Graph Cut Based Local Binary Patterns for Content Based Image Retrieval

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Abstract

In this paper, a new algorithm which is based on the graph cut theory and local binary patterns (LBP) for content based image retrieval (CBIR) is proposed. In graph cut theory, each node is compared with the all other nodes for edge map generation. The same concept is utilized at LBP calculation which is generating nine LBP patterns from a given 3×3 pattern. Finally, nine LBP histograms are calculated which are used as a feature vector for image retrieval. Two experiments have been carried out for proving the worth of our algorithm. It is further mentioned that the database considered for experiments are Brodatz 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 and other existing transform domain techniques.

Keywords: Feature Extraction; Local Binary Patterns; Image Retrieval

1. Introduction

With the rapid expansion of worldwide network and advances in information technology there is an explosive growth of multimedia databases and digital libraries. This demands an effective tool that allow users to search and browse efficiently through such a large collections. In many areas of commerce, government, academia, hospitals, entertainment, and crime preventions large collections of digital images are being created. Usually, the only way of searching these collections was by using keyword indexing, or simply by browsing. However, as the databases grew larger, people realized that the traditional keywords based methods to retrieve a particular image in such a large collection are inefficient. To describe the images with keywords with a satisfying degree of concreteness and detail, we need a very large and sophisticated keyword system containing typically several hundreds of different keywords. One of the serious drawbacks of this approach is the need of trained personnel not only to attach keywords to each image (which may take several minutes for one single image) but also to retrieve images by selecting keywords, as we usually need to know all keywords to choose good ones. Further, such a keyword based approach is mostly influenced by subjective decision about image content and also it is very difficult to change a keyword based system afterwards. Therefore, new techniques are needed to overcome these limitations. Digital image databases however, open the way to content based searching. It is common phrase that an image speaks thousands of words. So instead of manual annotation by text based keywords, images should be indexed by their own visual contents, such as color, texture and shape. The main advantage of this method is its ability to support the visual queries. Hence researchers turned attention to content based image retrieval (CBIR) methods. Several methods achieving effective feature extraction have been proposed in the literature [Rui et al., Smeulders et al., kokare et al., and Liu et al.].

Swain et al. proposed the concept of color histogram in 1991 and also introduced the histogram intersection distance metric to measure the distance between the histograms of images. Stricker et al. used the first three central moments called mean, standard deviation and skewness of each color for image retrieval. Pass et al. introduced color coherence vector (CCV). CCV partitions the each histogram bin into two types, i.e., coherent, if it belongs to a large uniformly colored region or incoherent, if it does not. Huang et al. used a new color feature called color correlogram which characterizes not only the color distributions of pixels, but also spatial correlation of pair of colors. Lu et al. proposed color feature based on vector quantized (VQ) index histograms in the discrete cosine transform (DCT) domain. They computed 12 histograms, four for each color component from 12 DCT-VQ index sequences.

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. Moghaddam et al. proposed the Gabor wavelet correlogram (GWC) for CBIR. Ahmadian et al. used the wavelet transform for texture classification. Moghaddam et al. introduced new algorithm called wavelet correlogram (WC). Saadatmand et al. improved the performance of WC algorithm by optimizing the quantization thresholds using genetic algorithm (GA). Birgale et al. and Subrahmanyam et al. 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).

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

To improve the retrieval performance in terms of retrieval accuracy, in this paper, we proposed the graph cut based local binary patterns (GCLBP) for CBIR. Two experiments have been carried out on Brodatz 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 LBP and other existing transform domain techniques.

The organization of the paper as follows: In section 1, a brief review of image retrieval and related work is given. Section 2, presents a concise review of local binary patterns (LBP). Section 3, presents the feature extraction, proposed system framework, and similarity measure. Experimental results and discussions are given in section 4. Based on above work conclusions are derived in section 5.

2. 2. Local Binary Patterns

Ojala et al. proposed the local binary pattern (LBP) operator which describes the surroundings of a pixel by generating a bit-code from the binary derivatives of a pixel as a complementary measure for local image contrast. The LBP operator takes the eight neighboring pixels using the center gray value as a threshold. The operator generates a binary code 1 if the neighbor is greater or equal than the center otherwise generates a binary code 0. The eight neighboring binary code can be represented by a 8-bit number. The LBP operator outputs for all the pixels in the image can be accumulated to form a histogram. Fig.1 shows an example of LBP operator.

For given a center pixel in the image, LBP value is computed by comparing it with those of its neighborhoods:

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

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

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).

The LBP measure the local structure by assigning unique identifiers, the binary number, to various micro-structures in the image. Thus, LBP capture many structures in one unified framework. In the example in Fig. 3(b), the local structure is a vertical edge with a leftward intensity gradient. Other microstructures are assigned different LBP codes, e.g., corners and spots, as illustrated in Fig. 4. By varying the radius R and the number of samples P, the structures are measured at different scales, and LBP allows for measuring large scale structures without smoothing effects, as is, e.g., the case for Gaussian-based filters.

