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Full Length Article

Local texton XOR patterns: A new feature descriptor for content-based image retrieval

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ABSTRACT

In this paper, a novel feature descriptor, local texton XOR patterns (LTxXORP) is proposed for content-based image retrieval. The proposed method collects the texton XOR pattern which gives the structure of the query image or database image. First, the RGB (red, green, blue) color image is converted into HSV (hue, saturation and value) color space. Second, the V color space is divided into overlapping subblocks of size 2×2 and textons are collected based on the shape of the textons. Then, exclusive OR (XOR) operation is performed on the texton image between the center pixel and its surrounding neighbors. Finally, the feature vector is constructed based on the LTxXORPs and HSV histograms. The performance of the proposed method is evaluated by testing on benchmark database, Corel-1K, Corel-5K and Corel-10K in terms of precision, recall, average retrieval precision (ARP) and average retrieval rate (ARR). The results after investigation show a significant improvement as compared to the state-of-the-art features for image retrieval.

1. Introduction

Content based image retrieval (CBIR) extracts the information from the images based on the content which presents in the images as feature descriptors. It resolves the essential problems of text based image retrieval by automatic extraction of low level features from the visual contents of image like color, texture, shape and spatial layout etc. A visual feature can consider only single perception while multiple visual features can perceive an image through different perceptions. The aim of this research is to enhance the performance of retrieval systems by designing effective and efficient algorithms for visual features as well as combination of such features. Contributions made toward improvement in the performance of image retrieval systems are given in References 1–4.

Texture measures the characteristics of images with respect to changes in certain directions and scales [5–7]. It extracts important information about structural arrangement of surfaces (like clouds, fabrics, bricks etc.) and their relationship to the surrounding environment. Mostly, texture information considers the behavior of a group of pixels rather than the nature of a single pixel. Natural images are the best examples of color and texture mosaic. Although most texture descriptors work on gray space, to optimize the performance of features sometimes they can be applied on color images. Various strategies are followed to extract texture features [8].

Wavelet transform based correlogram was proposed by Moghaddam et al. [9] for image retrieval. Further, the performance of wavelet correlogram was improved by quantization thresholds optimization using evolutionary genetic algorithm (GA) [10]. Birgale et al. [11] and Subrahmanyam et al. [12] combined the color (color histogram) and texture (wavelet transform) features for CBIR. Subrahmanyam et al. proposed a correlogram algorithm for image retrieval using wavelets and rotated wavelets (WC + RWC) [13].

The feature, local binary pattern (LBP) was proposed by Ojala et al. for the description of texture [14]. The LBP feature which is proposed by Ojala et al. was rotational variant. Then, the rotation variant LBP was converted into rotational invariant for texture classification [15,16]. For facial expression analysis and recognition, the LBP features are used in [17,18]. Heikkila et al. proposed the background modeling and detection by using LBP [19]. Huang et al. proposed the extensive LBP for the localization of shape [20]. Heikkila et al. used the LBP for interest region description [21]. Li and Staunton used the combination of Gabor filter and LBP for texture segmentation [22]. Zhang et al. proposed the local derivative pattern (LDP) for face recognition [23]. They have considered LBP as a nondirectional first order local pattern, which is the binary result of the first-order derivative in images.

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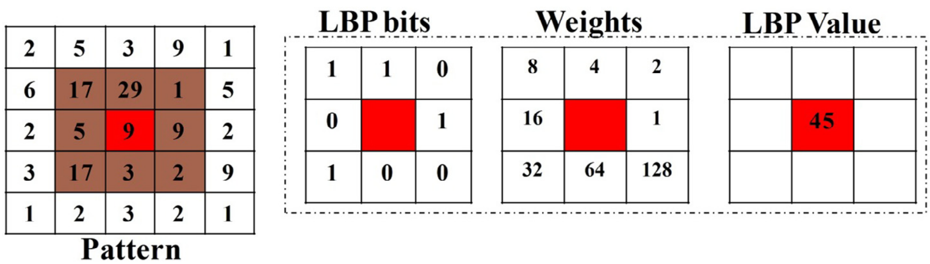


Fig. 1. Calculation of LBP.

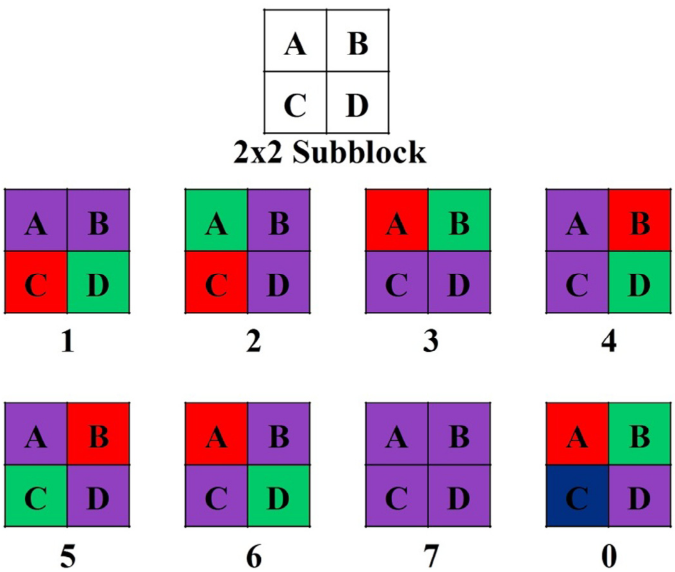


Fig. 2. The shape of the texton for feature extraction.

The block-based LBP texture feature used as the source for image description was proposed in Reference 24 for CBIR. The center-symmetric local binary pattern (CS-LBP) which is a modified version of the well-known LBP feature is combined with scale invariant feature transform (SIFT) in Reference 25 for a description of interest regions. Yao and Chen [26] have proposed two types of local edge pattern (LEP) histograms, one is LEPSEG for image segmentation and the other is LEPINV for image retrieval. The LEPSEG is sensitive to variations in rotation and scale, on the contrary, the LEPINV is resistant to variations in rotation and scale.

