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Color Histogram and Multi-resolution LMEBP Joint Histogram for Multimedia Image Retrieval

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ABSTRACT: In this paper, color histogram and multi-resolution local maximum edge binary patterns (LMEBP) joint histogram are integrated for content based image retrieval (CBIR). The local region of image is represented by LMEBP, which are evaluated by taking into consideration the magnitude of local difference between the center pixel and its neighbors. This LMEBP differs from the existing LBP in a manner that it extracts the information based on distribution of edges in an image. Further the joint histogram is constructed between uniform two rotational invariant first three LMEBP patterns. The color feature is extracted by calculating the histogram on RGB spaces. The experimentation has been carried out for proving the worth of our algorithm. It is further mentioned that the databases considered for experiment are Corel-1K and MIT VisTex. The results after being investigated show a significant improvement in terms of their evaluation measures as compared to previously available spatial and transform domain methods on their respective databases.

KEYWORDS: Color; Texture; Feature Extraction; Local Binary Patterns; local maximum edge binary patterns; Image Retrieval.

I.INTRODUCTION

Digital media is evolving so digital data archives in scientific, industrial, medical, environmental, educational, entertainment, web image searching and other applications. For accessing digital images in these applications it is required to have an efficient algorithm. Before 1990 text based image retrieval was being used for this pur-pose. To reduce the amount of labor for image annotation and different interpretation of image by different persons, in early 1990 CBIR came into picture [1]. Still there remain some challenging problems that attract the researchers' interest towards CBIR. Generally in CBIR, visual features related to color, shape, texture, and spatial layout are extracted in the form of color histogram [2], color coherence vector [3], color correlogram (CC) [4], Gabor transform [5] etc. These are arranged as multidimensional feature vectors and construct the feature database. For similarity/distance measurement many methods have been developed like Euclidean distance, city-block distance etc. Selection of feature descriptors and similarity/distance measures affect retrieval performances of an image retrieval system significantly. Moghaddam et al. proposed the Gabor wavelet correlogram (GWC) for CBIR [6, 7]. Ahmadian et al. used the wavelet transform for texture classification [8]. Moghaddam et al. introduced new algorithm called wavelet correlogram (WC) [9]. Saadatmand et al. [10, 11] improved the performance of WC algorithm by optimizing the quantization thresholds using genetic algorithm (GA). Birgale et al. [12] and Subrahmanyam et al. [13] combined the color (color histogram) and texture (wavelet transform) features for CBIR. Subrahmanyam et al. proposed correlogram algorithm for image retrieval using wavelets and rotated wavelets (WC+RWC) [14].

In development of local feature descriptor, scale invariant feature transform (SIFT) feature is proposed by Lowe et al. [15] in 2004. SIFT feature descriptor is invariant to scale, orientation and partially invariant to affine distortion and illumination changes. In SIFT the locations of extrema in difference of Gaussian (DoG) correspond to most stable feature with respect to scale variance, and are identified as interest feature points or keypoints. For each keypoint sequel HOG descriptor are calculated. Thus HOG feature is assumed to be originated from SIFT descriptor. HOG feature descriptor is introduced by Dalal et al. [16] in 2005 for solving the problem of pedestrian detection in static images. Ojala et al. proposed the local binary patterns (LBP) for texture description [17] and these LBPs are converted to rotational invariant for texture classification [18]. Pietikainen et al. proposed the rotational invariant texture classification using feature distributions [19]. Ahonen et al. [20] and Zhao et al [21] used the LBP operator facial expression analysis and recognition. Heikkila et al. proposed the background modeling and detection by using LBP [22]. Huang et al. proposed the extended LBP for shape localization [23]. Heikkila et al. used the LBP for interest region description [24]. Li et al. used the combination of Gabor filter and LBP for texture segmentation [25]. Zhang et al. proposed the local derivative pattern for face recognition [26]. They have considered LBP as a nondirectional first order local pattern, which are the binary results of the first-order derivative in images. Abdullah et al. [27] proposed fixed partitioning and salient points schemes for dividing an image into patches, in combination with low-level MPEG-7 visual descriptors to represent the patches with particular patterns. Jhanwar et al. [28] have proposed the motif co-occurrence matrix (MCM) for content based image retrieval. C H Lin et al. [29] combined the color feature, k-mean color histogram (CHKM) and texture features, motif co-occurrence matrix (MCM) and difference between the pixels of a scan pattern (DBPSP). Subrahmanyam et al. [30] have proposed the local maximum edge binary patterns (LMEBP) for image retrieval and object tracking applications. Their method extracts the features by taking into consideration the magnitude of local difference between the center pixel and its neighbors.

