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Local Derivative Patterns and their Magnitudes for Content Based Image Retrieval

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Abstract - This paper presents a new image indexing and retrieval algorithm by considering the magnitudes of the local derivative patterns (LDPs). LDP extract the high-order local information by encoding various distinctive spatial relationships contained in a given local region. Two experiments have been carried out for proving the worth of our algorithm. It is further mentioned that the database considered for experiments are Corel 1000 database (DB1), and MIT VisTex database (DB2). The results after being investigated shows a significant improvement in terms of their evaluation measures as compared to LBP, LDP and other existing transform domain techniques.

Keywords— *Local Derivative Patterns; Feature Extraction; Local Binary Patterns; Image Retrieval.*

I. INTRODUCTION

A. Motivation

Digital image libraries and other multimedia databases have been dramatically expanded in recent years. Storage and retrieval of images in such libraries has become a real demand in industrial, medical, and other applications. Content-based image indexing and retrieval (CBIR) is considered as a solution. In such systems, in the indexing algorithm, some features are extracted from every picture and stored as an index vector. The CBIR utilizes the visual contents of an image such as color, texture, shape, faces, spatial layout etc. in order to represent and index the image. The visual features can further be classified into general features which include color, texture and shape and domain specific features as human faces and finger prints. There is no single best representation of an image for all perceptual subjectivity, because the user may take the photographs in different conditions (view angle, illumination changes etc.). Learning of high level semantic concepts is a challenging task for CBIR systems. Comprehensive and extensive literature survey on CBIR is presented in [1]–[4].

Texture is another salient and indispensable feature for CBIR. Smith et al. used the mean and variance of the wavelet coefficients as texture features for CBIR [5]. Moghaddam et al. proposed the Gabor wavelet correlogram (GWC) for CBIR [6, 7]. Moghaddam et al. introduced new algorithm called wavelet correlogram (WC) [8]. Saadatmand et al. [9, 10] improved the performance of WC algorithm by optimizing the quantization thresholds using genetic algorithm (GA). Birgale et al. [11] and Subrahmanyam et al. [12] combined the color (color histogram) and texture (wavelet transform) features for CBIR. Ahmadian et al. used the wavelet transform for texture classification [13]. Do et al. proposed the wavelet transform (DWT) based texture image retrieval using generalized Gaussian density and Kullback-Leibler distance (GGD &KLD) [14]. Unser used the wavelet frames for texture classification and segmentation [15]. Manjunath et al. [16] proposed the Gabor transform (GT) for image retrieval on Bordatz texture database. They have used the mean and standard deviation features from four scales and six directions of Gabor transform. Kokare et al. used the rotated wavelet filters [17], dual tree complex wavelet filters (DT-CWF), dual tree rotated complex wavelet filters (DT-RCWF) [18], rotational invariant complex wavelet filters [19] for texture image retrieval. They have calculated the characteristics of image in different directions using rotated complex wavelet filters.

B. Related Work

The recently proposed local binary pattern (LBP) features are designed for texture description. Ojala et al. proposed the LBP [20] and these LBPs are converted to rotational invariant for texture classification [21]. pietikainen et al. proposed the rotational invariant texture classification using feature distributions [22]. Ahonen et al. [23] and Zhao et al [24] used the LBP operator facial expression analysis and recognition. Heikkila et al. proposed the background modeling and detection by using LBP [25]. Huang et al. proposed the extended LBP for shape localization [26]. Heikkila et al. used the LBP for interest region description [27]. Li et al. used the combination of Gabor filter and LBP for texture segmentation [28]. Zhang et al. proposed the local derivative pattern for face recognition [29]. They have considered LBP as a nondirectional first order local pattern, which are the binary results of the first-order derivative in images.

C. Main Contribution

To improve the retrieval performance in terms of retrieval accuracy, in this paper, we considered the magnitude of the local derivative patterns (LDPs) along with the sign LDPs. Two experiments have been carried out on Corel database and MIT VisTex databases for proving the worth of our algorithm. The results after being investigated shows a significant improvement in terms of their evaluation measures as compared to LBP, sign LDP and other existing transform domain techniques.

The organization of the paper as follows: In section I, a brief review of image retrieval and related work is given. Section II, presents a concise review of Local Binary Patterns. Section III, presents the local derivative patterns and proposed system framework. Experimental results and discussions are given in section IV. Based on above work conclusions are derived in section V.

