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Image Retrieval based on Macro Regions

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Image Retrieval based on Macro Regions

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Abstract- Various image retrieval methods are derived using local features, and among them the local binary pattern (LBP) approach is very famous. The basic disadvantage of these methods is they completely fail in representing features derived from large or macro structures or regions, which are very much essential to represent natural images. To address this multi block LBP are proposed in the literature. The other disadvantage of LBP and LTP based methods are they derive a coded image which ranges 0 to 255 and 0 to 3561 respectively. If one wants to integrate the structural texture features by deriving grey level co-occurrence matrix (GLCM), then GLCM ranges from 256 x 256 and 3562 x 3562 in case of LBP and LTP respectively. The present paper proposes a new scheme called multi region quantized LBP (MR-QLBP) to overcome the above disadvantages by quantizing the LBP codes on a multi-region, thus to derive more precisely and comprehensively the texture features to provide a better retrieval rate. The proposed method is experimented on Corel database and the experimental results indicate the efficiency of the proposed method over the other methods.

Keywords: multi block, LBP; LTP; dimensionality; GLCM.

I. Introduction

With the development in the computer technologies and the advent of the internet, there has been bang in the amount and the difficulty of digital data being produced, stored, conveyed, analyzed, and accessed. The lots of this information are multimedia in behavior, comprising digital images, audio, video, graphics, and text information. In order to construct use of this enormous amount of data, proficient and valuable techniques to retrieve multimedia information based on its content need to be developed. In all the features of multimedia, image is the prime factor. Image retrieval techniques are splitted into two categories text and content-based categories. The text-based algorithm comprises some special words like keywords. Keywords and annotations should be dispenses to each image, when the images are stored in a database. The annotation operation is time consuming and tedious. Furthermore, the annotations are sometimes incomplete and it is possible that some image features may not be mentioned in annotations [1]. In a CBIR system, images are automatically indexed by their visual contents through extracted low-level features, such as shape, texture, color, size and so on [1, 2]. However, extracting all visual features of an image is a difficult task and there is a problem namely semantic gap. In the semantic gap, presenting high-level visual concepts using low-level visual concept is very hard. In order to alleviate these limitations, some researchers use both techniques together using different features. This combination improves the performance compared to each technique separately [3, 4]. A typical CBIR system automatically extract visual attributes (color, shape, texture and spatial information) of each image in the database based on its pixel values and stores them in to a different database within the system called feature database [5,6]. The feature data for each of the visual attributes of each image is very much smaller in size compared to the image data. The feature database contains an abstraction of the images in the image database; each image is represented by a compact representation of its contents like color, texture, shape and spatial information in the form of a fixed length real-valued multi-component feature vectors or signature. The users usually prepare query image and present to the system.

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II. Related Work

There are various method has been proposed to extract the features of images from very large database. Jisha. K. P, Thusnavis Bella Mary. I, Dr. A. Vasuki [7] proposed the semantic based image retrieval system using gray level co-occurrence matrix (GLCM) for texture attribute extraction. On the basis of texture features, semantic explanation is given to the extracted textures. The images are regained according to user contentment and thereby lessen the semantic gap between low level features and high level features. Swati garwal, A. K. Verma, Preetvanti Singh [8] proposed algorithm enlightened for image retrieval based on shape and texture features not only on the basis of color information. This algorithm [8] is skilled and examined for large image database. Xiang-Yang Wang, Hong-Ying Yang, Dong-Ming Li [9] proposed a new content-based image retrieval technique using color and texture information, which achieves higher retrieval effectiveness. The experimental results of this color image retrieval algorithm [9] is more accurate and efficient in retrieving the user-interested images. Heng Chen and Zhicheng Zhao [10] described relevance feedback method for image retrieval. Relevance feedback (RF) is an efficient method for content-based image retrieval (CBIR), and it is also a realistic step to shorten the semantic gap between low-level visual feature and high-level perception. SVM-based RF algorithm is proposed to advances the performance of image retrieval [10]. Monika Daga, Kamlesh Lakhwani [11] proposed a new CBIR classification using the negative selection algorithm (NSA) of ais. Matrix laboratory functionalities are being used to extend a fresh CBIR system which has reduced complexity and an effectiveness of retrieval is increasing in percentage depending upon the image type.S. Nandagopalan, Dr. B. S. Adiga, and N. Deepak [12] they proposed a novel technique for generalized image retrieval based on semantic contents. The algorithm [12] groupthree feature extraction methods specifically color, texture, and edge histogram descriptor. G. Pass [13]proposed a novel method to describe spatial features in a more precise way. Moreover, this model [13] is invariant to scaling, rotation and shifting. In the proposed method segmentations are objects of the images and all images are segmented into several pieces and ROI (Region of Interest) technique is applied to extract the ROI region to enhance the user interaction. Yamamoto [14] proposed a content-based image retrieval system which takes account of the spatial information of colors by using multiple histograms. The proposed system roughly captures spatial information of colors by dividing an image into two rectangular sub-images recursively.