The extension of the LBP and the LDP in the text cannot sufficiently deal with the range of exterior variations that usually occur in unrestrained natural images due to aging, illumination, facial expression, pose, partial occlusions, etc. In order to deal with this difficulty, the local ternary pattern (LTP) [27] has been proposed for face recognition under different lighting environment. Subrahmanyam et al. have proposed the various pattern based features, local maximum edge patterns (LMEBP) [28], local tetra patterns (LTrP) [29] and directional local extrema patterns (DLEP) [30] for natural/texture image retrieval and directional binary wavelet

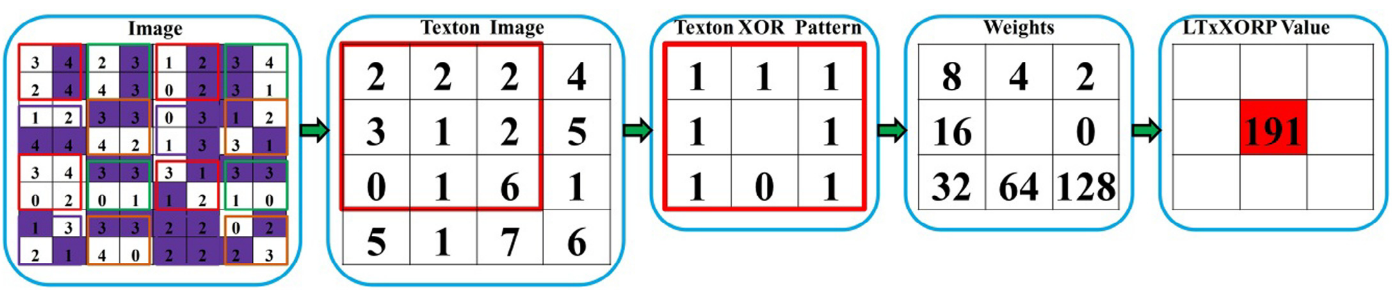


Fig. 3. Sample calculation of LTxXORP operator for an image.

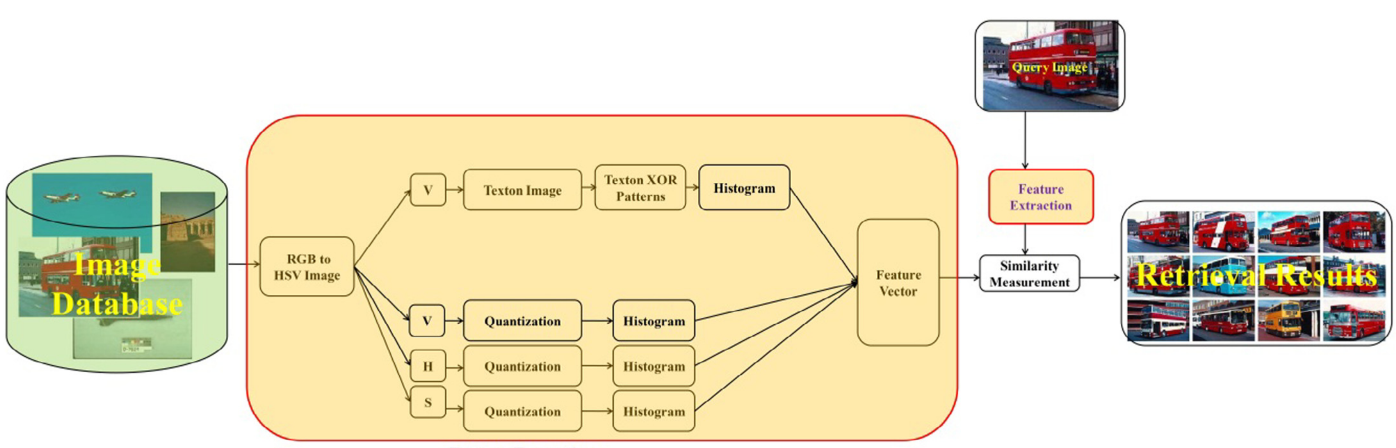


Fig. 4. Proposed image retrieval system framework.

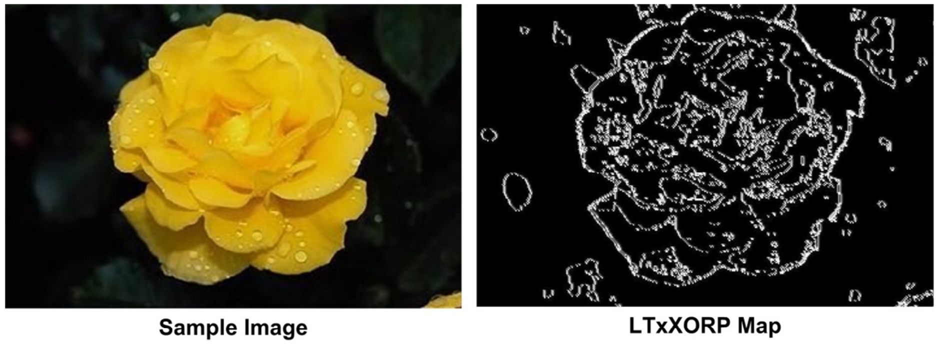


Fig. 5. The LTxXORP feature map extracted from a sample image.

patterns (DBWP) [31], local mesh patterns (LMeP) [32] and local ternary co-occurrence patterns (LTCoP) [33] for medical image retrieval. Gonde et al. [34] have proposed the texton co-occurrence matrix for content based image retrieval. Vipparthi and Nagar [35] have proposed the integration of color and local derivative patterns named as ICLDP for content-based image retrieval. Zhang et al. have proposed the binary Gabor patterns [36] and monogenic LBP [37] for texture classification application.

In literature, various existing texton features collect the relationship between the adjacent pixels in the gray scale image based on co-occurrence matrix, but the relationship between the center pixel and its neighbors in an image is not considered. In this paper, we propose the relationship between the center texton value and its surrounding neighbors in a texton image. The main contributions of this work are summarized as follows. (a) A new feature descriptor, named local texton XOR pattern (LTxXORP) is proposed for feature extraction, (b) the proposed LTxXORPs collect the features from the V plane of the HSV color image for image retrieval, (c) further, the performance of the proposed method is improved by integrating it with the HSV color histogram. The evaluation of the proposed method is done on benchmark image database.