II. LOCAL BINARY PATTERNS (LBP)

The LBP operator introduced by Ojala et al. [19] as shown in Fig. 1. For given a center pixel in the image, a LBP value is computed by comparing it with those of its neighborhoods:

$$LBP_{P,R}=\sum_{i=0}^{P-1}2^i\times f(g_p-g_c) \tag{1}$$

$$f(x)=\begin{cases}1 & x\ge 0\\ 0 & x<0\end{cases} \tag{2}$$

where g_c is the gray value of the center pixel, g_i is the gray value of its neighbors, P is the number of neighbors and R is the radius of the neighborhood. Fig. 2 shows the examples of circular neighbor sets for different configurations of (P,R).

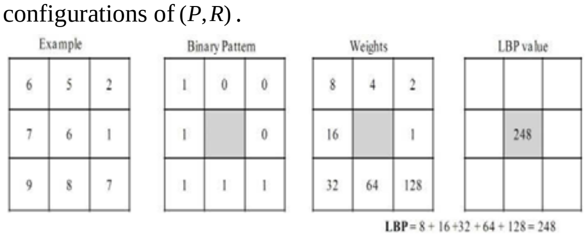

Fig. 1: LBP calculation for 3×3 pattern

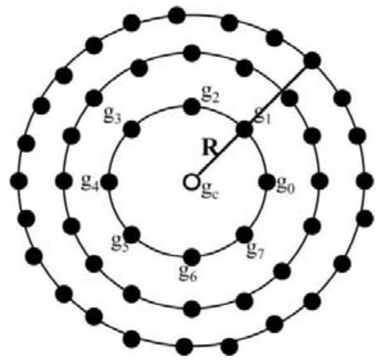

Fig. 2: Circular neighborhood sets for different *(P,R)*

III. LOCAL DERIVATIVE PATTERNS (LDP)

A. Local Derivative Patterns (LDP)

Baochang Zhang et al. proposed the LDP operator for face recognition [29]. In this scheme, LBP is conceptually regarded as the nondirectional first-order local pattern operator; because LBP encodes all-direction first-order derivative binary result while LDP encodes the higher-order derivative information which contains more detailed discriminative features that the first-order local pattern (LBP) cannot obtain from an image.

Given an image *I*, the first-order derivatives along 0^0, 45^0, 90^0 and 135^0 directions are denoted as where I'_α, where $\alpha=0^0$, 45^0, 90^0 and 135^0. Let g_c be a center point in I, and g_p, p=1,2,…,8 be the neighboring point around g_c. The four first-order derivatives at g_c can be written as:

$$I'_{0^0}(g_c)=I(g_c)-I(g_1); \tag{3}$$

$$I'_{45^0}(g_c)=I(g_c)-I(g_2); \tag{4}$$

$$I'_{90^0}(g_c)=I(g_c)-I(g_3); \tag{5}$$

$$I'_{135^0}(g_c)=I(g_c)-I(g_4); \tag{6}$$

The second-order directional LDP, $LDP_\alpha^2(g_c)$, in α direction at g_c is defined as

$$LDP_\alpha^2(g_c)=\left\{f(I'_\alpha(g_c),I'_\alpha(g_1)),\,f(I'_\alpha(g_c),I'_\alpha(g_2)),......\atop ....,\,f(I'_\alpha(g_c),I'_\alpha(g_8))\right\} \tag{7}$$

where *f(.,.)* is a binary coding function determining the types of local pattern transitions. It encodes the co-occurrence of two derivative directions at different neighboring pixels as

$$f(I'_\alpha(g_c),I'_\alpha(g_p))=\begin{cases}0, & if\ I'_\alpha(g_c)*I'_\alpha(g_1)>0\\ 1 & if\ I'_\alpha(g_c)*I'_\alpha(g_1)\le 0\end{cases} \tag{8}$$
$$p=1,2,......8$$

The more details of the LDP is available in [28].

B. Magnitude of LDPs

The magnitude LDPs are calculated by using the first order derivatives in α direction at g_c is defined as:

$$MLDP_{\alpha}^{2}(g_c) = \left\{ \overline{f}(I_{\alpha}^{'}(g_c), I_{\alpha}^{'}(g_1)), \overline{f}(I_{\alpha}^{'}(g_c), I_{\alpha}^{'}(g_2)), \ldots \right. \\ \left. \ldots, \overline{f}(I_{\alpha}^{'}(g_c), I_{\alpha}^{'}(g_8)) \right\} \quad (9)$$

where $\overline{f}(.,.)$ is a binary coding function determining the types of local pattern transitions. It encodes the co-occurrence of two derivative directions at different neighboring pixels as

$$f(I_{\alpha}^{'}(g_c), I_{\alpha}^{'}(g_p)) = \begin{cases} 1, & if\ I_{\alpha}^{'}(g_c) \le I_{\alpha}^{'}(g_1) \\ 0 & if\ I_{\alpha}^{'}(g_c) > I_{\alpha}^{'}(g_1) \end{cases} \quad (10)$$
$$p = 1, 2, \ldots\ldots 8$$

Further, these binary coded is converted into gray values by multiplying with weights as shown in Fig. 1.