To improve the retrieval performance in terms of retrieval accuracy, in this paper, we combine the color (HSV histogram) and texture (LMEBP joint histogram) features. The experiments have been carried out on Corel-1K and MIT Vistex databases for proving the worth of our algorithm. The results after investigation show a significant improvement in terms of their evaluation measures as compared to other existing color & texture and spatial and transform domain features.

The organization of the paper as follows: In section 1, a brief review of image re-trieval and related work is given. Section 2, 3 and 4 presents a concise review of local binary patterns, local maximum edge binary patterns and HSV histogram calculation respectively. Section 5, presents the proposed system framework and similarity meas-ure. Experimental results and discussions are given in section 6. Based on above work conclusions are derived in section 7.

II. LOCAL BINARY PATTERNS

The LBP operator was introduced by Ojala *et al.* [17] for texture classification. Success in terms of speed (no need to tune any parameters) and performance is reported in many research areas such as texture classification [17-19], face recognition [24-26], object tracking [30], image retrieval [31] and finger print recognition.

Given a center pixel in the 3×3 pattern, LBP value is computed by comparing its gray scale value with its neighborhoods based on Eq. (1) and Eq. (2):

$$LBP_{P,R} = \sum_{i=1}^{P} 2^{(i-1)} \times f(I(g_i) - I(g_c)) \quad (1)$$

$$f(x) = \begin{cases} 1 & x \geq 0 \\ 0 & else \end{cases} \quad (2)$$

where $I(g_c)$ denotes the gray value of the center pixel, $I(g_i)$ is the gray value of its neighbors, P stands for the number of neighbors and R, the radius of the neighborhood.

Fig. 1 shows an example of obtaining an LBP from a given 3×3 pattern. The histograms of these patterns extract the distribution of edges in an image.

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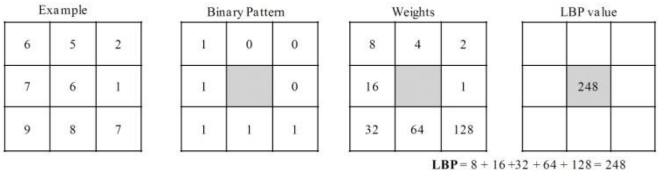

Fig. 1. LBP calculation for 3×3 pattern

III. LOCAL MAXIMUM EDGE BINARY PATTERNS

Subrahmanyam et al. [30] have proposed the local maximum edge binary patterns (LMEBP) for image retrieval and object tracking applications. In proposed LMEBP for a given image the first maximum edge is obtained by the magnitude of local difference between the center pixel and its eight neighbors as shown below:

$$I^{'}(g_i) = I(g_c) - I(g_i); \quad i = 1, 2, ..., 8 \tag{3}$$

$$i_1 = \arg_i \left(\max \left(\left| I^{'}(g_1) \right|, \left| I^{'}(g_2) \right|, ..., \left| I^{'}(g_8) \right| \right) \right) \tag{4}$$

where, *max(x)* calculates the maximum value in an array *'x'*.
If this edge is positive, assign '1' to this particular center pixel otherwise '0'.

$$I^{new}(g_c) = f\left(I^{'}(g_{i_1})\right) \tag{5}$$

$$f(x) = \begin{cases} 1 & x \geq 0 \\ 0 & else \end{cases} \tag{6}$$

The LMEBP is defined as:

$$LMEBP(I(g_c)) = \left\{ I^{new}(g_1); I^{new}(g_2); ....I^{new}(g_8) \right\} \tag{7}$$

The uniform pattern refers to the uniform appearance pattern which has limited discontinuities in the circular binary presentation. In this paper, the pattern which has less than or equal to two discontinuities in the circular binary presentation is considered as the uniform pattern and remaining patterns considered as non-uniform patterns.
The distinct values for given query image is $P(P-1)+3$ by using uniform patterns [31]. But these features are not rotational invariant. The rotational invariant patterns $(LMEBP_{P,R}^{riu2})$ can be constructed by adding all eight patterns in the each row [31]. The distinct values for a given query image is $P+2$ by using rotational invariant patterns $(LMEBP_{P,R}^{riu2})$. After LMEBP calculation, the joint histogram is constructed between first, second and third LMEBPs for feature vector generation.