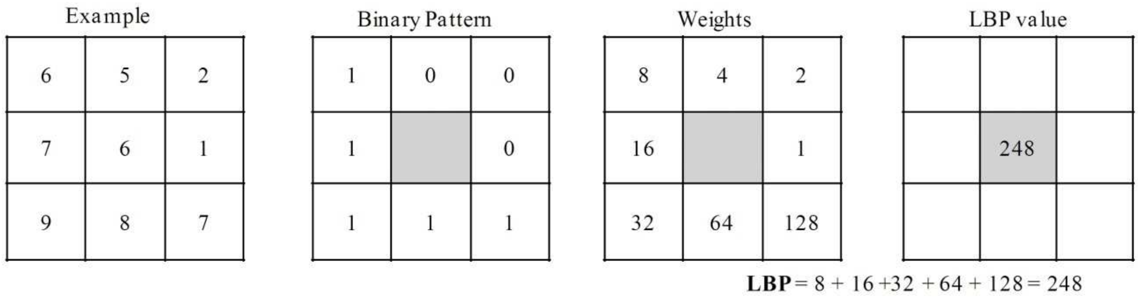


Fig. 1: LBP calculation for 3×3 pattern

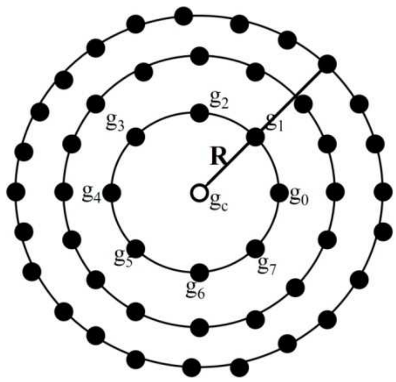


Fig. 2: Circular neighborhood sets for different (P,R)

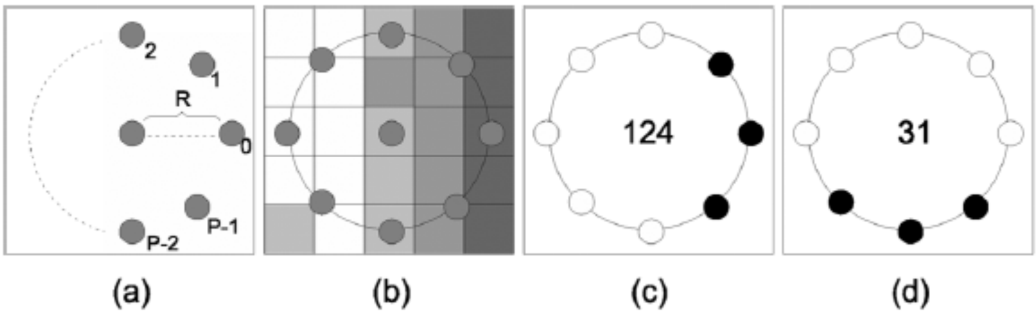


Fig. 3. Illustration of LBP. (a) The LBP filter is defined by two parameters; the circle radius R and the number of samples P on the circle. (b) Local structure is measured w.r.t. a given pixel by placing the center of the circle in the position of that pixel. (c) Samples on the circle are binarized by thresholding with the intensity in the center pixel as threshold value. Black is zero and white is one. The example image shown in (b) has an LBP code of 124. (d) Rotating the example image in (b) 900 clockwise reduces the LBP code to 31, which is the smallest possible code for this binary pattern. This principle is used to achieve rotation invariance.

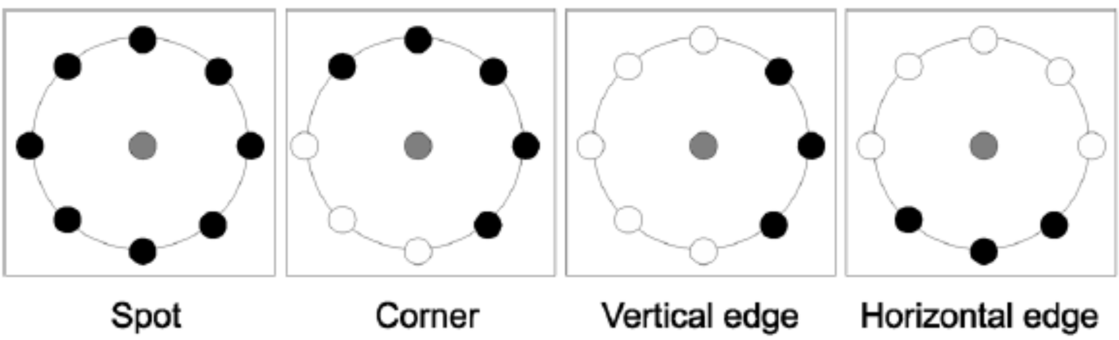


Fig. 4: Various microstructures measured by LBP. The gray circle indicates the center pixel. Black and white circles are binarized samples; black is zero and white is one.

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

$$H_{LBP}(l) = \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f(LBP(j,k),l);\ l \in [0,(2^P - 1)] \quad (3)$$

$$f(x,y) = \begin{cases} 1 & x = y \\ 0 & else \end{cases} \quad (4)$$

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

3. 3. Feature Extraction

The weighted graph (Li Xi et al.,) with no self loops is $G = (V, E, W)$, where $V = \{1, 2, ..., N\}$ the node set is (N=m.n is the total number of pixels in $Q \in R^{m \times n}$) $E \subseteq V \times V$ represents the edge set, and $W = (w_{ij})_{N \times N}$ denotes an affinity matrix with the element w_{ij} being the edge weight between nodes i and j.
Based on the above graph cut theory we compare the each pixel of 3×3 pattern with remaining eight pixel gray values for generating binary code. Finally, nine LBP patterns are collected for LBP histogram calculation and these are used as a feature vector for image retrieval. The flowchart of the proposed system is shown in Fig. 5 and algorithm for the same is given below:

3.1 Proposed System Framework (GCLBP)

Algorithm:

Input: Image; Output: Retrieval Result

1. Load the input image.
2. Collect the 3×3 pattern for a center pixel i.
   - Construct the graph cut for 3×3 pattern.
   - Generate nine LBP patterns.
   - Go to next center pixel.
3. Calculate the graph cut LBP (GCLBP) histograms.
4. Form the feature vector by concatenating the nine LBP features.
5. Calculate the best matches using Eq. (5).
6. Retrieve the number of top matches.