Texture plays an important role in image processing applications. Texture and its features plays a major role in various image and video processing applications [15-29]. The local descriptors such as local binary pattern (LBP) have shown very promising discriminative ability in several applications [30]. The LBP is widely adopted in the Computer Vision research community for its simplicity as well as effectively [31]. Various variants of LBP are available through the published literature which is inspired by the great success of LBP. Some typical examples are Local Ternary Pattern (LTP) [32], Local Derivative Pattern (LDP) [33], Interleaved Intensity Order Based Local Descriptor (IOLD) [34], and Local Tetra Pattern (LTrP) [35]. These descriptors are mainly computed over the raw intensity values. In order to utilize the richer local information, many researchers performed some kind of preprocessing before the feature extraction. Some typical examples are Sobel Local Binary Pattern (SOBEL-LBP) [36], Local Edge Binary Pattern (LEBP) [37], Semi Structure Local Binary Pattern (SLBP) [38] and Spherical Symmetric 3D Local Ternary Pattern (SS-3D-LTP) [39]. James has compared the preprocessed images directly which is obtained by multiple filtering [40] for face recognition.

The rest of the paper organized as follows: Section III gives the proposed algorithm, section IV describes about results and discussions and finally section V conclude the paper.

III. Methodology

The present paper intends to reduce the dimensionality and complexity issues of LBP coded image while preserving the significant local texture features precisely and accurately. To address these issues, the proposing strategy divide the image into multi regions and on each region of the image, employed LBP quantization for CBIR. This strategy consist of seven steps

Step One: Compute HSV color histograms of the images using HSV quantization.

Step Two: Convert the color image into HSV color space as given below.

In color image processing, there are various color models in use today. In order to extract grey level features from color information, the proposed method utilized the HSV color space. In the RGB model, images are represented by three components, one for each primary color – red, green and blue. Hue is a color attribute and represents a dominant color. Saturation is an expression of the relative purity or the degree to which a pure color is diluted by white light. HSV color space is a non-linear transform from RGB color space that can describe perceptual color relationship more accurately than RGB color space. Based on the above the present paper used HSV color space model conversion.

HSV color space is formed by hue (H), saturation (S) and value (V). Hue denotes the property of color such as blue, green, red. Saturation denotes the perceived intensity of a specific color. Value denotes brightness perception of a specific color. However, HSV color space separates the color into hue, saturation, and value which means observation of color variation can be individually discriminated. In order to transform RGB color space to HSV color space, the transformation is described as follows:

The transformation equations for RGB to HSV color model conversion is given below i.e from equations 1 to 5.

$$V = \max(R, G, B) \tag{1}$$

$$\mathrm{S} = \frac{\mathrm{V} - \min(\mathrm{R,G,B})}{\mathrm{V}} \tag{2}$$

$$\mathrm{H} = \frac{\mathrm{G-B}}{6\mathrm{S}}\ if\quad \mathrm{V} = \mathrm{R} \tag{3}$$

$$\mathrm{H} = \frac{1}{3} + \frac{\mathrm{B-R}}{6\mathrm{S}}\ if\quad \mathrm{V} = \mathrm{G} \tag{4}$$

$$\mathrm{H} = \frac{1}{3} + \frac{\mathrm{R-G}}{6\mathrm{S}}\ if\quad \mathrm{V} = \mathrm{B} \tag{5}$$

where the range of color component Hue (H) is [0,255], the component saturation (S) range is [0,1] and the Value (V) range is [0,255]. In this, the color component Hue (H) is considered as color information for the classification of facial images.

Step Three: convert the grey level image into a multi-region-LBP image [MR-LBP] as given below.

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The 'Local Binary Pattern' (LBP) operator, first introduced by Ojala et al. [11], is a robust but theoretically and computationally simple approach for texture analysis. It brings together the separate statistical and structural approaches to texture analysis of both stochastic micro textures and deterministic macro textures simultaneously.

LBP is a simple operator. It is calculated by computing the binary differences between the grey value of a given pixel x and the grey values of its p neighboring pixels on a circle or radius R around x. the LBP operator is rotation invariant when the smallest value of p-1 bitwise shift operations on the binary pattern is selected. Local Binary Pattern (LBP) is based on the concept of texture primitives. This approach is a theoretically, computationally simple and efficient methodology for texture analysis. To represent the formations of a textured image, the LBP approach, models 3×3 neighborhood as illustrated in Figure 1. A 3×3 circular neighborhood consists of a set of nine elements, P = {pc, p0, p1, …, p7}, where pc represents the grey level value of the central pixel and pi (0≤i≤7) represent the grey level values of the peripheral pixels. Each 3×3 circular neighborhood then can be characterized by a set of binary values bi (0≤i≤7) as given in equation 6.

$$b_i = \begin{cases} 0 & \Delta p_i \geq 0 \\ 1 & \Delta p_i < 0 \end{cases} \tag{6}$$

where Δpi= pi-pc.

