NEW LOCAL EDGE BINARY PATTERNS FOR IMAGE RETRIEVAL

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ABSTRACT

A new method, called local edge binary patterns (LEBP), is introduced in the paper, which takes the advantages of local binary patterns and local edges into account. Furthermore, several extensions to LEBP are also discussed in detail. Center-symmetric local binary pattern (CS-LBP) and direction local binary pattern (D-LBP) are chosen as examples to prove the performance of the new method on two commonly used texture databases. Experimental results show that LEBP can greatly improve the performance of the traditional local binary patterns in texture image retrieval.

***Index Terms*—** CS-LBP, D-LBP, LEBP, image retrieval

1. INTRODUCTION

Texture analysis has been an active research topic in the past decades with numerous algorithms being developed [1]. Recently, local binary pattern (LBP) was proposed by Ojala et al [2] and it has been proven a robust and computationally simple approach to describe local structures. Since Ojala's work, LBP methodology has been developed with large number of extensions for improved performance, such as improvement of its discriminative capability and robustness, selection of its neighborhood, and combination with other approaches [3-6]. The LBP and its extensions have been extensively exploited in many applications, such as texture analysis and classification [7], face recognition [8], image retrieval [9].

Recently, Heikkilä et al [4] developed CS-LBP for interest region description because of the size of the original LBP. Different from LBP, pixel values are not compared to the central pixel but to the opposing pixel symmetrically. Furthermore, a threshold is set to increase the operator's robustness in flat areas. However, the central pixel is ignored in CS-LBP. Hence, D-LBP was introduced in our previous work [9], where a new definition of direction was introduced and direction variation of the central pixel with respect to opposing pixels symmetrically was used to define binary patterns.

On the other hand, local gradient and edge have been playing an important role in computer vision and pattern recognition. For instance, SIFT [10] and HOG [11] has been successfully used in many fields. For LBP and its extensions, only the differences of pixel intensities are considered. In order to improve the discriminability of those local binary patterns, we introduced a new method, called local edge binary patterns (LEBP). The proposed method is reminiscent of the traditional local binary patterns, but it is computed around edges for improved performance. Experimental results demonstrate that it can greatly outperform its peers for texture image retrieval.

The rest of the paper is organized as follows: In Section 2, we review the related works briefly. The proposed LEBP and the extensions are presented in detail in Section 3. Section 4 reports the experimental results. Finally, we draw conclusion in Section 5.

2. RELATED WORKS

2.1. LBP

The original LBP ($LBP_{P,R}$) and the rotation-invariant LBP ($LBP_{P,R}^{riu2}$) are given respectively in [3] as,

$$LBP_{P,R} = \sum_{i=0}^{P-1} s(p_i - p_c) \times 2^i, s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{i=0}^{P-1} s(p_i - p_c), & if\ U(LBP_{P,R}) \leq 2 \\ P+1, & Otherwise \end{cases} \quad (2)$$

where P is the number of sampling pixels on a circle, R is the circle radius, p_c is the gray value of the central pixel and p_i is the gray value of each sampling pixels; the superscript ^{riu2} refers to the use of rotation invariant uniform patterns that have a U value of at most two. The uniformity measure U corresponds to the number of transitions from 0 to 1 or 1 to 0 between successive bits in the circular representation of the obtained code, which is defined as

$$U(LBP_{P,R}) = |s(p_{P-1} - p_c) - s(p_0 - p_c)| + \sum_{i=1}^{P-1} |s(p_i - p_c) - s(p_{i-1} - p_c)| \quad (3)$$

2.2. CS-LBP

Center-symmetric local binary pattern (CS-LBP) was proposed for interest region description because of the high-dimension of LBP. It is defined as follows,

$$CS\_LBP_{P,R,\tau} = \sum_{i=0}^{P/2-1} s(p_i - p_{i+P/2} - \tau) \times 2^i \qquad (4)$$

where p_i and $p_{i+P/2}$ are the gray values of opposing pixels symmetrically to the central pixel. The threshold τ is set to obtain the robustness on flat regions. Given P neighbors, $CS\_LBP_{P,R,\tau}$ produces only $2^{P/2}$ binary patterns.