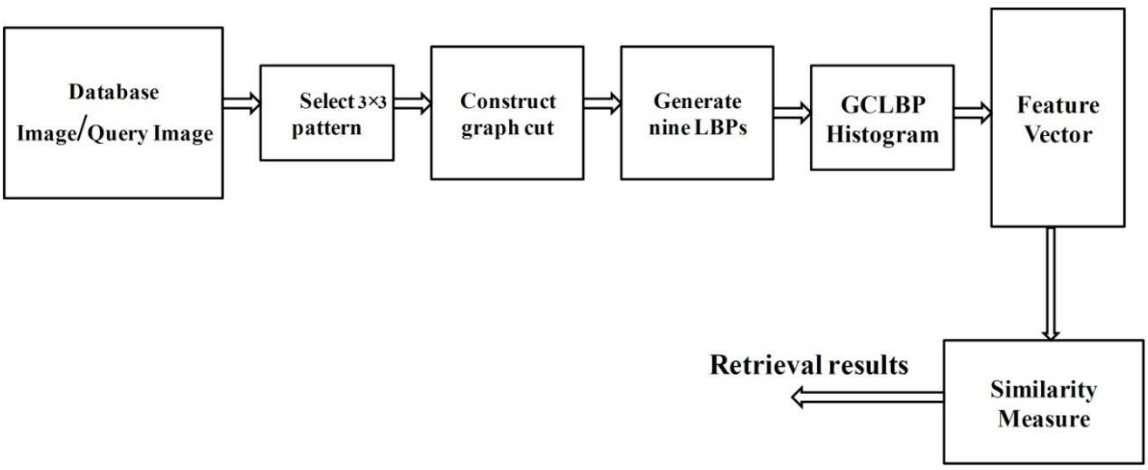


Fig. 5: Proposed system framework

3.2 Similarity Measurement

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

$$D(Q, I_1) = \sum_{i=1}^{Lg} \left| \frac{f_{I_1,i} - f_{Q,i}}{1 + f_{I_1,i} + f_{Q,i}} \right| \quad (5)$$

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

4. Experimental Results and Discussions

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

4.1. Database (DB1)

The database DB1 used in our experiment that consists of 116 different textures comprising of 109 textures from Brodatz texture photographic album [Brodatz P.], seven textures from USC database [http://sipi.usc.edu/database/]. The size of each texture is 512×512 and is further divided into sixteen 128×128 non-overlapping sub-images, thus creating a database of 1856 (116×16) images.

$$Precision\,(P) = \frac{No.of\ Relevant\ Images\ Retrieved}{Total\ No.of\ Images\ Retrieved} \times 100 \quad (6)$$

$$Group\ Precision\,(GP) = \frac{1}{N_1} \sum_{i=1}^{N_1} P \quad (7)$$

$$Average\ Retrieval\ Precision\,(ARR) = \frac{1}{\Gamma_1} \sum_{j=1}^{\Gamma_1} GP \quad (8)$$

$$Recall\,(R) = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ Number\ of\ relevant\ images} \quad (9)$$

$$Group\ Recall\,(GR) = \frac{1}{N_1} \sum_{i=1}^{N_1} R \quad (10)$$

$$Average\ Retrieval\ Rate\,(ARR) = \frac{1}{\Gamma_1} \sum_{j=1}^{\Gamma_1} GR \quad (11)$$

where N_1 is number of relevant images and Γ_1 is number of groups.

Table 1: Retrieval results of proposed method (GCLBP) and LBP in terms of average retrieval precision (ARP) (%)

Method	**Number of top matches considered**								
	1	**3**	**5**	**7**	**9**	**11**	**13**	**15**	**16**
LBP	100	89.17	84.67	81.71	79.01	76.33	73.86	71.18	69.65
GCLBP	100	93.19	89.73	87.27	85.02	82.71	80.47	77.88	76.45

Table 2: Retrieval results of proposed method (GCLBP) and LBP in terms of average retrieval rate (ARR) (%)

Method	**Number of top matches considered**						
	16	**32**	**48**	**64**	**80**	**96**	**112**
LBP	69.65	80.16	84.47	87.05	89.02	90.44	91.63

GCLBP	76.45	84.57	87.85	89.79	91.13	92.18	93.03
DT-CWT	74.16	83.83	87.13	89.11	90.48	91.48	92.3
DT-RCWT	72.33	80.88	84.32	86.28	87.82	88.98	89.92

Table 3: Performance of proposed method (GCLBP) with different distance measures in terms of average retrieval rate (ARR) (%)

Method	Distance Measure	Number of top matches considered						
		16	32	48	64	80	96	112
GCLBP	Manhattan	79.89	86.82	89.61	91.30	92.46	93.34	94.04
	Canberra	77.73	85.09	88.24	90.02	91.37	92.32	93.07
	Euclidean	78.81	85.59	88.43	90.24	91.54	92.47	93.25
	d_1	76.45	84.57	87.85	89.79	91.13	92.18	93.03