The organization of the paper is summarized as follows: The brief review of image retrieval and related work are given in section 1. The review of the existing state-of-the-art features for image retrieval is given in section 2. The proposed system framework and query matching are illustrated in Section 3. Experimental results and discussions are summarized in section 4. Based on above work, conclusions and future scope are made in section 5.

2. Local patterns

2.1. Local Binary Patterns (LBP)

Initially, LBP is proposed for texture classification by Ojala et al. [14]. Further, LBP is used for other applications like, face recognition, image retrieval, palmprint recognition, etc. and achieved success due to its speed (not required to tune the parameters) and performance. The LBP is defined based on the relationship between the center pixel and its surrounding neighbors in an image. The relationship which is collected between the center pixel and its neighbors is based on the edge between the neighbor and the center pixel. If the neighbor pixel gray value is more than or equal to the center

Fig. 6. Sample images of Corel-1K database.

pixel, that LBP bit is coded as '1'; otherwise it is coded as '0' (see in Eq. (1) and Eq. (2)).

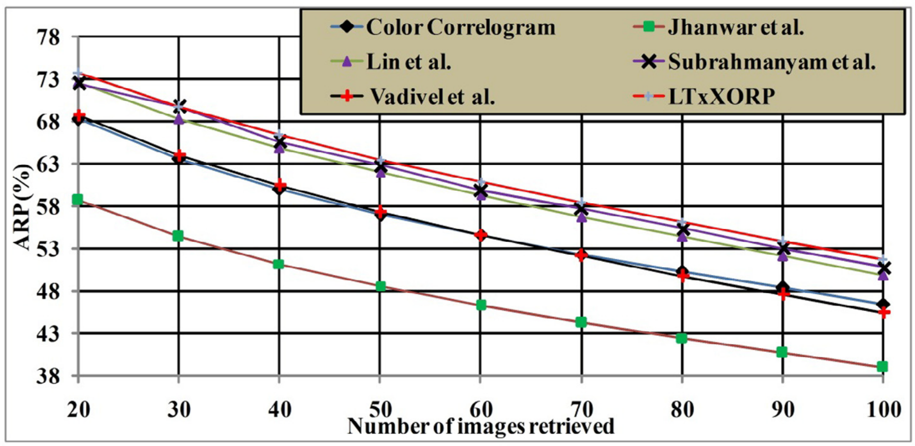
$$LBP_{P,R} = \sum_{i=1}^{P} 2^{(i-1)} \times f_1(I(g_i) - I(g_c)) \tag{1}$$

$$f_1(x) = \begin{cases} 1 & x \geq 0 \\ 0 & else \end{cases} \tag{2}$$

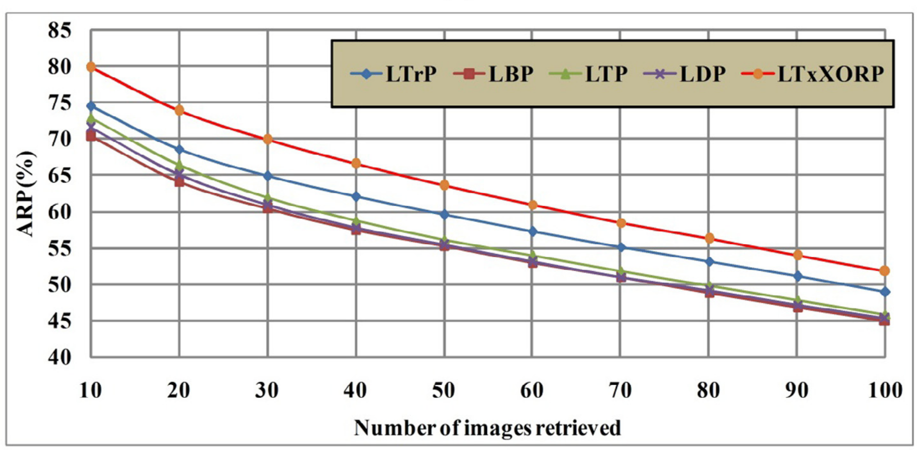
where $I(g_c)$ denotes the gray value of the center pixel, $I(g_p)$ represents the gray value of its neighbors, P stands for the number of neighbors and R the radius of the neighborhood.

After computing the LBP pattern for each pixel *(j, k)*, the whole image is represented by building a histogram as shown in Eq. (3).

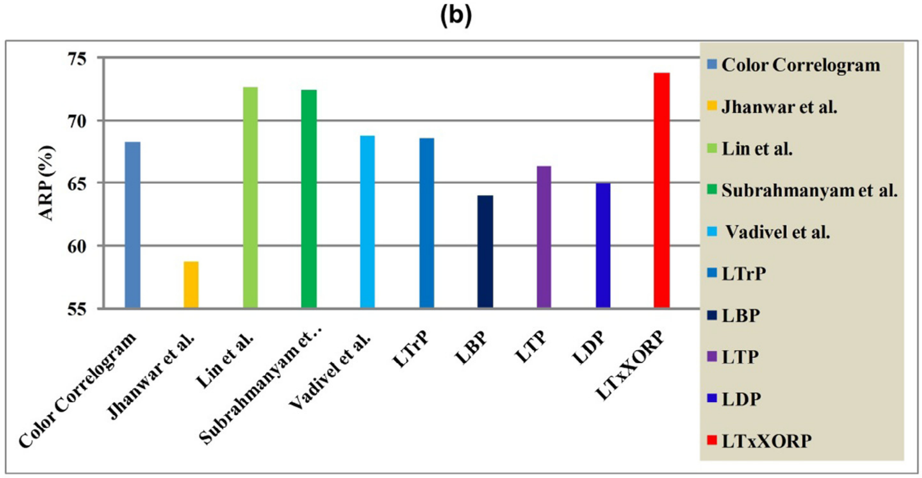
$$H_{LBP}(l) = \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f_2(LBP(j,k), l); l \in [0, (2^P - 1)] \tag{3}$$



(a)



(b)



(c)

Fig. 7. Comparison of proposed method with various existing methods in terms of ARP on Corel-1K database.