IV. PROPOSED SYSTEM FRAMEWORK

In this paper, a new algorithm is proposed by calculating the joint histogram between the multi-resolution rotational invariant LMEBP subimages. Finally, feature vector is constructed by concatenating the features collected using joint histograms.

Algorithm:
Input: Image; *Output: Retrieval results.*

1. Load the input image.
2. Calculate the three multi-resolution images using Gaussian filter bank.
3. Calculate the LMEBP on each multi-resolution image and make them into rotational invariant.
4. Calculate the joint histogram between them.
5. Form the feature vector by concatenating histograms.
6. Calculate the best matches using Eq. (1.3).
7. Retrieve the number of top matches.

A. Similarity Measurement

In the presented work d_1 similarity distance metric is used as shown below:

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$$D(Q,T)=\sum_{i=1}^{Lg}\left|\frac{f_{T,i}-f_{Q,i}}{1+f_{T,i}+f_{Q,i}}\right| \tag{8}$$

where Q is query image, Lg is feature vector length, T is image in database; $f_{I,i}$ is i^{th} feature of image I in the database, $f_{Q,i}$ is i^{th} feature of query image Q.

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

For the work reported in this paper, retrieval tests are conducted on Corel-1K and MIT VisTex and results are presented in the following subsections.

A. Corel-1K Database

Corel database [35] consists of 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. Some researchers think that Corel database meets all the requirements to evaluate an image retrieval system, due its large size and heterogeneous content. We have collected 1000 images to form database Corel–1K. These images are collected from 10 different domains namely *Africans*, *beaches*, *buildings*, *buses*, *dinosaurs*, *elephants*, *flowers*, *horses*, *mountains* and *food*. Each category has N_G (100) images with resolution of either 256×384 or 384×256.

In all experiments, each image in the database is used as the query image. For each query, the system collects n database images $X=(x_1, x_2, \ldots, x_n)$ with the shortest image matching distance computed using Eq. (10). If the retrieved image $x_i=1, 2, \ldots, n$ belongs to same category as that of the query image then we say the system has appropriately identified the expected image else the system fails to find the expected image.
The performance of the proposed method is measured in terms of average precision, average recall and average retrieval rate (ARR) as shown below:

$$Precision\,(P)=\frac{No.of\ \ Relevant\,Images\,Retrieved}{Total\ No.of\ \ Images\,Retrieved}\times 100 \tag{9}$$

$$Group\,Precision\,(GP)=\frac{1}{N_1}\sum_{i=1}^{N_1}P \tag{10}$$

$$Average\,Retrieval\,Precision\,(ARP)=\frac{1}{\Gamma_1}\sum_{j=1}^{\Gamma_1}GP \tag{11}$$

$$Recall\,(R)=\frac{Number\,of\ \ relevant\,images\,retrieved}{Total\,Number\,of\ \ relevant\,images} \tag{12}$$

$$Group\,Recall\,(GR)=\frac{1}{N_1}\sum_{i=1}^{N_1}R \tag{13}$$

$$Average\,Retrieval\,Rate\,(ARR)=\frac{1}{\Gamma_1}\sum_{j=1}^{\Gamma_1}GR \tag{14}$$

where N_1 is number of relevant images and Γ_1 is number of groups.
Table 1 and Table 2 summarize the retrieval results of various methods in terms of average retrieval precision and average retrieval rate respectively. Fig. 3 (c) summarize the performance of proposed method with different distance measures in terms of average retrieval rate.
From Tables 1 to 2, it is clear that the proposed method is outperforming the other existing techniques in terms of ARR and ARP.