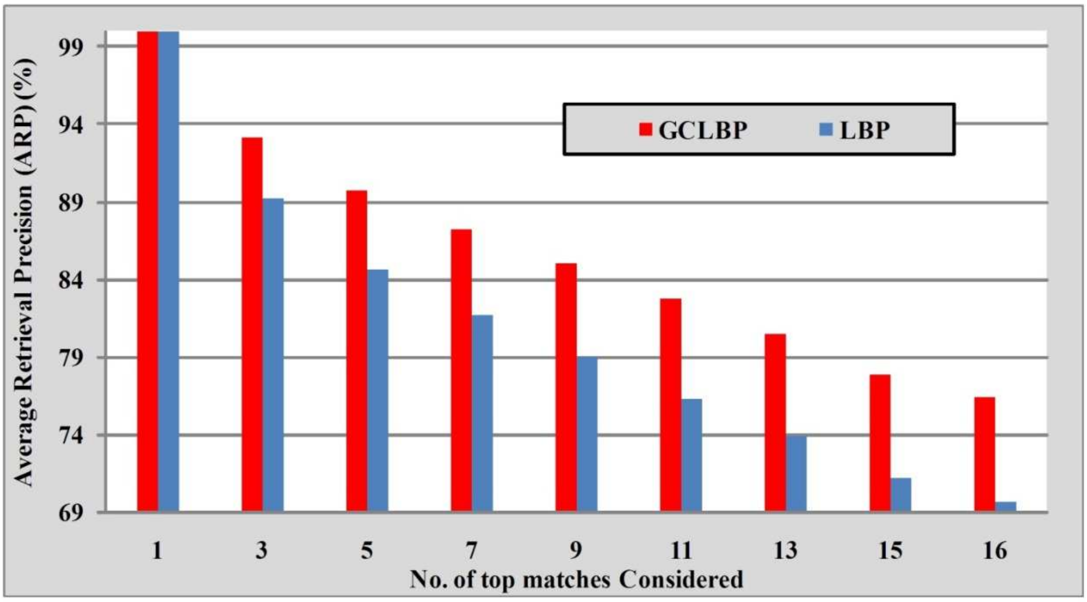
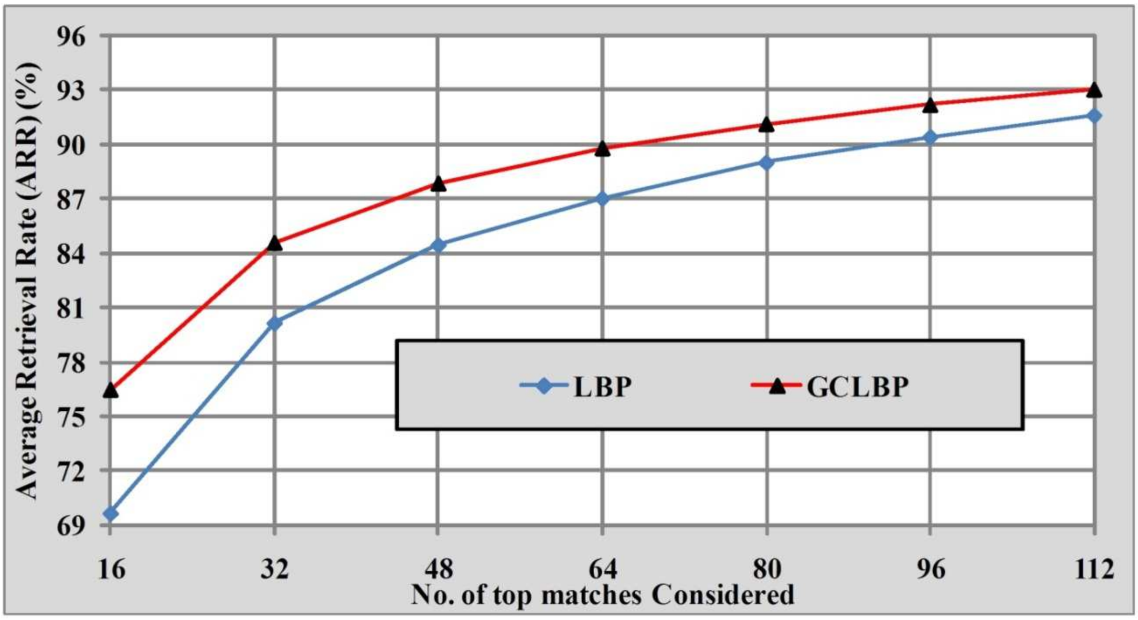
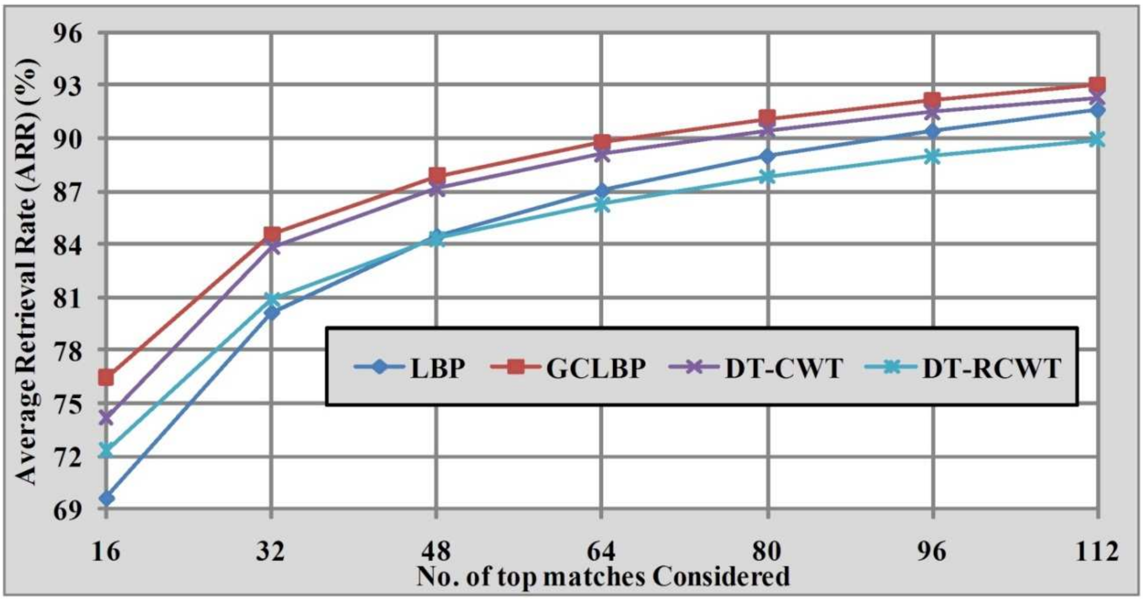