2.3. D-LBP

In [9], we introduced the direction local binary pattern (D-LBP), which also takes the central pixel into account. Firstly, it gives the definition of the direction as follows.

Define 1: $p_i \to p_c$ and $p_c \to p_{i+P/2}$ are regarded as positive direction if $p_i \ge p_c$ and $p_c \ge p_{i+P/2}$, respectively, or else, as negative direction.

Define 2: p_c, p_i and $p_{i+P/2}$ are regarded as consistent direction if $p_i \to p_c$ and $p_c \to p_{i+P/2}$ have the same direction, or else as inconsistent direction.

Then, $D\_LBP_{P,R}$ is given as,

$$D\_LBP_{P,R} = \sum_{i=0}^{P/2-1} (s(p_i - p_c) \odot s(p_c - p_{i+P/2})) \times 2^i \quad (5)$$

3. LOCAL EDGE BINARY PATTERN

3.1. LEBP

Local gradients and edge have been proved playing an important role in computer vision and pattern recognition, many interesting descriptors have been presented in recent years, such as SIFT [10] and HOG [11]. From the related works, we learn that local binary patterns, such as LBP, CS-LBP, D-LBP and other extensions, are defined only by the gray differences between the local pixels. We can't say that is not the deficiency of local binary patterns. In this paper, we try to fuse the binary patterns with local edge, and presented a new method. We call this new method as local edge binary patterns (LEBP).

In [11], local image gradients are computed using a centered derivative mask [−1, 0, 1]. In this paper, we introduced a new method to define the local edge by combining the definition of direction in D-LBP. For a neighborhood (P,R), the local edge is defined as follows,

$$\begin{cases} e_i = p_i - p_c \\ e_{i+P/2} = p_c - p_{i+P/2}, i \in [0, P/2-1] \\ e_c = p_c - p_c = 0 \end{cases} \qquad (6)$$

where e_i, $e_{i+P/2}$ and e_c denote the edge value of pixel p_i, $p_{i+P/2}$ and p_c respectively.

Combing with different coding strategies, we can get different local edge binary patters. We take CS-LBP and D-LBP as examples. The LEBP of them are called CS_LEBP and D_LEBP respectively.

$$CS\_LEBP_{P,R} = \sum_{i=0}^{P/2-1} s(e_i - e_{i+P/2}) \times 2^i \qquad (7)$$

Eq. (7) can be further re-written as follows based on Eq. (6).

$$CS\_LEBP_{P,R} = \sum_{i=0}^{P/2-1} s(p_i + p_{i+P/2} - 2p_c) \times 2^i \qquad (8)$$

In CS-LEBP, threshold τ is canceled because of the difficulty of finding an adaptive threshold for all regions.

$$D\_LEBP_{P,R} = \sum_{i=0}^{P/2-1} (s(e_i - e_c) \odot s(e_c - e_{i+P/2})) \times 2^i \qquad (9)$$

Based on Eq. (5), it can be further denoted as,

$$D\_LEBP_{P,R} = \sum_{i=0}^{P/2-1} (s(p_i - p_c) \odot s(p_{i+P/2} - p_c)) \times 2^i \qquad (10)$$

3.2. Extensions of LEBP

According to the extensions of LBP in [3], we can get the extensions of LEBP as follows.

Combining neighborhood of different sizes: the operators with different P and R, such as $D\_LEBP_{8,1+16,2}$ and $CS\_LEBP_{8,1+16,2+24,3}$, can be combined together for image classification and retrieval.

Rotation invariant LEBPs : By the definition of $LBP^{ri}_{P,R}$ (the superscript ^{ri} stands for "rotation invariant"), the rotation invariant LEBP can also be derived as $CS\_LEBP^{ri}_{P,R}$ and $D\_LEBP^{ri}_{P,R}$.

$$CS\_LEBP^{ri}_{P,R} = min\{ROR(CS\_LEBP_{P,R}, i)\} \qquad (11)$$

$$D\_LEBP^{ri}_{P,R} = min\{ROR(D\_LEBP_{P,R}, i)\} \qquad (12)$$

where $i = 0,1,\cdots,P/2-1$. The function $ROR(x,i)$ performs a circular anti-clockwise bitwise shift on the $x-$bit number by i times.