For each 3×3 neighborhood, a unique LBP code is derived from the equation 7.

$$LBP_{P,R} = \sum_{i=0}^{i=7} b_i \times 2^i \tag{7}$$

Every pixel in an image generates an LBP code. A single LBP code represents local micro texture information around a pixel by a single integer code LBP ϵ [0, 255].

p0	p1	p2
p3	pc	p4
p5	p6	p7

→

b0	b1	b2
b7		b3
b6	b5	b4

→

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

→ LBP

Figure 1: Representation of LBP

The $LBP_{P,R}$ operator produces 2^P different output values, corresponding to the 2^P different binary patterns that can be formed by the P pixels in the neighbor set. Achieving rotation invariance, when the image is rotated, the grey values gp will correspondingly move along the perimeter of the circle, so different $LBP_{P,R}$ may be computed. To achieve rotational invariance a unique identifier to each LBP is assigned in the present paper as specified in equation 8.

$$LBP^{ri}_{P,R}(x,y) = \min\{ROR(LBP_{P,R}, i) \mid i = 0,1,2,\ldots,P-1\} \tag{8}$$

where the superscript 'ri' stands for "rotation invariant". The function $ROR(LBP_{P,R}, i)$ performs a circular bit-wise right shift on the P-bit number $LBP_{P,R}$i times to the right (|i| < P). LBP is a local texture operator with low computational complexity and low sensitivity to changes in illumination LBP has the following advantages.

1. The local texture character can be described efficiently.
2. It is easy to use.
3. The whole image character description can be easily extended.

Though LBP is widely used in various image classification and recognition approaches, but it suffers with following disadvantages.

1. In the course of analysis, its window size is fixed.
2. It neglects the effect of the central pixel in local region.
3. It can't avoid the variety of local greyscale caused by the illumination.
4. Sensitive to image rotation.
5. Loss of global texture information.
6. Sensitive to noise.

Step Three (a): Formation of Multi Region Local Binary Pattern (MR-LBP)

The basic LBP operators with any (P, R) (where P corresponds to the number of neighboring pixels on a circle of radius of R) only capable of extracting features on small spatial neighborhood i.e. micro level features and thus they fail in capturing larger scale structures or macro structures which are also dominant and essential features on faces. Further the grey level comparison between center pixel and the neighboring pixel may also prone to noise effect, especially when the neighboring pixels grey level values are equal or less than one to centre pixel value [41]. To overcome this Multi Region Local Binary Pattern (MB-LBP) features are introduced in the literature [42, 43]. The Multi Region Local Binary Pattern (MR-LBP) approach maintains the size of the region as V *W where V and W are multiples of three. The region of size V * W is subdivided into nine multi regions LBP's of size N*M where N=V/3 and M=W/3. This gives the uniformity in the formation of MR-LBP. The mechanism of encoding a large neighborhood or square region into LBP is the basis for MR-LBP. The region size VxW denotes the scale of MR-LBP for R=3 and S=3, it particularly derives the basic LBP and in this case N=1 and M=1.

The average value of each of the nine sub regions represents the grey level value of pixels of basic LBP. Based on this LBP code is generated and this represents the MR-LBP code. The scalar values i.e. average pixel grey level values of each sub region of

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size N*M can be computed very efficiently from integral image. Therefore MR-LBP features extraction process is very fast. However it only incurs a little more cost when compared to basic LBP operator (8,1). Even as 'P' increases the basic LBP feature extraction becomes costlier. The basic parameters V and W of the MR-LBP influence the overall structure of the features. If V and W are small then MR-LBP captures only the local features and when V and W are large (especially V and W>=9) the MR-LBP captures both micro and macro structure features. The average grey level values of sub regions N*M over comes the noise effect, makes MR-LBP as robust, and provides large scale information in addition to micro level information. The MR-LBP mechanism on a region size9*9 is shown in Figure 2, the block sizes are 3*3.

50	24	20	15	12	23	18	19	24
51	25	19	33	12	16	31	32	12
43	49	16	15	45	18	28	27	34
24	23	15	11	10	14	21	22	45
25	19	14	12	11	15	23	24	53
24	20	16	51	15	14	28	29	34
24	49	26	18	25	23	9	24	13
31	42	23	4	5	15	17	28	1
14	12	13	11	15	19	5	11	9

(a)

33	21	25
20	17	31
26	15	13

(b)

1	1	1
1		1
1	0	0

(c)

$(207)_{10}$

(d)

Figure 2: Multi Region-Local Binary Pattern Code generation (a) Division of Region of size 9*9 into '9' sub regions of 3*3 (b) Representation of average values of '9' sub region of 3*3 (c) MR-LBP Representation (d) MR-LBP Code.