Fig. 6: comparison of proposed method (GCLBP) with LBP on DB1 database in terms of ARP

Table 1 and Fig. 6 summarize the retrieval results of the proposed method (GCLBP), and LBP in terms of average retrieval precision and Table 2 and Fig. 7 illustrate the performance of proposed method (GCLBP), LBP and other transform domain techniques in terms of average retrieval rate. Table 3 and Fig. 8 summarize the performance of proposed method (GCLBP) with different distance measures in terms of average retrieval rate.



(a)



(b)

Fig. 7: Comparison of proposed method (GCLBP) with: (a) LBP on DB1 database in terms of ARR, (b) with LBP and other transform domain features on DB1 database in terms of ARR.

From the Tables 1 to 3 and Fig. 6 to 8 the following can be observed:

1. The average retrieval precision of proposed method (GCLBP) (100% to 76.45%) is more as compared to LBP (100% to 69.65%).
2. The average retrieval rate of GCLBP (76.45% to 93.03%) is more compared to LBP (69.65% to 91.63%), DT-CWT (74.16% to 92.3%), and DT-RCWT (72.33% to 89.92%).
3. The performance of the proposed method with Manhattan distance (79.89% to 94.04%) is more as compared to Canberra (77.73% to 93.07%), Euclidean (78.81% to 93.25%), and $_{d1}$ distance (76.45% to 93.03%).

From Tables 1 to 3, Fig. 6 to 8, and above observations, it is clear that the proposed method is outperforming the LBP and other transform domain techniques. Fig. 9 illustrates the retrieval results of query image based on the proposed method (GCLBP).