The uniform LBP/LDP 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.

Fig. 3 shows all uniform patters for *P=8*. The distinct values for given query image is $P(P-1)+3$ by using uniform patterns.

After identifying the LP (LBP/LDP) pattern of each pixel *(j, k)*, the whole image is represented by building a histogram:

$$H_S(l) = \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f(LP_{P,R}^{u2}(j,k), l);\ l \in [0, P(P-1)+3] \quad (11)$$

$$f(x,y) = \begin{cases} 1 & x = y \\ 0 & othrwise \end{cases} \quad (12)$$

where the size of input image is $N_1 \times N_2$.

C. Proposed System Framework (LDPM)

In this paper, we proposed the new technique by considering the magnitudes of LDPs for image retrieval. The algorithm for the proposed image retrieval system is given below:

Algorithm:

Input: Image; Output: Retrieval results.

1. Load the input image and convert it into gray scale.
2. Perform the first order derivatives along 0^0, 45^0, 90^0 and 135^0 directions.
3. Calculated the second order LDPs in 0^0, 45^0, 90^0 and 135^0 directions using Eq. (7).
4. Calculate the LDP histograms in 0^0, 45^0, 90^0 and 135^0 directions using Eq. (11).
5. Calculated the second order MLDPs in 0^0, 45^0, 90^0 and 135^0 directions using Eq. (9).
6. Calculate the MLDP histograms in 0^0, 45^0, 90^0 and 135^0 directions using Eq. (11).
7. Form the feature vector by concatenating the both LDP and MLDP histograms.
8. Calculate the best matches using Eq. (13).
9. Retrieve the number of top matches.

D. Similarity Measurement

In the presented work d_1^2 similarity distance metric is used as shown below:

$$D(Q, I_1) = \sum_{i=1}^{Lg} \left| \frac{f_{I,i} - f_{Q,i}}{1 + f_{I,i} + f_{Q,i}} \right|^2 \quad (13)$$

where Q is query image, Lg is feature vector length, I_1 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.

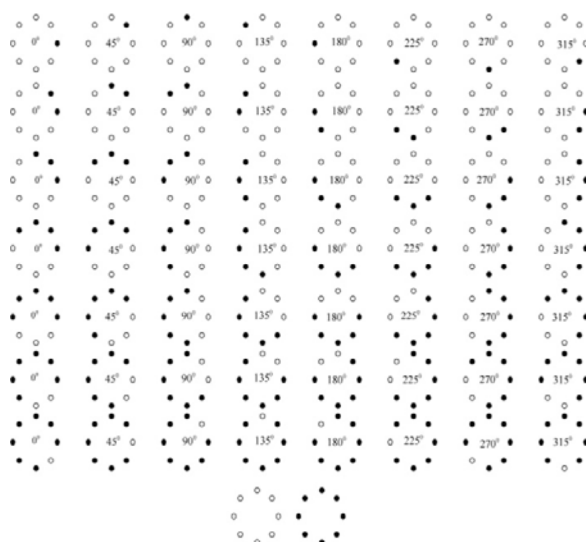

Fig. 3: Uniform patters when P=8. The black and white dots represent the bit values of 1 and 0 in the S_LP operator.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

For the work reported in this paper, retrieval tests are conducted on two different databases (Corel 1000, and MIT VisTex) and results are presented separately.

A. Database DB1

Corel database [30] contains large amount of images of various contents ranging from animals and outdoor sports to natural images. These images are pre-classified into different categories of size 100 by domain professionals. Some researchers think that Corel database meets all the requirements to evaluate an image retrieval system, because of its large size and heterogeneous content. In this paper, we collected the database DB1 contains 1000 images of 10 different categories (groups *G*). Ten categories are provided in the database namely *Africans, beaches, buildings, buses, dinosaurs, elephants, flowers, horses, mountains and food*. Each category has 100 images ($N_G = 100$) and these have either 256×384 or 384×256 sizes. Fig. 4 depicts the sample images of Corel 1000 image database (one image from each category).