The MR-LBP code is evaluated in the same way as represented in equation 6 and 7. This way the MR-LBP code represents some advantages:

- It is robust
- MR-LBP can be calculated efficiently using integral images
- The MR-LBP represents both micro structures i.e. by taking the average of each block and also macro structures by representing 9 blocks under single 3*3 neighborhood.
- The resulting binary patterns as features of MR-LBP can detect diverse image structures such as lines, edges, spots, corners [67] at different scale and location.
- There will be fewer number MR-LBP code features when compared to basic LBP. A basic LBP with image dimension PxQ generates(P-1)*(Q-1) LBP codes, where as a MR-LBP with a region size of VxW generates a total number of (P*Q)/(V*W) LBP codes in a non-overlapped manner. Therefore the implementation of the MR-LBP code feature selection is significantly easier.

Step Four: To overcome the high dimensionality problem the present paper quantized the MR-LBP coded image in to 10 levels ranging from 0 to 9. This reduced the dimension of the GLCM into 10 x 10. The quantization process is done using the following equation 9.

$$I(x,y) = \begin{cases} 0 \;\; if\, I(x,y) \geq 0 \;and\, I(x,y) < 26 \\ 1 \;\; I(x,y) \geq 26 \;and\, I(x,y) < 50 \\ 2 \;\; I(x,y) \geq 50 \;and\, I(x,y) < 75 \\ 3 \;\; I(x,y) \geq 75 \;and\, I(x,y) < 100 \\ 4 \;\; I(x,y) \geq 100 \;and\, I(x,y) < 125 \\ 5 \;\; I(x,y) \geq 125 \;and\, I(x,y) < 150 \\ 6 \;\; I(x,y) \geq 150 \;and\, I(x,y) < 175 \\ 7 \;\; I(x,y) \geq 175 \;and\, I(x,y) < 200 \\ 8 \;\; I(x,y) \geq 200 \;and\, I(x,y) < 225 \\ 9 \;\; I(x \cdot y) \geq 225 \;and\, I(x \cdot y) \leq 255 \end{cases} \qquad (9)$$

Step Five: Derive GLCM on quantized MR-LBP coded image. The GLCM is constructed with varying distances d =1, 2, 3 and 4. And on each d four GLCM's are constructed with 0°, 45°, 90° and 135°. Thus the present paper derived sixteen GLCM's and four GLCM's on each di = {1, 2, 3, 4} .

The grey level co-occurrence matrix (GLCM) was introduced by Haralick et al. [44]. It is a second order statistical method which is reported to be able to characterize textures as an overall or average spatial relationship between grey tones in an image [45]. Its development was inspired by the conjectured from Julesz [46] that second order probabilities were sufficient for human discrimination of texture. The GLCM approach has been used in a number of applications, e.g.[47-51]. In general, GLCM could be computed as follows. First, an original texture image D is re-quantized into an image G with reduced number of grey level, Ng. A typical value of Ng is 16 or 32. Then, GLCM is computed from G by scanning the intensity of each pixel and its neighbor, defined by displacement d and angle ø. A displacement, d could take a value of 1,2,3,…n whereas an angle, ø is limited 0°, 45°, 90° and 135°.

Step Six: Derive GLCM features with 0°, 45°, 90° and 135° on each di ={1,2,3,4} . The average values of 0°, 45°, 90° and 135°are considered by the present paper as feature vectors for image retrieval.

From the literature survey, the present paper found the 'grey level co-occurrence matrix' (GLCM) is a benchmark method for extracting Haralick features such as [44] (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 [48] (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. The GLCM features are defined below.

$$P_x(i) = \sum_{j=0}^{G-1} P(i,j)$$

$$P_y(j) = \sum_{i=0}^{G-1} P(i,j)$$

$$\mu_x = \sum_{i=0}^{G-1} i \sum_{j=0}^{G-1} P(i,j) = \sum_{i=0}^{G-1} i P_x(i)$$

$$\mu_y = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} j P(i,j) = \sum_{j=0}^{G-1} j P_x(j)$$

$$\sigma^2{}_x = \sum_{i=0}^{G-1} (i-\mu_x)^2 \sum_{j=0}^{G-1} P(i,j) = \sum_{i=0}^{G-1} \left(P_x(i) - \mu_x(i)\right)^2$$

$$\sigma^2{}_y = \sum_{j=0}^{G-1} \left(i-\mu_y\right)^2 \sum_{i=0}^{G-1} P(i,j) = \sum_{j=0}^{G-1} \left(P_y(j) - \mu_x(j)\right)^2$$

and

$$P_{x+y}(k) = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j)\; i+j=k$$

for k=0, 1, 2, 3…,2(G-1).

$$P_{x-y}(k) = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j) \quad |i-j| = k$$

for k=0, 1, 2, 3…,(G-1).

where G is the number of grey levels used. μ is the mean value of P.

μ_x, μ_y, σ_x and σ_y are the means and standard deviations of Px, Py. Px(i) is ith entry in the marginal-probability matrix obtained by summing the rows of P(i, j).

- Homogeniety, Angular Second Moment (ASM):

$$\text{ASM}= \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{P(i,j)\}^2 \tag{10}$$

ASM is a measure of homogeneity of an image. A homogeneous scene will contain only a few grey levels, giving a GLCM with only a few but relatively high values of P (i, j). Thus, the sum of squares will be high.