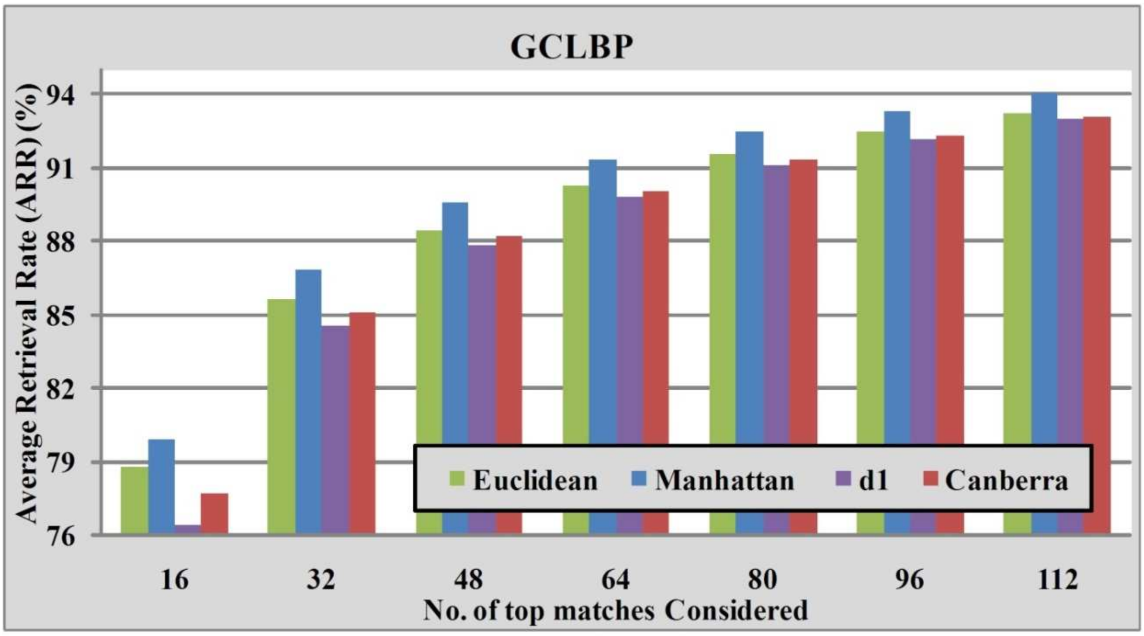


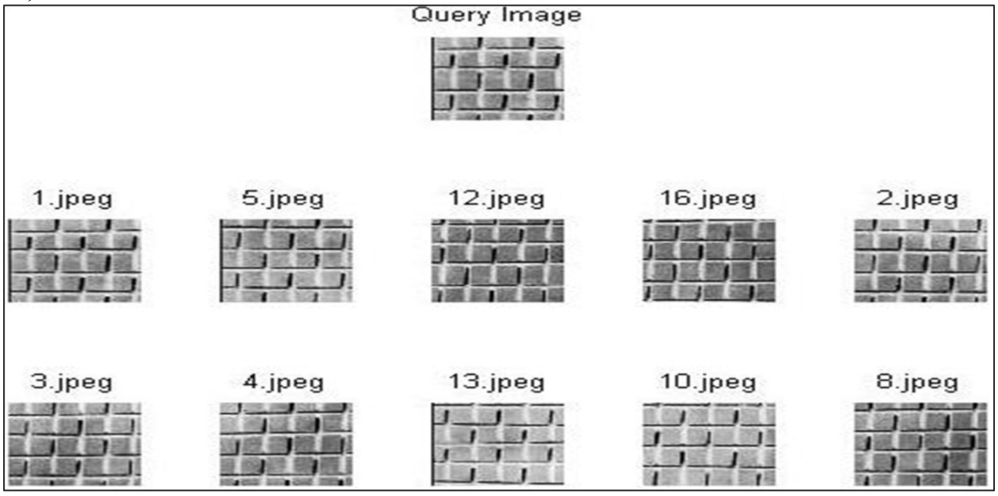
Fig. 8: Performance of proposed method (GCLBP) with different distance measures on DB1 database in terms of ARR.

4.2. Database DB2

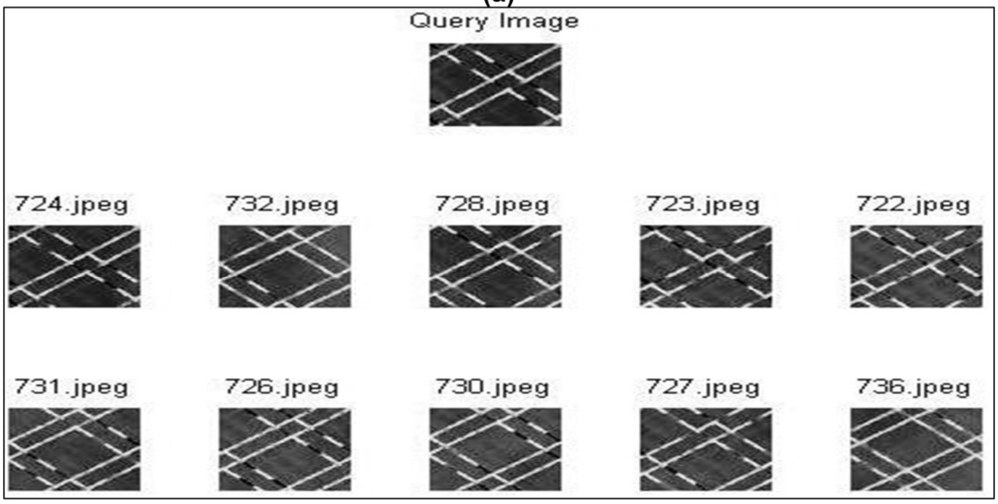
The database DB2 used in our experiment consists of 40 different textures [http://vismod.www.media.mit.edu]. The size of each texture is 512×512 . Each 512×512 image is divided into sixteen 128×128 non-overlapping sub-images, thus creating a database of 640 (40×16) images. The performance of the proposed method is measured in terms of ARP and ARR.

Table 4: Retrieval results of proposed method (GCLBP) and LBP in terms of average retrieval precision (ARP) (%)

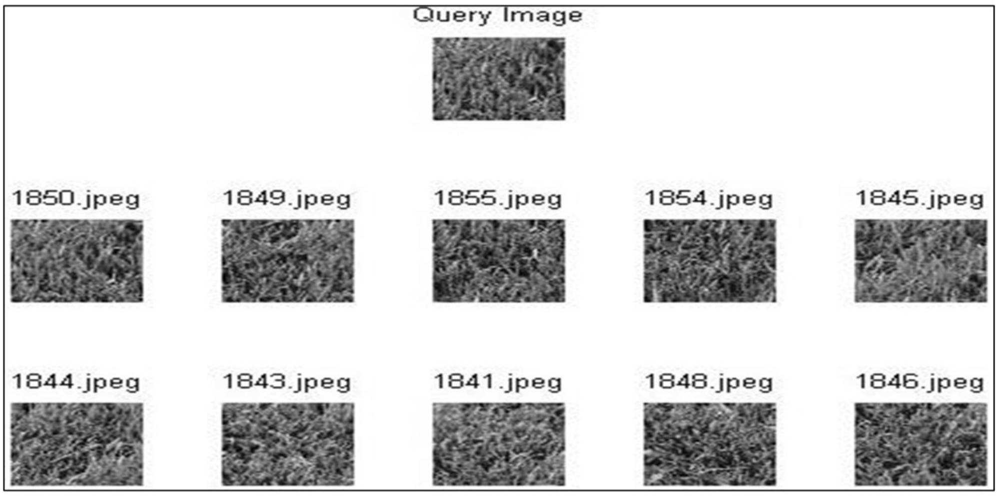
Method	Number of top matches considered								
	1	3	5	7	9	11	13	15	16
LBP	100	93.85	90.90	88.37	85.45	82.69	79.85	76.35	74.39
GCLBP	100	97.13	95.25	93.05	90.45	87.52	84.87	81.46	79.44



(a)



(b)



(c)

Fig. 9: Retrieval results of proposed method (GCLBP) of query image: (a) 1, (b) 724, and (c) 1850 of database DB1.