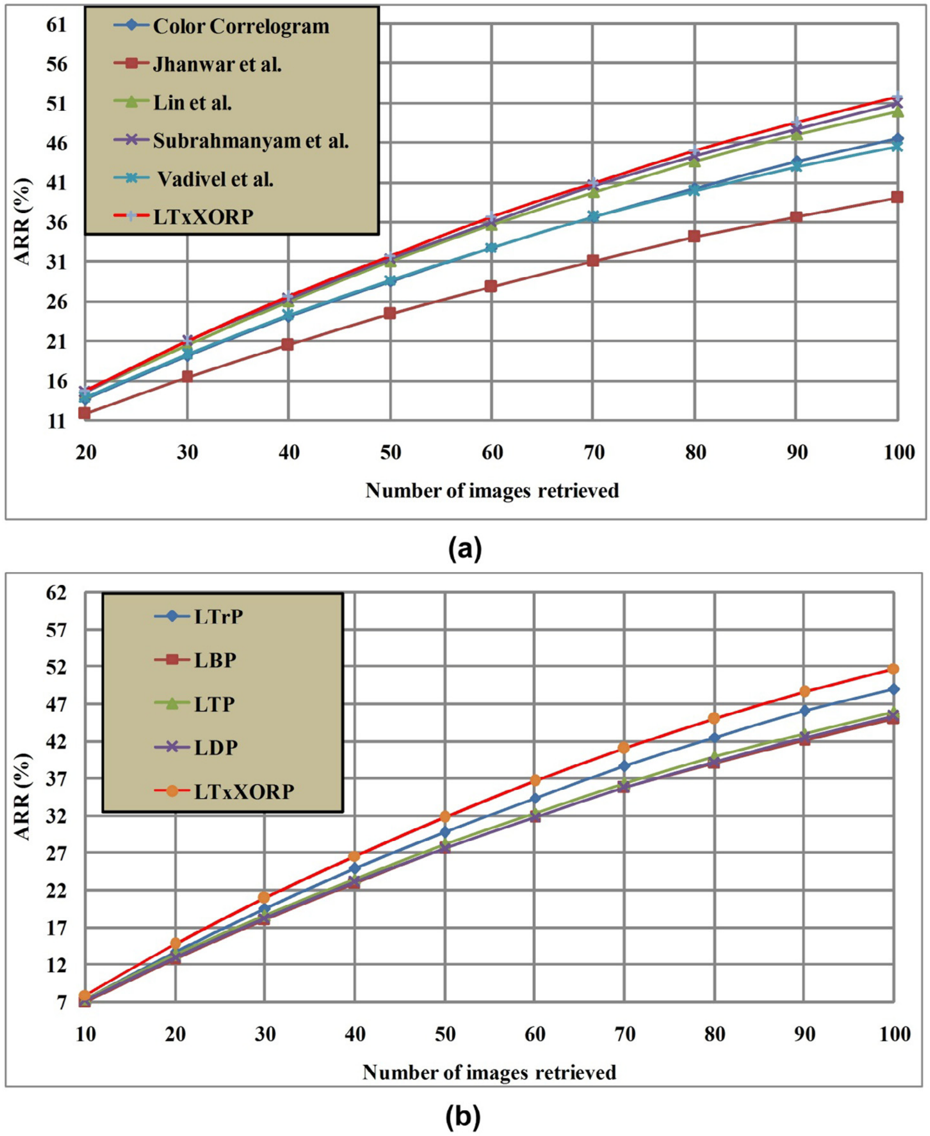


Fig. 8. Comparison of proposed method with various existing methods in terms of ARR on Corel-1K database.

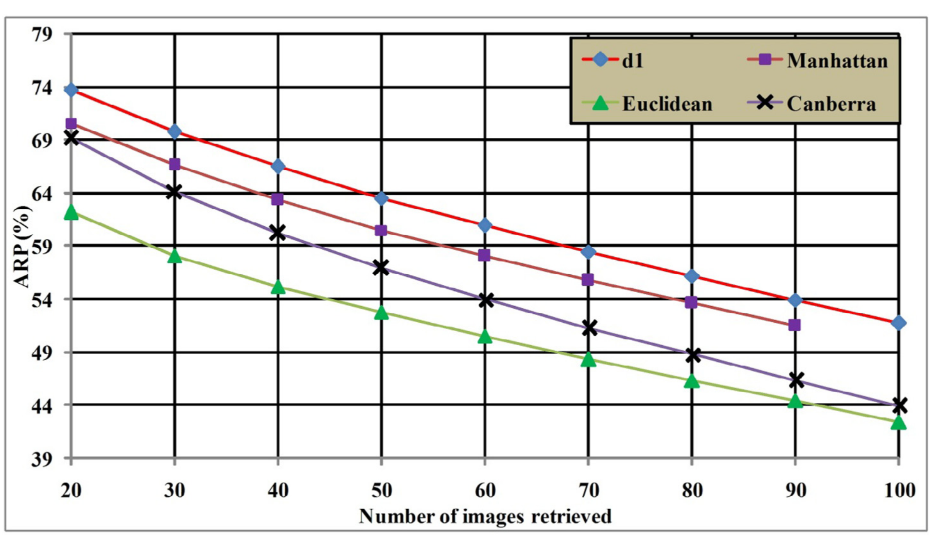


Fig. 9. Comparison of proposed method with various distance measures in terms of ARR on Corel-1K database.

Fig. 10. Query retrieval results of the proposed method on Corel-1K database.

Table 1
Results of proposed method with various quantization levels in terms of ARP on Corel-1K, Corel-5K and Corel-10K databases.