- Energy

$$\text{Energy}: \sum_{i,j} P(i,j)^2 \tag{11}$$

- Local Homogeneity, Inverse Difference Moment (IDM)

$$\text{IDM}= \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} \text{P(i,j)} \tag{12}$$

IDM is also influenced by the homogeneity of the image. Because of the weighting factor (1+(i)2)−1 IDM will get small contributions from inhomogeneous areas (i != j). The result is a low IDM value for inhomogeneous images, and a relatively higher value for homogeneous images.

- Contrast :

$$\text{Contrast} = \sum_{n=0}^{G-1} n^2 \left\{\sum_{i=1}^{G} \sum_{j=1}^{G} P(i,j)\right\}, |i-j| = n \tag{13}$$

This measure of contrast or local intensity variation will favor contributions from P (i, j) away from the diagonal, i.e. i ! = j.

- Correlation :

$$\text{Correlation} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{\{iXj\}XP(i,j) - \{\mu_x X \mu_y\}}{\sigma_x X \sigma y} \tag{14}$$

Correlation is a measure of grey level linear dependence between the pixels at the specified positions relative to each other.

- Entropy :

$$\text{Entropy}= -\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j) X \log\left(P(i,j)\right) \tag{15}$$

Inhomogeneous scenes have low first order entropy, while a homogeneous scene has high entropy.

- Sum of Squares, Variance:

$$\text{VARIANCE}= \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i-\mu)^2 P(i,j) \tag{16}$$

This feature puts relatively high weights on the elements that differ from the average value of P(i, j).

- Sum of Average :

$$\text{AVERAGE}= \sum_{i=0}^{2G-1} i P_{x+y}(i) \tag{17}$$

- Sum Entropy(SENT) :

$$\text{SENT}= -\sum_{i=0}^{2G-2} P_{x+y}(i) log\left(P_{x+y}(i)\right) \tag{18}$$

- Difference Entropy(DENT):

$$\text{DENT}= -\sum_{i=0}^{G-1} P_{x+y}(i) log\left(P_{x+y}(i)\right) \tag{19}$$

- Inertia :

$$\text{INERTIA}= \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{i-j\}^2 X P(i,j) \tag{20}$$

- Cluster Shade :

$$\text{SHADE}= \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \left\{i+j-\mu_x-\mu_y\right\}^3 X P(i,j) \tag{21}$$

- Cluster Prominence:

$$\text{PROM}= \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \left\{i+j-\mu_x-\mu_y\right\}^4 X P(i,j) \tag{22}$$

Step Seven: Use similarity distance measure for comparing the query image feature vector and feature vectors of the database images.

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The present model extracts all 16 GLCM features on the MR-LBP and also HSV color space histograms on the database images and query image. The present retrieval model selects 16 top images from the database images that are matching with query image. And also experimented with more number of top images and retrieval performance is measured. The image retrieval is accomplished by measuring the distance between the query image and database images. The present paper used Euclidean distance as the distance measure and as given below

$$Dist_s(T_n, I_n) = \left(\sum_{i,j=1} \left|f_i(T_n) - f_j(I_n)\right|^2\right)^{1/2} \tag{23}$$

Where Tn query image, In image in database;

IV. Results and Discussions

The present paper carried out image retrieval on Corel database [52]. This database consists of a large number of images of various contents ranging from animals to outdoor sports to natural images. These images have been pre classified into different categories each of size 100 by domain professionals. Researchers are of the opinion that the Corel database meets all the requirements to evaluate an image retrieval system, due to its large size and heterogeneous content. For our experiment, we have collected 1000 images form database compromising 10 classes. That is each class consists of 100 images. The classes of image are displayed in Figure 3 i.e. African, Sea shore, Tombs, Bus, Dinosaur, Elephants, Fancy Flowers, Horses, Valleys and Evening Skies. Each category has images with resolution of either 256x384 or 384X256. The performance of the present model is evaluated in terms of average precision (APR), average recall rate (ARR) and accuracy. Precision is the ratio of number of retrieved images Vs. the number of relevant images retrieved. The recall is the ratio of number of relevant image retrieval Vs. total number of relevant images in the database.

$$precision = \frac{Numberofrelevantimagesretried}{Totalnumberofimage\quad sretrieved} \tag{24}$$

$$Recall \quad = \frac{Numberofrelevantimagesretrieved}{Totalnumberofrelevantimagesindatabase} \tag{25}$$

$$APR(n) \quad = \frac{1}{N_C}\sum_{i=1}^{N_C} precision\ (I_{i,}) \tag{26}$$

$$ARR(n) \quad = \frac{1}{N_C}\sum_{i=1}^{N_C} recall\ (I_{i,}) \tag{27}$$

$$Accuracy = \frac{APR(n) + (ARR(n))}{2} \tag{28}$$

Where $precision\ (I_{i,})$ is precision value of image I_i , Nc is number of images in each category.