Table 4 and Fig. 10 summarize the retrieval results of the proposed method (GCLBP) and LBP in terms of average retrieval precision and Table 5 and Fig. 11 illustrate the performance of proposed method (GCLBP) and LBP in terms of average retrieval rate. Table 6 and Fig. 12 summarize the performance of proposed method (GCLBP) with different distance measures in terms of average retrieval rate.

From the Tables 4 to 6 and Fig. 10 to 12 the following can be observed:

1. The average retrieval precision of proposed method (GCLBP) (100% to 79.44%) is more as compared to

LBP (100% to 74.39%).

2. The average retrieval rate of GCLBP (79.44% to 97.24%) is more compared to LBP (74.39% to 97.08%).
3. The performance of the proposed method with d_1 distance (79.44% to 97.24%) is more as compared to Canberra (74.7% to 93.48%), Euclidean (80.07% to 97.20%), and Manhattan distance (80.47% to 95.46%).

From Tables 4 to 6, Fig. 10 to 12, and above observations, it is clear that the proposed method is outperforming the LBP and other transform domain techniques.

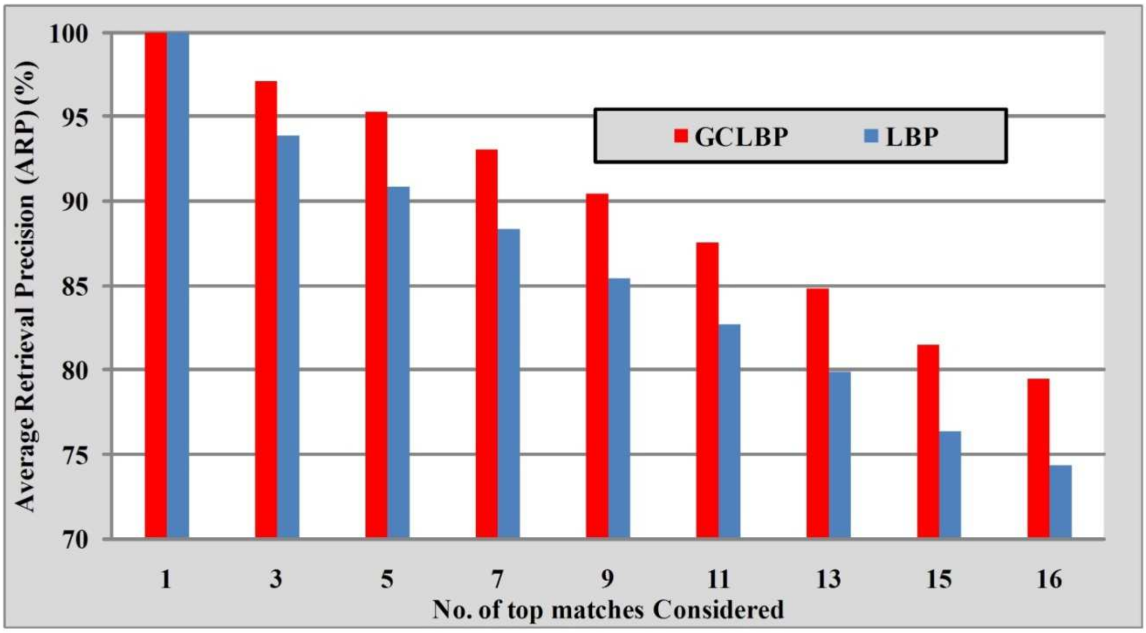


Fig. 10: comparison of proposed method (GCLBP) with LBP on DB2 database in terms of ARP

Table 5: Retrieval results of proposed method (GCLBP) and LBP in terms of average retrieval rate (ARR) (%)

Method	Number of top matches considered						
	16	32	48	64	80	96	112
LBP	74.39	86.69	91.14	93.77	95.35	96.36	97.08
GCLBP	79.44	88.36	92.00	94.22	95.54	96.53	97.24