Database	Quantization levels									
	4	8	12	16	20	24	28	32	36	40
Corel-1K	79.83	79.25	78.87	78.64	78.43	77.84	77.52	77.19	76.98	76.94
Corel-5K	60	60.82	60.51	60.38	59.99	59.7	59.26	58.89	58.55	58.24
Corel-10K	50.6	51.05	50.79	50.41	49.95	49.53	49.24	48.96	48.75	48.56

$$f_2(x,y)=\begin{cases}1 & x=y\\ 0 & else\end{cases} \tag{4}$$

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

Figure 1 illustrates the sample calculation for the LBP for a given 3×3 pattern. The histograms of these patterns hold the information on the allocation of edges in an image.

2.2. Texton co-occurrence matrix

Gonde et al. [34] have proposed the texton co-occurrence matrix for image retrieval. First, they divided the image into non-overlapping 2×2 subblocks and then they collected the relationship between the pixel gray values in a 2×2 subblock for texton image generation. After calculation of texton image, co-occurrence matrix operation is performed on the texton image to form the final feature vector generation. Figure 2 illustrates the texton shapes which are considered for the texton image generation.

2.3. Local texton XOR patterns (LTxXORPs)

In this paper, seven different Texton shapes are considered for the texton image generation (see in Fig. 2). Let the image be divided into overlapping 2×2 subblocks named as I_1. For easy analysis, we consider the positions of gray values as "A, B, C, D". The subblocks are coded based on the texton shape which is given as follows.

$$Tx(x,y)=\begin{cases}1, & I_1(A)=I_1(B)\,\&\,I_1(C)\neq I_1(D)\\ 2, & I_1(B)=I_1(D)\,\&\,I_1(A)\neq I_1(C)\\ 3, & I_1(C)=I_1(D)\,\&\,I_1(A)\neq I_1(B)\\ 4, & I_1(A)=I_1(C)\,\&\,I_1(B)\neq I_1(D)\\ 5, & I_1(A)=I_1(D)\,\&\,I_1(B)\neq I_1(C)\\ 6, & I_1(B)=I_1(C)\,\&\,I_1(A)\neq I_1(D)\\ 7, & I_1(A)=I_1(B)=I_1(C)=I_1(D)\\ 0, & I_1(A)\neq I_1(B)\neq I_1(C)\neq I_1(D)\end{cases} \tag{5}$$

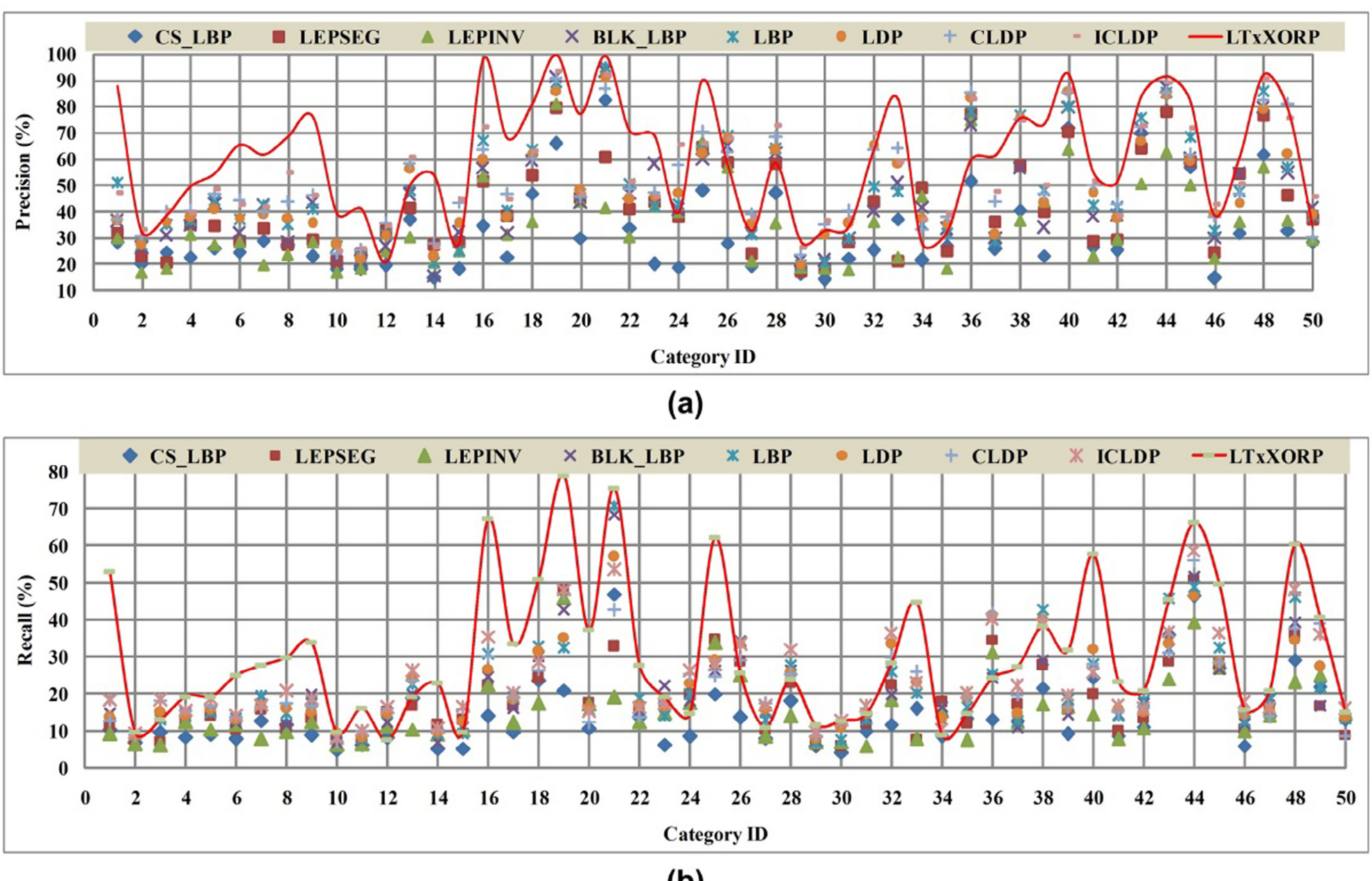


Fig. 11. Comparison of LTxXORP with other existing methods on Corel-5K. (a) Category-wise performance in terms of precision, (b) category-wise performance in terms of recall.