The present paper compute GLCM features on MR-QLBP using various distance values: D = 1, 2, 3, 4 and color histograms. The query matching is performed using Euclidean distance. The present retrieval model selects 16 top images from the database images that are matching with query image. And also experimented with more number of top images and retrieval performance is measured. Figure 4(a)- 4(e) shows five examples of retrieval images, i.e. one image from each class, by the proposed method with D=4 for 16 top matched images and top left most image is the query image.

Figure 3: Considered 10 classes of Corel database from top left to bottom right African, Sea shore, Tombs, Bus, Dinosaur, Elephants, Fancy Flowers, Horses, Valleys and Evening Skies.

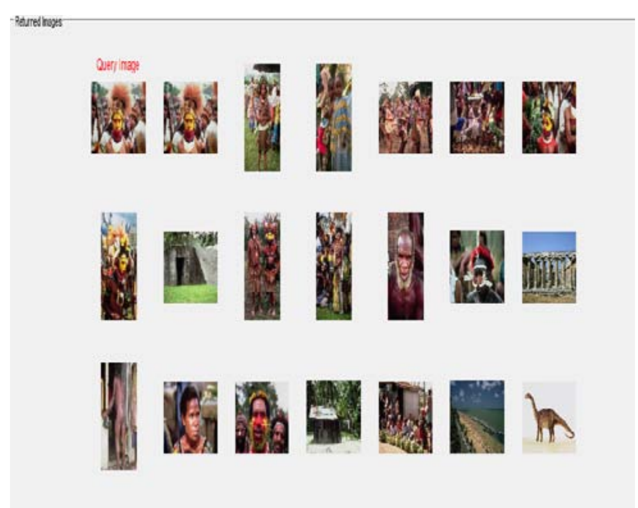

Figure 4(a): Retrieved African images by the proposed method

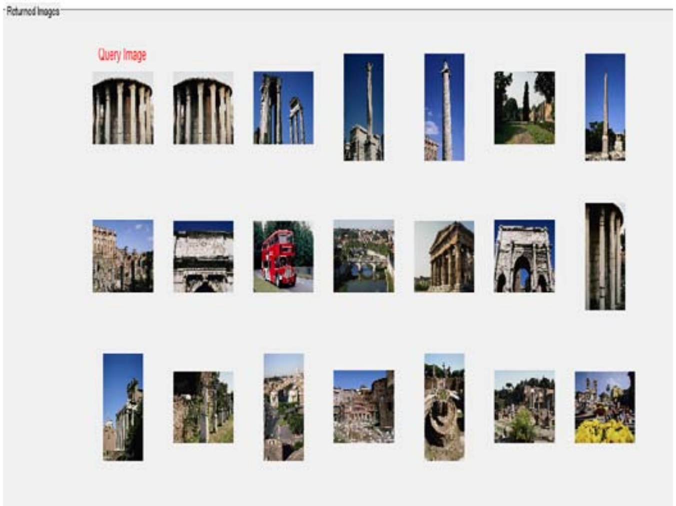

Figure 4 (b) : Retrieved monuments by the proposed method

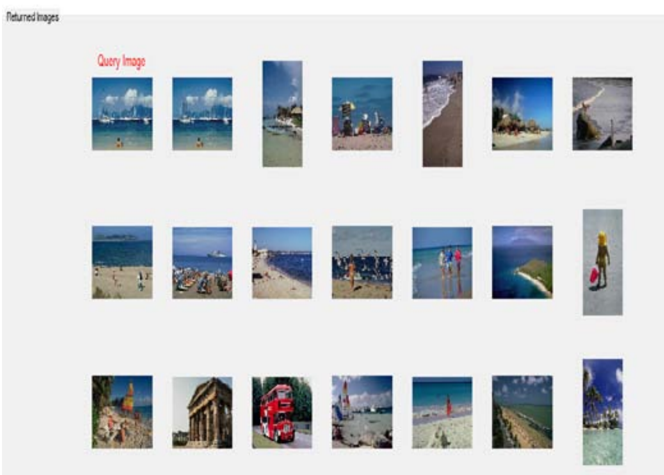

Figure 4(c): Retrieved beach sand images by the proposed method

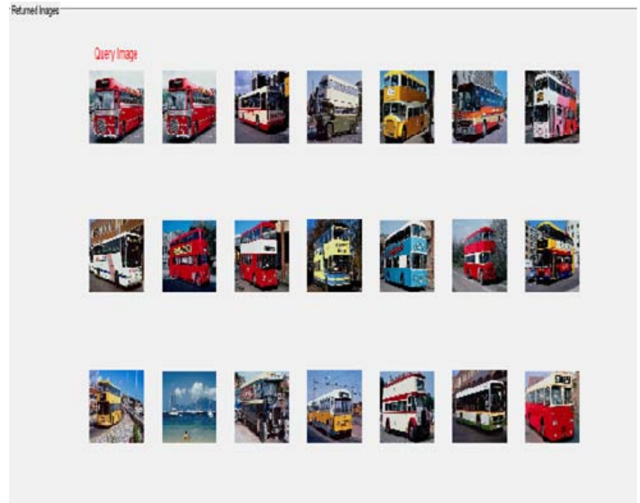

*Figure 4 (d):*Retrieved busses by the proposed method

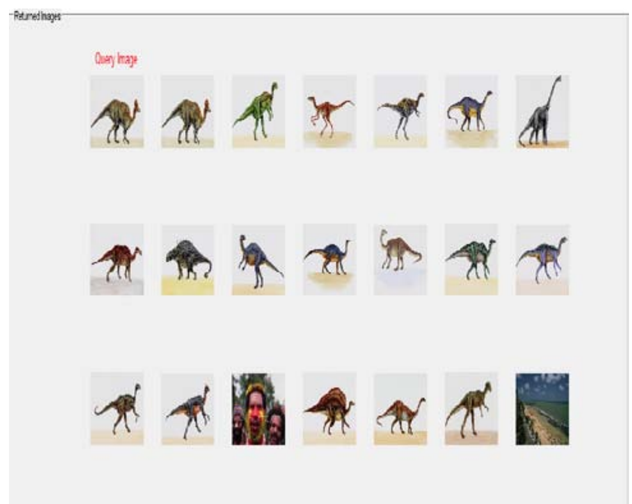

Figure 4(e): Retrieved dinosaurs by the proposed method