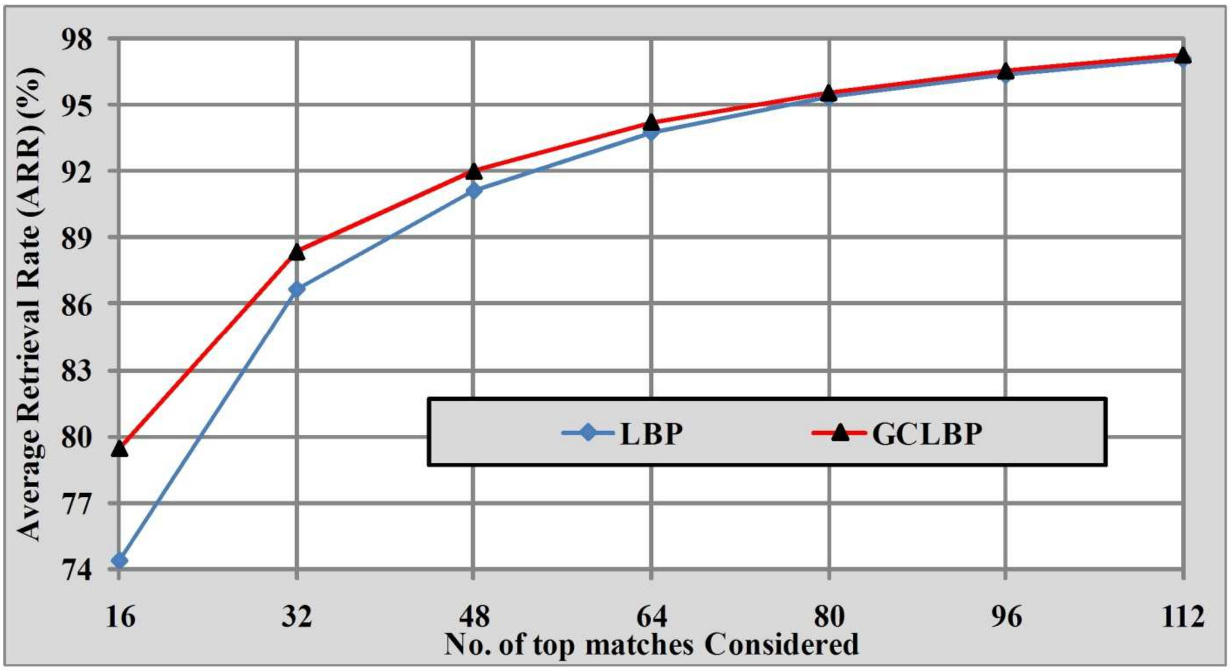


Fig. 11: Comparison of proposed method (GCLBP) with LBP on DB2 database in terms of ARR.

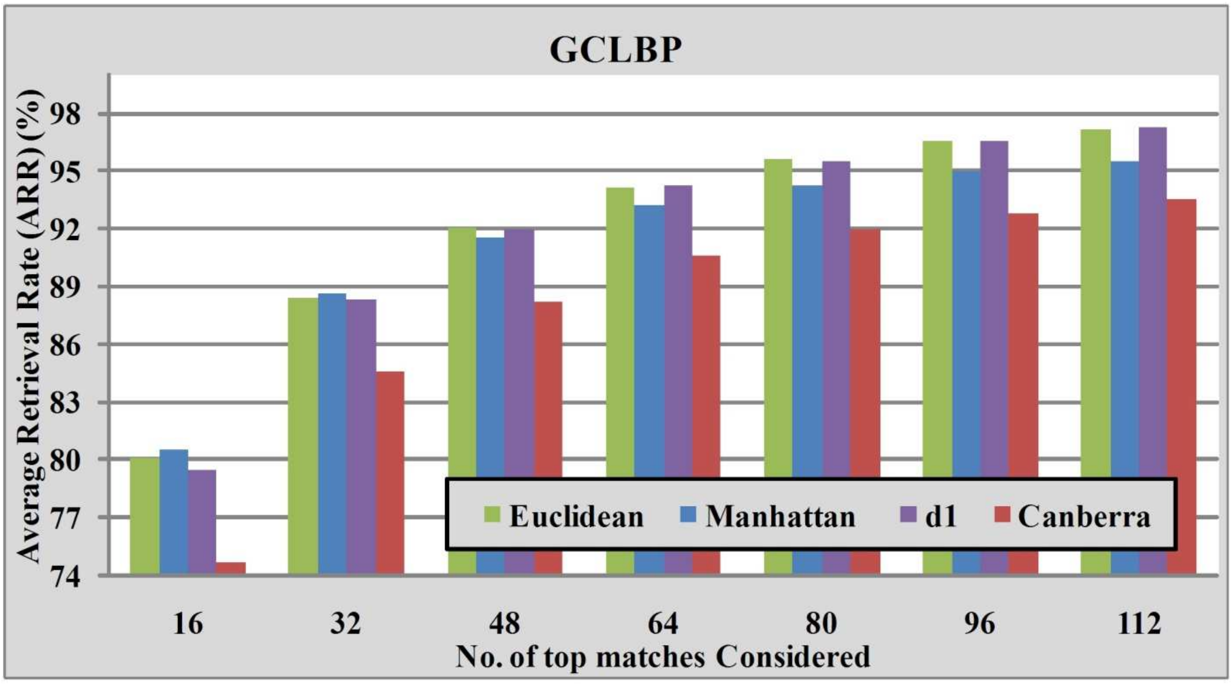


Fig. 12: Performance of proposed method (GCLBP) with different distance measures on DB2 database in terms of ARR.

Table 6: Performance of proposed method (GCLBP) with different distance measures in terms of average retrieval rate (ARR) (%)

Method	Distance Measure	Number of top matches considered						
		16	32	48	64	80	96	112
GCLBP	Manhattan	80.47	88.62	91.560	93.21	94.23	94.97	95.46
	Canberra	74.70	84.57	88.260	90.58	92.00	92.81	93.48
	Euclidean	80.07	88.44	92.07	94.17	95.56	96.52	97.20
	d_1	79.44	88.36	92.00	94.22	95.54	96.53	97.24

5. Conclusion

A new algorithm which is based on the graph cut theory and local binary patterns (LBP) for content based image retrieval (CBIR) is proposed in this paper. The proposed method extracts the nine LBP patterns from a given 3×3 pattern and these are used as the features. Two experiments have been carried out 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 and other existing transform domain techniques.

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