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Table 1. Results of all techniques in terms of precision on Corel–1K database. PM: MultiJoint_LMEBP_HSV_Hist

Category	Precision (*n*=20) (%)					
	Jhanwar et al.	C H Lin et al	CC	LBP	Multi_DBC Co-occurrence +Color Hist	PM
Africans	53.15	68.3	80.4	56.9	72.1	82.5
Beaches	43.85	54	41.2	51.95	55.1	49.25
Buildings	48.7	56.2	55.6	61.65	76.1	81.25
Buses	82.8	88.8	76.7	95.15	99.9	94.85
Dinosaurs	95	99.3	99	98.5	99.5	99.4
Elephants	34.85	65.8	56.2	39.9	54.0	66.45
Flowers	88.35	89.1	92.9	89.5	93.4	87.25
Horses	59.35	80.3	76.5	65.65	84.8	91.4
Mountains	30.8	52.2	33.7	37.45	38.6	36.2
Food	50.4	73.3	70.6	65.75	88.5	81.05
TOTAL	**58.7**	**72.7**	**68.2**	**66.2**	**76.2**	**76.9**

n–Number of top matches considered

Table 2. Results of all techniques in terms of recall on Corel–1K database. PM: Multi-Joint_LMEBP_HSV_Hist

Category	Recall (*n*=100) (%)					
	Jhanwar et al.	C H Lin et al	CC	LBP	Multi_DBC Co-occurrence +Color Hist	PM
Africans	32.21	42.1	46.29	38.42	43.2	51.4
Beaches	29.04	32.1	25.29	35.72	39.2	29.5
Buildings	27.7	36.5	35.01	35.93	43.4	51.0
Buses	48.66	61.7	60.97	72.26	73.9	75.9
Dinosaurs	81.44	94.1	89.59	91.3	90.4	92.7
Elephants	21.42	33.1	34.14	26.8	34.8	37.1
Flowers	63.53	75	77.69	66.32	75.1	55.5
Horses	35.84	47.6	36.13	42.3	50.8	56.1
Mountains	21.75	27.7	21.02	26.62	26.3	23.2
Food	29.02	49	39.27	40.03	57.5	52.8
TOTAL	**39.0**	**49.8**	**46.5**	**47.5**	**53.5**	**55.3**

B. MIT VisTex Database

The MIT VisTex database is used in our experiment which consists of 40 different textures [36]. The size of each texture is 512×512. Each 512×512 image is divided into sixteen 128×128 non-overlapping sub-images, thus creating a database of 640 (40×16) images. The performance of the proposed method is measured in terms of average retrieval rate (ARR) is given by Eq. (15).

$$ARR = \frac{No.of\ Relevant\ Images\ Retrieved}{Total\ No.of\ Relevant\ Images\ in\ Database} \times 100 \quad (15)$$

This database is used to compare the performance of the proposed method (Multi_Joint_LMEBP+color hist.) with LBP and other existing methods. Fig. 2 (a) & Table 3 illustrate the retrieval results of proposed method and other existing methods in terms of average retrieval precision. From Fig. 2 (b) & Table 3 it is evident that the proposed method is outperforming the other existing methods

Table 4 illustrates the comparison between proposed method and other existing methods in terms of average retrieval rate on MIT VisTex database. From Table 4, it is clear that the proposed method outperforms the other existing spatial and transforms domain methods. The results of the proposed method are also compared with the different distance measures as shown in Table 5.

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Table 3: Performance of various methods in terms of ARP on MIT VisTex database.

	1	3	5	7	9	11	13	15	16
LBP_riu2	100	93.0	88.3	85.3	82.0	78.5	74.9	71.0	69.1
Multi_Joint_LMEBP	100	99.9	99.8	99.3	97.7	96.2	94.2	91.7	90.2
Multi_DBC_Co-occurrence	100	99.7	99.6	98.6	97.2	95.7	93.7	91.2	89.7
Joint_LMEBP	100	99.9	99.9	98.9	97.5	96.0	94.0	91.5	90.0

Table 4: Performance of various methods in terms of ARR on MIT VisTex database.