The "uniform" LEBPs: At a pixel, it gives a uniform LBP if the corresponding binary code sequence has no more than two transitions between "0" and "1" among all pairs of the adjacent binary codes.

Based on $LBP^{u2}_{P,R}$ (superscript ^{u2} means that the uniform pattern has a U transitions at most 2), $CS\_LEBP^{u2}_{P,R}$ and $D\_LEBP^{u2}_{P,R}$ can also be obtained. The definition of $U(CS\_LEBP_{P,R})$ and $U(D\_LEBP_{P,R})$ are given follows.

"Uniform" and rotation invariant LEBPs: Based on the definition of $LBP^{riu2}_{P,R}$, $CS\_LEBP^{riu2}_{P,R}$ and $D\_LEBP^{riu2}_{P,R}$ can also be derived respectively as follows,

$$CS\_LEBP_{P,R}^{riu2}=\begin{cases}\sum_{i=0}^{P/2-1}s(e_i-e_{i+P/2}), U(CS\_LEBP_{P,R})\le 2\\ P/2+1, \quad\quad \text{otherwise}\end{cases} \quad (13)$$

$$D\_LEBP_{P,R}^{riu2}=\begin{cases}\sum_{i=0}^{P/2-1}t(e_i,e_c,e_{i+P/2}), U(D\_LEBP_{P,R})\le 2\\ P/2+1, \quad\quad \text{otherwise}\end{cases} \quad (14)$$

where, $t(e_i,e_c,e_{i+P/2})=s(e_i-e_c)\odot s(e_c-e_{i+P/2})$,

$$U(CS\_LEBP_{P,R})=\left|s(e_{P/2-1}-e_{P-1})-s(e_0-e_{P/2})\right| + \sum_{i=0}^{P/2-2}\left|s(e_i-e_{P/2+i})-s(e_{i+1}-e_{P/2+i+1})\right|$$ and

$$U(D\_LEBP_{P,R})= \sum_{i=0}^{P/2-2}\left|s(e_i-e_c)\odot s(e_c-e_{P/2+i})-s(e_{i+1}-e_c)\odot s(e_c-e_{P/2+i+1})\right| + \left|s(e_{P/2-1}-e_c)\odot s(e_c-e_{P-1})-s(e_0-e_c)\odot s(e_c-e_{P/2})\right|$$

4. EXPERIMENTAL RESULTS

4.1. Dataset and evaluation protocol

In order to analyze the performance of the proposed methods for image retrieval, the experiments are conducted on three commonly used image databases, Brodatz (DB1, http://www.ux.uis.no/~tranden/brodatz.html), CUReT (DB2, http://www.robots.ox.ac.uk/~vgg/research/), Corel (DB3, http://wang.ist.psu.edu/docs/related/).

$L1$-distance is chosen as the measurement of two normalized histograms. In addition, precision-recall and *ANMRR* [12] (Average Normalized Modified Retrieval Rank) given in Eq. (15) and (16) are chosen as the benchmark for computing results for the experiments.

$$precision=n/L,\quad recall=n/N \quad (15)$$

where L is the number of retrieved images, n is the number of relevant image in the retrieved images and N is the number of all relevant images in the database.

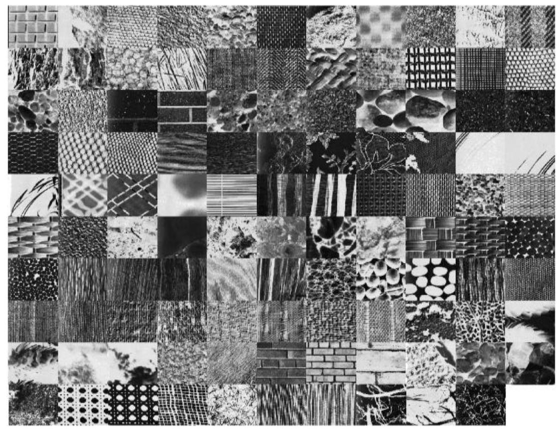
$$ANMRR=\frac{1}{M}\sum_{q=1}^{M}\frac{\frac{1}{T(q)}\sum_{k=1}^{T(q)}R^*(k)-0.5\times[1+T(q)]}{1.25K(q)-0.5\times[1+T(q)]} \quad (16)$$

where M is number of query images, $T(q)$ is the size of the ground truth set for a query image q. If $R(k)\le K(q)$, $R^*(k)=R(k)$, or else it is set $1.25K(q)$, where $R(k)$ is the ranking of the ground truth images by the retrieval algorithm, and $K(q)=\min(4*T(q),2*GTM)$, GTM is the maximum of $T(q)$ for all queries.