After calculating the texton image, we collect the center and its surrounding neighbors for each pixel on the texton image and perform the XOR operation between the center texton and its surrounding neighbor textons. The local texton XOR patterns are coded as follows.

$$LTxXORP_{P,R} = \sum_{i=1}^{P} 2^{(i-1)} \times f_3(Tx(g_i) \otimes Tx(g_c)) \tag{6}$$

$$f_3(x \otimes y) = \begin{cases} 1 & x \neq y \\ 0 & else \end{cases} \tag{7}$$

where $Tx(g_i)$ represents the shape of texton for the neighbor pixel g_i, $Tx(g_c)$ represents the shape of texton for the center pixel g_c, $\otimes$ represents the XOR operation between the variables.

Eventually, the given texton image is converted to LTxXORP maps with values ranging from 0 to 2^P-1. After calculation of LTxXORP, the whole map is represented by building a histogram supported by Eq. (8).

$$H_{LTxXORP}(l) = \sum_{j=1}^{N_1}\sum_{k=1}^{N_2} f_2(LTxXORP(j,k), l); l \in [0, (2^P - 1)] \tag{8}$$

Figure 3 illustrates the detailed representation of LTxXORP for a given image.

3. Proposed system framework

3.1. Image retrieval system

In this paper, we integrate the concepts of texton and local binary patterns with XOR operation. First, the RGB image is converted into HSV and the V space is divided into overlapping 2×2 subblocks. Secondly, the texton operation is performed on each subblock and coded with the texton shape value to form the texton image. After calculation of the texton image, the XOR operation is performed between the center pixel and its surrounding neighbors in a texton image. The histograms are generated for texton XOR image and HSV color spaces. Finally, the feature vector is generated by concatenating the histograms. Figure 4 illustrates the flowchart of the proposed image retrieval system and the algorithm for the same is given as follows.

Algorithm:

Input: Image; Output: Retrieval result:

1. Load the RGB image and convert into HSV.
2. Calculate the texton image for V color space.
3. Collect the LTxXORPs for each pixel of texton image.
4. Calculate the histogram for LTxXORPs.
5. Compute the histograms for H, S and V color spaces.
6. Construct the feature vector by concatenating all histograms.

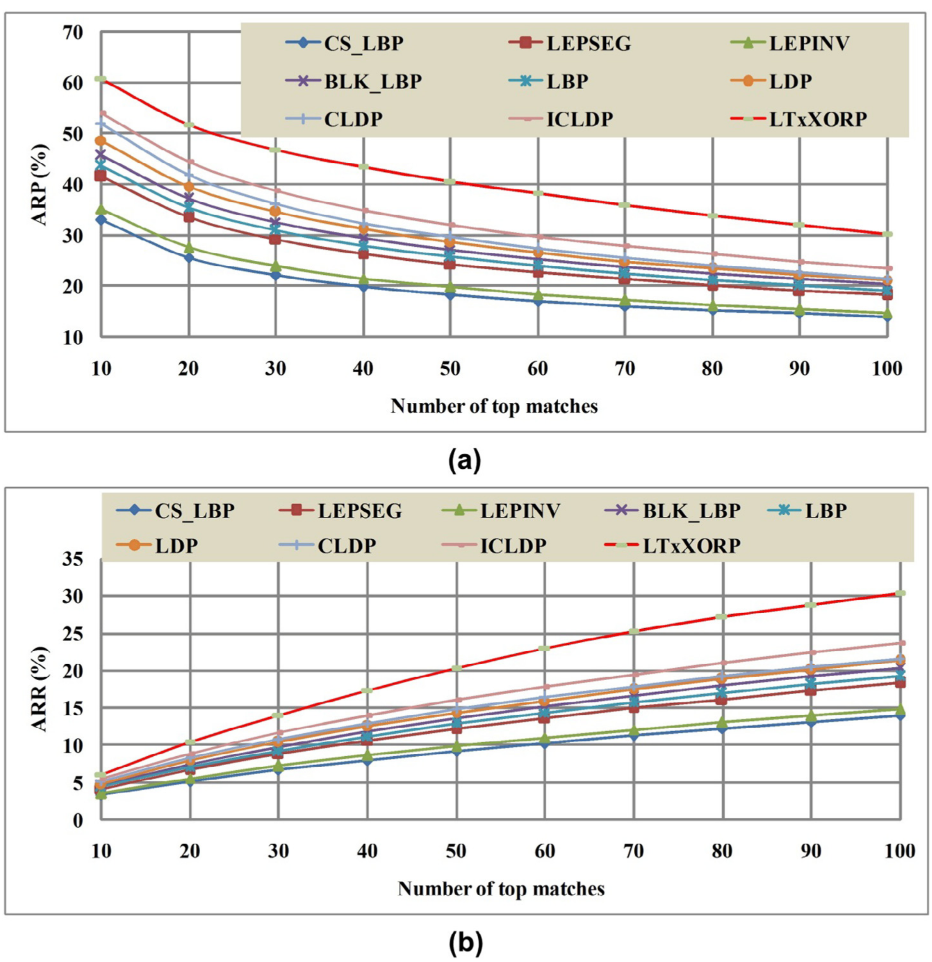


Fig. 12. Comparison of various methods in terms of ARP and ARR on Corel-5K database.

Fig. 13. Two examples of image retrieval by LTxXORP on Corel-5K database.

7. Compare the query image with the image in the database using similarity distance measure.
8. Retrieve the images based on the best matches.

Figure 5 illustrates the feature map which is extracted using the proposed feature extraction scheme.