The performance of the proposed method is measured in terms of average precision and average recall by Eq. (14) and (15) respectively.

$$Precision\left[P(I_q,n)\right]=\frac{No.of\ Relevant\ Images\ Retrieved}{Total\ No.of\ Images\ Retrieved} \quad (14)$$

$$Recall\left[R(I_q,n)\right]=\frac{No.of\ Relevant\ Images\ Retrieved}{Total\ No.of\ Relevant\ Images\ in\ Database} \quad (15)$$

where I_q is the query image and *n* is number of top matches considered.

Table I and II summarizes the retrieval results of the proposed method LDPM (LDP_P_R+MLDP_P_R), LDP_P_R, LBP_P_R and other transform domain methods (WC and GWC) in terms of average retrieval precision and recall respectively. From Table I, Table II, and Fig. 5, it is clear that the proposed method showing better performance compared to LBP_P_R, LDP_P_R and other transform domain methods in terms of average retrieval precision and recall.

Fig. 4: Sample images from Corel 1000 (one image per category)

B. Database DB2

The database DB2 used in our experiment consists of 40 different textures [31]. 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. (16).

$$ARR = \frac{1}{|DB|}\sum_{i=1}^{|DB|} R(I_i, n)\Big|_{n=16} \quad (16)$$

The database DB2 is used to compare the performance of the proposed method LDPM (LDP_P_R+MLDP_P_R) with, LBP_P_R, LDP_P_R, GGD &KLD [14], DT-CWT [18], DT-RCWT [18], and DT-CWT+DT-RCWT. Table III summarizes average retrieval rate of all methods. From Table III and Fig. 6, it is evident that the proposed method LDPM_P_R (87.31%/88.22%) is outperforming the T1 (80.78%), T2 (75.78%), T3 (82.34%), LBP_P_R (82.23%/81.2%) and LDP_P_R (85.03%/81.01%).

The results of the proposed method are also compared with the different distance measures as shown in Table IV. From Table IV, it is found that the d12 distance is outperforming (87.31%/88.22%) the L1 distance (87.13%/88.12%), L2 distance (80.5%/79.6%), and Canberra (87.11%/88.13%).

V. CONCLUSIONS

A new image indexing and retrieval algorithm is proposed in this paper by combining sign LDPs and magnitude LDPs. Two experiments have been carried out on Corel database and MIT VisTex for proving the worth of our algorithm. The results after being investigated shows a significant improvement in terms of their evaluation measures as compared to LBP, LDP and other existing transform domain techniques.

TABLE I RESULTS OF ALL TECHNIQUES IN TERMS OF PRECISION ON DB1 DATABASE

Category	WC [11]	GWC[8]	LBP_8_1	LBP_16_2	LDP_8_1	LDP_16_2	LDPM_8_1	LDPM_16_2
Africans	57.7	52.9	61.8	64.4	62.4	66	66.4	68
Beaches	49.3	42	55.4	54.3	59.4	58	58.9	59.4
Buildings	50.9	47.8	65.4	63.3	73.1	66	72.8	72.8
Buses	87.1	88.3	96.7	96.4	97.5	95.4	98.2	97.2
Dinosaurs	74.6	96.2	98.4	96.7	96.2	96.6	97.1	97.4
Elephants	55.7	65.9	46.3	50.7	54.4	60	55.7	63.4
Flowers	84.3	75.5	92.2	92.5	90.3	89.1	90.2	90.5
Horses	78.9	73	76.7	79.1	77.2	75.8	77.8	76.8
Mountains	47.2	35.2	41.9	43.3	39.6	44.3	43.6	46.1
Food	57.1	63.2	68.6	66.2	84.1	76.9	83	78.3
Total	**64.3**	**64.1**	**70.3**	**70.7**	**73.42**	**72.81**	**74.37**	**75.0**

