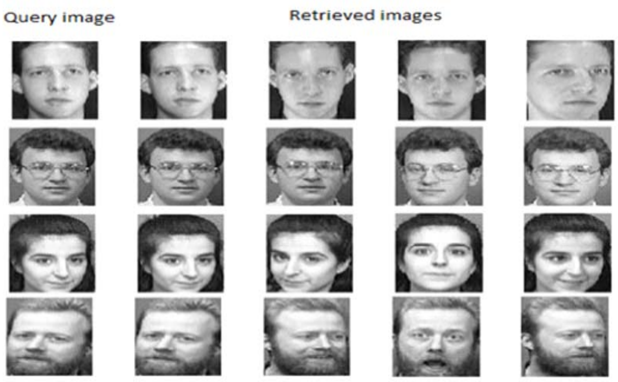

Fig9.Query images and corresponding image retrieval results of ORL face image database

V.CONCLUSIONS

A novel image retrieval algorithm called local tri-directional weber pattern is proposed in this paper. The existing techniques like LBP, CSLBP, and LTP extracts local information structure based on the difference of current pixel with its neighbourhood pixels and ignore the original intensity. The proposed method not only accounts the original intensity of pixel but also exploits the relation between neighbourhood pixels in different directions based on magnitude of differential excitation. The magnitude of differential excitation is considered to obtain salient features within a local neighbourhood to simulate human being's perception of patterns. Experimental results conducted on Brodatz texture database and ORL face image database indicate that the proposed method is superior to the existing patterns LBP, CSLBP and LTP in terms of average precision rate and average recall rate.

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