3.2. Query matching

Feature vector for query image Q is represented as $f_Q = (f_{Q1}, f_{Q2}, \ldots\ldots\ldots f_{QLg})$ obtained after the feature extraction. Similarly each image in the database is represented with feature vector $f_{DBj} = (f_{DBj1}, f_{DBj2}, \ldots\ldots f_{DBjLg})$; $j = 1, 2, \ldots\ldots, |DB|$. The goal is to select n best images that resemble the query image. This involves selection of n top matched images by measuring the distance between the query image and the image in the database $|DB|$. In order to match the images we use four different similarity distance metrics as follows.

$$\textit{Manhattan distance measure}: D(Q, I_1) = \sum_{i=1}^{Lg} \left| f_{DBji} - f_{Q,i} \right| \tag{9}$$

$$\textit{Euclidean distance measure}: D(Q, I_1) = \left(\sum_{i=1}^{Lg} \left(f_{DBji} - f_{Q,i} \right)^2 \right)^{1/2} \tag{10}$$

$$\textit{Canberra distance measure}: D(Q, I_1) = \sum_{i=1}^{Lg} \frac{\left| f_{DBji} - f_{Q,i} \right|}{\left| f_{DBji} \right| + \left| f_{Q,i} \right|} \tag{11}$$

$$d_1 \textit{ distance measure}: D(Q, I_1) = \sum_{i=1}^{Lg} \left| \frac{f_{DBji} - f_{Q,i}}{1 + f_{DBji} + f_{Q,i}} \right| \tag{12}$$

where f_{DBji} is the i^{th} feature of the j^{th} image in the database $|DB|$.

4. Experimental results

The efficiency of the proposed method is tested by performing three experiments on benchmark databases. The databases which are used for evaluation are Corel-1K, Core-5K and Corel-10K.

In experiments #1, #2 and #3, images from Corel database [38] are used. The Corel database consists of great number of images of a variety of contents ranging from animals to outdoor sports to natural images. These images are pre-classified into different categories each of size 100 by area professionals. Some experts believe that the Corel database meets all the necessities to assess an image retrieval system due to its large size and mixed content.

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 calculated using Eq. (12). If the retrieved image $x_i = 1, 2, \ldots\ldots, n$ belongs to the same category as that of the query image then we say that the system has suitably identified the predictable image otherwise the system fails to find the predictable image.

The performance of the proposed method is evaluated in terms of average precision/average retrieval precision (ARP), average recall/average retrieval rate (ARR) as shown below:

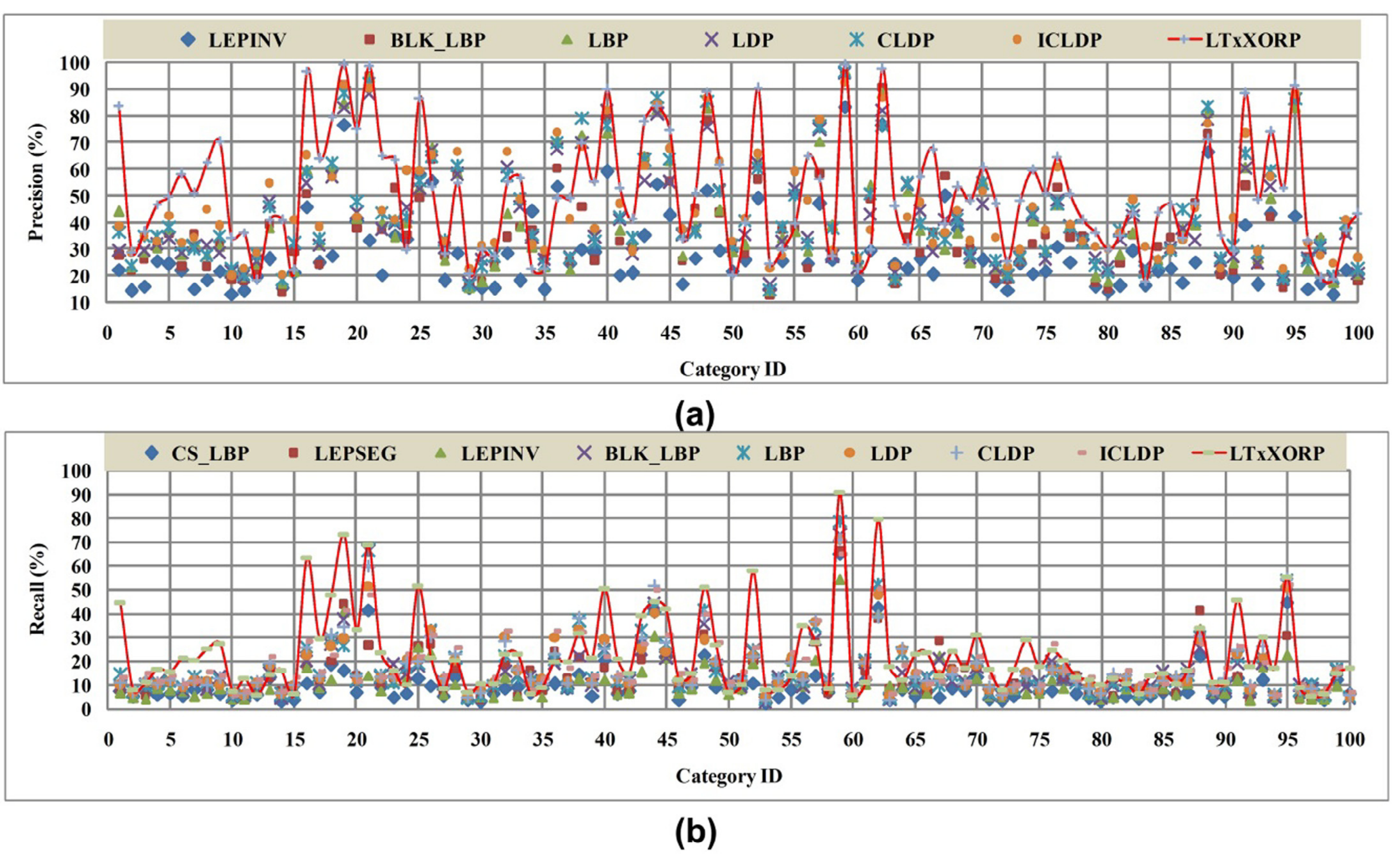


Fig. 14. Comparison of LTxXORP with other existing methods on Corel-10K. (a) Category-wise performance in terms of precision, (b) category-wise performance in terms of recall.