Category	WC [11]	GWC[8]	LBP_8_1	LBP_16_2	LDP_8_1	LDP_16_2	LDPM_8_1	LDPM_16_2
Africans	31.1	33.2	38.1	37.6	37.57	39.83	40.03	38.47
Beaches	28.6	26.2	35.4	29.6	37.42	33.79	38.45	35.44
Buildings	30.5	26.5	33.7	29.6	38.03	35.53	37.38	40
Buses	64	65.1	70.5	74.2	76.32	65.55	77.52	75.65
Dinosaurs	28.8	65	75.1	67.9	77.78	72.26	80.3	81.75
Elephants	30.7	37	25.4	25.4	28.91	30.25	28.48	31.14
Flowers	65.3	50.4	65.6	66	64.04	64.62	62.44	62.78
Horses	39.9	39.5	42.2	43.4	43.36	37.56	40.46	38.52
Mountains	25.1	20.1	26.9	24.6	25.1	25.55	27.84	28.57
Food	36.4	43.1	37.2	35	48.75	42.7	48.42	43.6
Total	**38**	**40.6**	**44.9**	**43.3**	**47.72**	**44.76**	**48.2**	**47.61**

All evaluation values are in percentage (%)

TABLE III RESULTS OF ALL TECHNIQUES IN TERMS OF AVERAGE RETRIEVAL RATE ON DB2 DATABASE

T1: DT-CWT; T2: DT-RCWT; T3:T1+T2

GGD&KLD	T1	T2	T3	LBP_8_1	LBP_16_2	LDP_8_1	LDP_16_2	LDPM_8_1
76.57%	80.78	75.78	82.34	82.23	81.2	85.03	81.01	87.31

TABLE IV RESULTS OF PROPOSED METHOD WITH DIFFERENT DISTANCE MEASURES IN TERMS OF AVERAGE RETRIEVAL RATE ON DB2 DATABASE

Distance	City Block (L1)	Euclidian (L_2)	Canberra	d_1^2
LDPM_8_1	87.13%	80.50%	87.11%	**87.31%**
LDPM_16_2	88.12%	79.61%	88.13%	**88.22%**

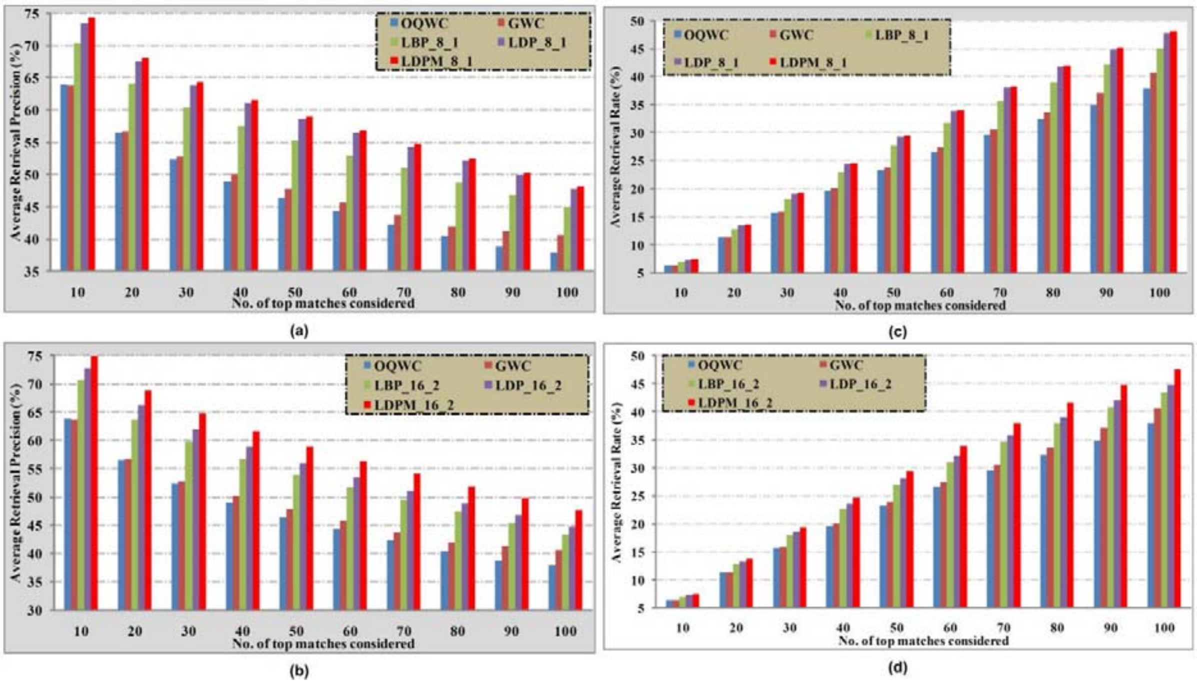

Fig. 5: Comparison of proposed method (LDPM) with other existing methods in terms:
(a)–(b) average retrieval precision, (c)–(d) average retrieval rate.