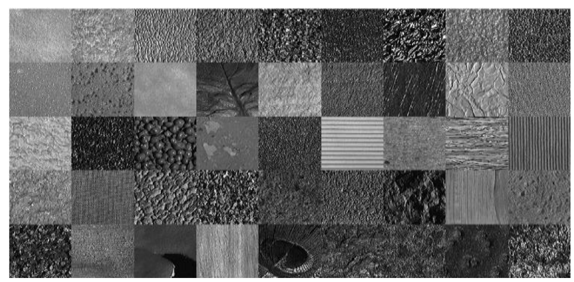
The proposed descriptors proved by two experiments on two commonly used texture image databases. For the operators, we chose $P=8\,\&\,R=1$, $P=16\,\&\,R=2$ and $P=24\,\&\,R=3$, respectively. For CS-LBP, we chose $\tau=5$. The bins of each descriptor are given in Table 1.

Experiment #1: $CS\_LEBP_{8,1}$ and $D\_LEBP_{8,1}$ are compared with $CS\_LBP_{8,1}$, $D\_LBP_{8,1}$ respectively and precision-recall is chosen as the evaluation criterion.

Experiment #2: The performance of uniform and rotation invariant descriptors among CS-LEBP, D-LEBP and LBP are compared in terms of *ANMRR*.



(a) 109 texture images from the Brodatz album



(b) 45 texture images from CUReT database

(c) 10 class images from the Corel database

Fig.1 Image databases

4.2. The performance on DB1

Database DB1 comprises of 109 different texture chosen from Brodatz photographic album. Example textures are shown in Fig. 1 (a). Each image (512×512) is further divided into sixteen 128×128 non-overlapping sub-images, thereby creating 1744 images. In this experiment, all images are chosen as query images. For Eq. (16), $M=1744$, $T=16$ and $K=32$.

For experiment #1, Fig 2 (a)-(b) give the average precision-recall graphs averaged over all queries. It is obvious that $CS\_LEBP_{8,1}$ and $D\_LEBP_{8,1}$ obtain better performance than their original methods respectively.

Experiment #2 results are given in Table 1. It gives that $CS\_LEBP^{riu2}_{8,1+16,2+24,3}$ (0.21, 30-bins), followed by $LBP^{riu2}_{8,1+16,2+24,3}$ (0.22, 54-bins).

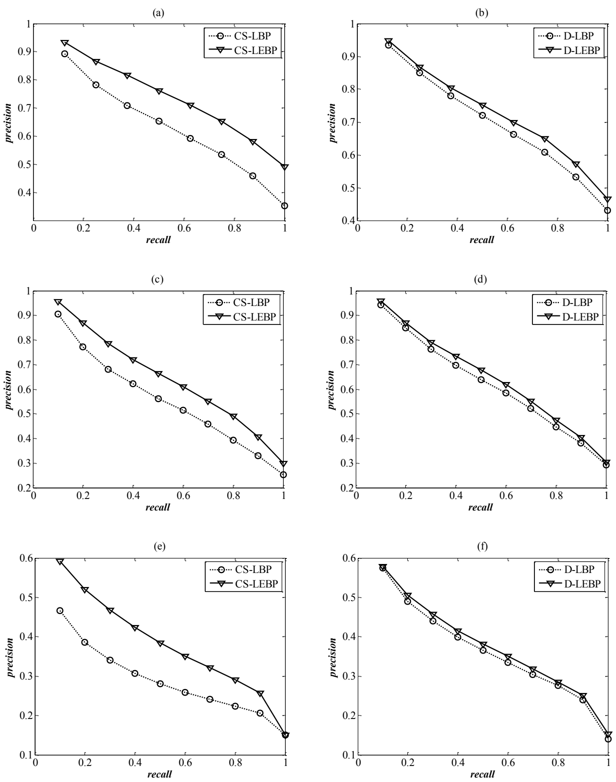


Fig. 2. Comparison of $CS\_LEBP_{8,1}$ and $D\_LEBP_{8,1}$ with $CS\_LBP_{8,1}$ and $D\_LBP_{8,1}$ respectively