The average precision, recall rates and accuracy computed based on MR-QLBP and HSV histograms listed in Tables 1. The best performance of integrated Q-LBP is obtained when D = 4. The average precession, recall rates and accuracy of proposed method for different d values are plotted in graphs, indicated in Figure 5, Figure 6 and Figure 7 respectively.

Table 1: Average precision rate of all classes of images with various distance measures for 16 top matched images

Proposed method		Distance parameter			
		d=1	d=2	d=3	d=4
MR-QLBP	Precision	0.70	0.71	0.72	0.74
	Recall	0.37	0.41	0.42	0.44
	Accuracy	0.54	0.56	0.57	0.59

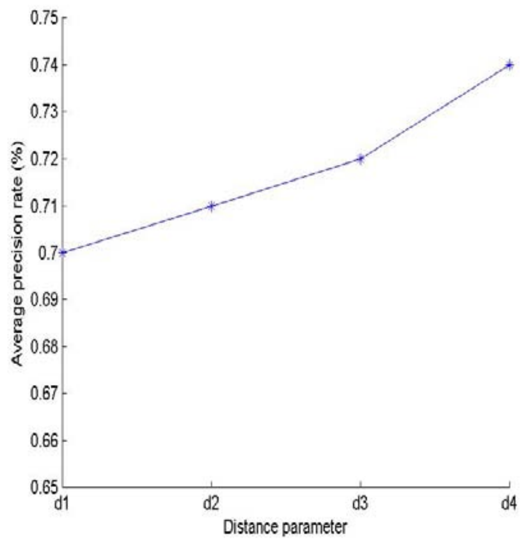

Figure 5: Average precision graph for proposed method (MR-QLBP) for different d values

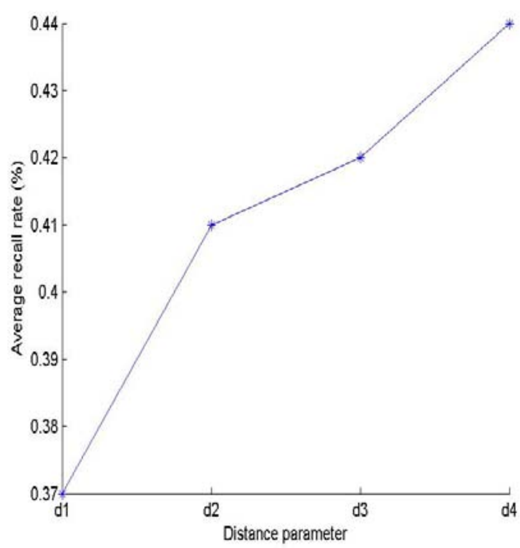

Figure 6: Average recall graph for proposed method (MR-QLBP) for different d values

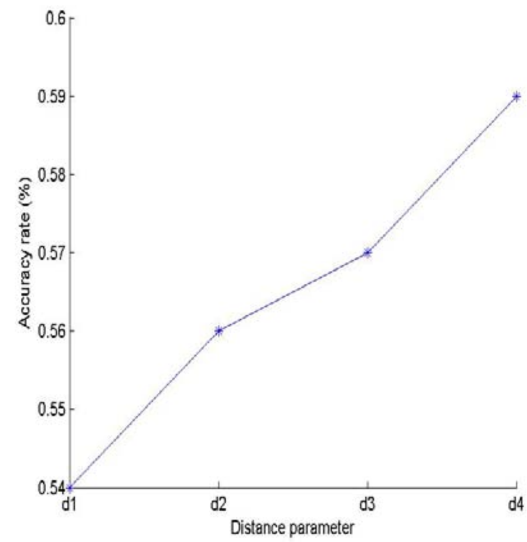

Figure 7: Accuracy graph for proposed method (MR-QLBP) for different d values

The average precision rate of proposed method MR-QLBP and existing methods i.e. hierarchical clustering algorithms (HCA), Content Based Image Retrieval Using Clustering (CBIR-C), Fuzzy C-Means clustering scheme (FCMC) is given in Table 2 and plotted graphs as shown in Figure 8, Figure 9 and Figure 10. From these graphs, it is clearly seen that the proposed MR-QLBP outperforms the HCA, CBIR-C, and FCMC over the considered database using both ARP, ARR and average accuracy evaluation metrics.