	16	20	30	40	50	60	70	80	90	100
DT-CWT	80.7	81.3	83.8	86.3	88.4	90.0	91.4	92.5	93.3	94.1
DT-RCWT	75.7	77.3	81.9	84.5	86.4	87.9	89.1	90.0	91.0	91.7
DT-CWT+DT-RCWT	82.3	83.3	84.9	87.2	89.2	90.6	91.8	92.7	93.5	94.2
LBP	82.2	86.7	91.9	93.3	94.8	95.9	96.6	97.0	97.4	97.6
LBP_riu2	69.1	74.8	81.8	86.2	88.8	90.8	92.3	93.4	94.4	95.1
Multi_Joint_LMEBP	90.1	92.3	95.0	96.3	97.3	98.0	98.5	98.9	99.2	99.5
Multi_DBC_Co-occurrence	89.7	91.8	94.58	95.8	96.9	97.6	98.1	98.4	98.8	99.1
Joint_LMEBP	89.9	92.1	94.8	96.1	97.1	97.8	98.3	98.7	99.08	99.3

Table 5: Performance of proposed method with various distance measures in terms of ARR on MIT VisTex database.

	16	32	48	64	80	96	112
Manhattan	86.82	92.94	95.26	96.63	97.56	98.35	99.01
Canberra	89.59	94.97	96.76	97.97	98.58	99.20	99.60
Euclidean	78.70	86.87	89.97	92.30	94.73	96.34	97.45
d_1	89.95	95.11	96.91	98.06	98.69	99.21	99.62

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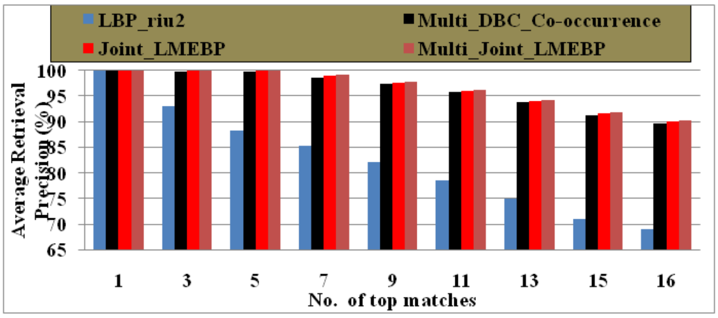
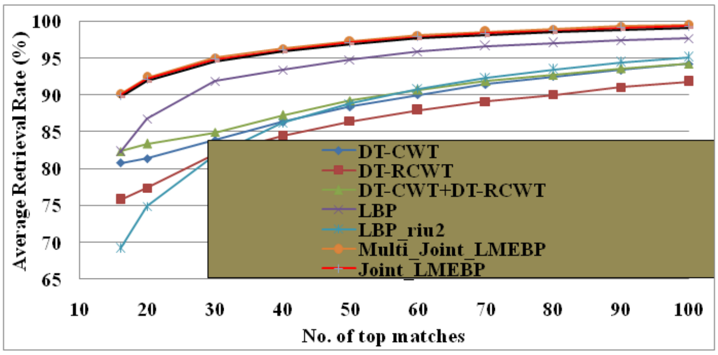
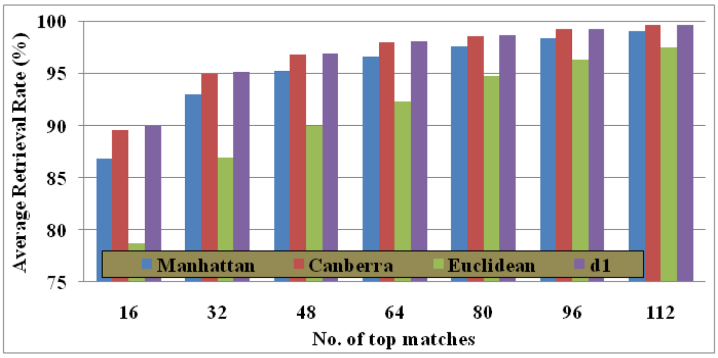


(a)



(b)



(c)

Figure 2 Comparison of proposed method with LMEBP, LBP, DBC and other exiting transform domain methods in terms of: (a) average retrieval precision, (b) average retrieval rate and (c) performance of proposed method using various distance measures MIT VisTex database .

VI.CONCLUSION

In this paper, a new image indexing and retrieval algorithm is proposed by combining joint histogram between first three Multi_Joint LMEBPs and color histogram on HSV spaces. The experiments have been conducted on Corel-1K and MIT VisTex databases for proving the worth of our algorithm. The results after being investigated show a significant improvement in terms of their evaluation measures as compared to previously available color, texture and combined color and texture features for image retrieval.

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