4.3. The performance on DB2

Database DB2 includes 45 classes (each class has 20 texture images) chosen form CUReT database. Example textures are shown in Fig. 1 (b). All images are chosen as query images. For Eq. (16), $M = 900$, $T = 20$ and $K = 40$.

For experiment #1, Fig. 2 (c)-(d) gives the average precision-recall graphs averaged over all queries. It is obvious that the introduced LEBP operators obtain better performance than their originals respectively.

Experiment #2 results are also given in Table 1. It shows that $CS\_LEBP^{riu2}_{8,1+16,2+24,3}$ (0.18, 30-bins) is better as compared to the other operators, followed by $CS\_LEBP^{riu2}_{8,1+16,2}$ (0.20, 16-bins) and $LBP^{riu2}_{8,1+16,2+24,3}$ (0.20, 54-bins).

4.4. The performance on DB3

Database DB3 includes 10 classes color images (each class has 100 images). Example images are shown in Fig. 1 (c). All the images are chosen as query images and ANMRR is chosen as the evaluation scheme. For Eq. (16), $M = 1000$, $T = 100$ and $K = 200$.

For experiment #1, Fig. 2 (e)-(f) gives the average precision-recall graphs averaged over all queries. It is obvious that the introduced LEBP operators obtain better performance than their originals respectively.

Table 1 also gives the experimental results of experiment #2. It shows that $CS\_LEBP^{riu2}_{8,1+16,2+24,3}$ (0.52, 30-bins) is better as compared to the other operators.

Table 1 Average *ANMRR* over DB1, DB2 and DB3
(Lower *ANMRR* is better)

Operators		Bins	DB1	DB2	DB3
CS-LEBP	$CS\_LEBP^{riu2}_{8,1}$	6	0.35	0.36	0.56
	$CS\_LEBP^{riu2}_{16,2}$	10	0.27	0.23	0.55
	$CS\_LEBP^{riu2}_{24,3}$	14	0.28	0.26	0.56
	$CS\_LEBP^{riu2}_{8,1+16,2}$	16	0.23	0.20	0.54
	$CS\_LEBP^{riu2}_{8,1+16,2+24,3}$	30	**0.21**	**0.18**	**0.52**
D-LEBP	$D\_LEBP^{riu2}_{8,1}$	6	0.42	0.31	0.55
	$D\_LEBP^{riu2}_{16,2}$	10	0.32	0.36	0.58
	$D\_LEBP^{riu2}_{24,3}$	14	0.34	0.27	0.60
	$D\_LEBP^{riu2}_{8,1+16,2}$	16	0.28	0.27	0.55
	$D\_LEBP^{riu2}_{8,1+16,2+24,3}$	30	0.26	0.27	0.56
LBP	$LBP^{riu2}_{8,1}$	10	0.30	0.29	0.56
	$LBP^{riu2}_{16,2}$	18	0.28	0.25	0.54
	$LBP^{riu2}_{24,3}$	26	0.28	0.22	0.58
	$LBP^{riu2}_{8,1+16,2}$	28	0.23	0.22	0.54
	$LBP^{riu2}_{8,1+16,2+24,3}$	54	0.22	0.20	0.54

5. CONCLUSION

The local edge binary pattern (LEBP), a simple yet effective texture analysis approach, has been introduced in this paper. The contribution of LEBP is to incorporate edges into the local binary patterns. The effectiveness of LEBPs is evaluated by conducting image retrieval on commonly used texture and color image databases. Experimental results demonstrate that LEBP can significantly outperform its peers for image retrieval.

6. ACKNOWLEDGMENTS

This work was supported by the Backbone Teacher grant of Henan Province (2010GGJS-059), the International Cooperation Project of Henan Province (134300510057).

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