Table 2: Average precession rate on each class of images between existing and proposed method for 16 top retrieved images

	Image category and the precision (%)					
Methods	Africans	monuments	Sand	Buses	Dinosaurs	Average
HCA [53]	0.39	0.42	0.44	0.48	0.5	0.45
CBIR_C[54]	0.4	0.43	0.46	0.49	0.52	0.46
FCMC[55]	0.61	0.6	0.66	0.67	0.7	0.64
MR-QLBP	0.69	0.71	0.73	0.74	0.72	0.72

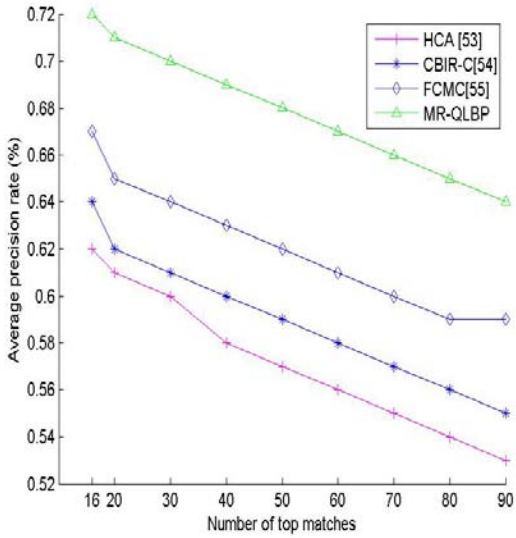

Figure 8: Average Performance curve (precision) using HCA, CBIR-C, FCMC and proposed MR-QLBP method

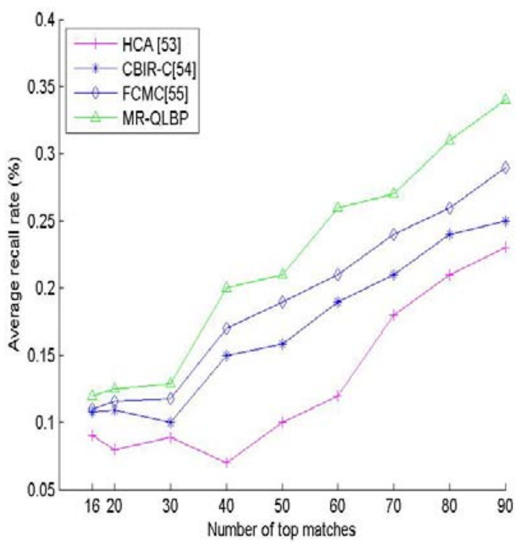

Figure 9: Average Performance curve (recall) using HCA, CBIR-C, FCMC and proposed MR-QLBP method

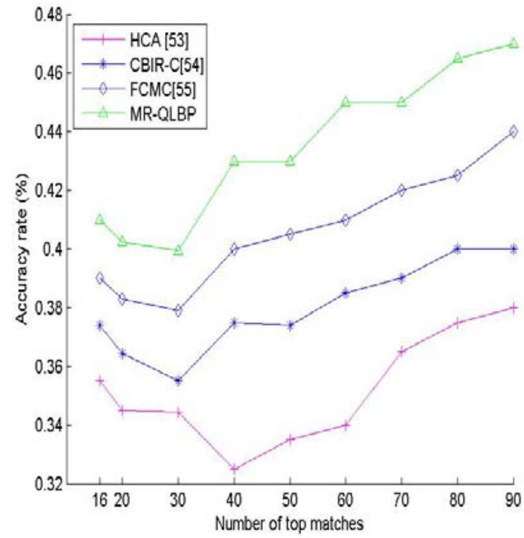

Figure 10: Average accuracy graph using HCA, CBIR-C, FCMC and proposed MR-QLBP method

V. Conclusions

The present paper has proposed and successfully implemented the quantized approach for image retrieval i.e. MR-QLBP on Corel databases. The proposed MR-QLBP captured image features efficiently. The GLCM features are evaluated and retrieval performance is noted using average precision, average recall and accuracy parameters. The proposed method showing evocative performance compare with other existing methods. The proposed method also compared with the existing methods and the precision and recall graphs indicates the high performance of the proposed method when compared with existing methods HCA, CBIR-C and FCMC.

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