For the query image I_q, the precision is defined as follows:

$$Precision: P(I_q) = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ Number\ of\ images\ retrieved} \tag{13}$$

$$Average\ Retrieval\ Precision: ARP = \frac{1}{|DB|}\sum_{i=1}^{|DB|} P(I_i)\Big| \tag{14}$$

$$Recall: R(I_q) = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ Number\ of\ relevant\ images\ in\ the\ database} \tag{15}$$

$$Average\ Retreival\ Rate: ARR = \frac{1}{|DB|}\sum_{i=1}^{|DB|} R(I_i)\Big| \tag{16}$$

4.1. Corel-1K database

In this experiment, Corel-1K database [38] is used. For experimentation we selected 1000 images which are collected from 10 different domains and have 100 images per domain. The performance of the proposed method is measured in terms of ARP and ARR as shown in Eqs. (13–16). Figure 6 illustrates the sample images of Corel-1K database.

The performance of the various methods in terms of ARP on Corel-1K database is depicted in Fig. 7. Figure 8 illustrates the retrieval results of proposed method and other existing methods in terms of ARR on Corel-1K database. From Fig. 7 and Fig. 8, it is apparent that the proposed method shows a significant development as compared to the state-of-the-art methods in terms of precision, ARP, recall and ARR on Corel-1K database. Figure 9 illustrates the analysis of the proposed method (LTxXORP) with various similarity distance measures on Corel-1K database in terms of ARP. From Fig. 9, it is observed that the d_1 distance measure outperforms the other distance measures in terms of ARP on Corel-1K database. Figure 10 illustrates the query results of the proposed method on Corel-1K database.

4.2. Corel-5K database

The Corel-5K database contains 5000 natural images of 50 different categories. Each category contains 100 images. The 50 categories are natural images like, animals, peoples, beaches, buildings, buses, etc. The performance of the proposed image retrieval system is evaluated based on precision, recall, ARP and ARR.

Table 1 depicts the image retrieval results of the proposed method with various quantization levels of gray scale images on Corel-1K, Corel-5K and Corel-10K databases in terms of ARP. From Table 1, it is observed that the quantization levels 4 and 8 outperform the others in terms of ARP on Corel-1K, Corel-5K and Corel-10K database. The category-wise performance of the various methods in terms of average precision and average recall is illustrated in Fig. 11a and b respectively on the Corel-5K database. Further, the performance of the various methods is also evaluated in terms of ARP and ARR on the Corel-5K database. The ARP and ARR results are illustrated in Fig. 12a and b respectively.

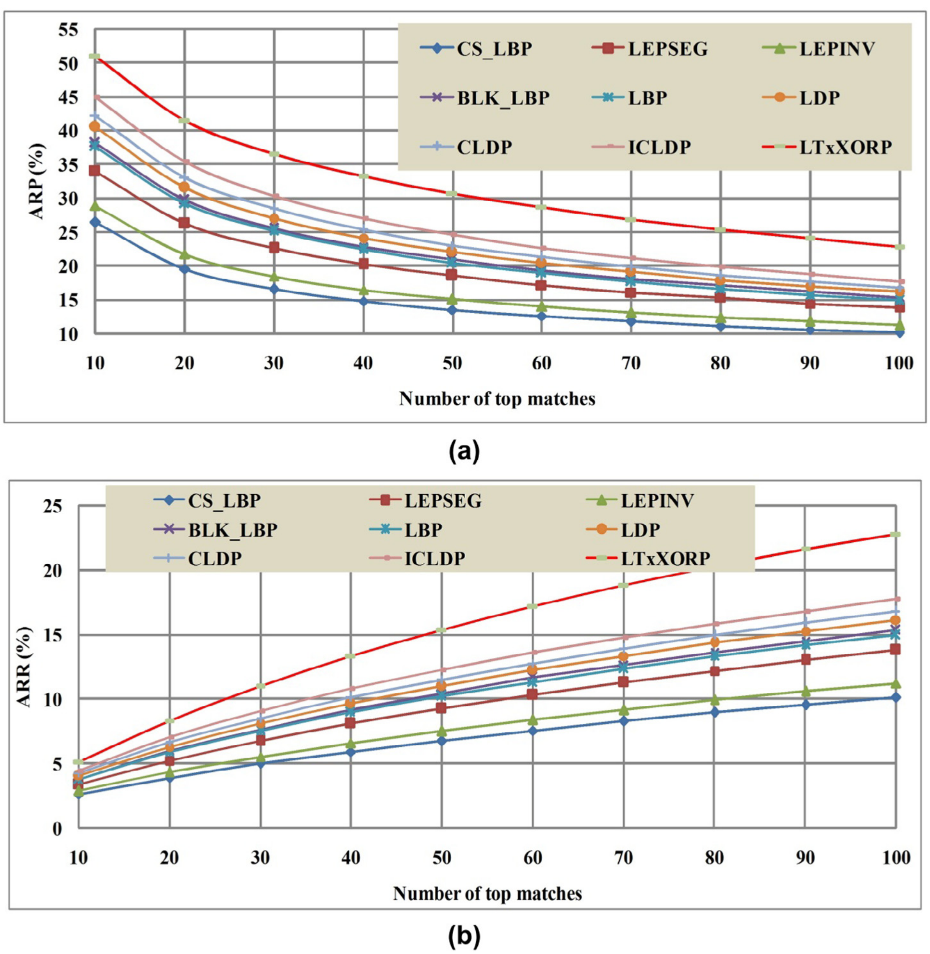


Fig. 15. Comparison of various methods in terms of ARP and ARR on Corel-10K database.

From Table 1, Fig. 11 and Fig. 12, it is evident that the proposed method shows a significant development as compared to the state-of-the-art methods in terms of their evaluation measures on Corel-5K database. Figure 13 depicts the query retrieval results of LTxXORP on Corel-5K database.

4.3. Corel-10K database

The Corel-10K database contains 10,000 natural images of 100 different categories. Each category contains 100 images. The performance of the proposed image retrieval system is evaluated based on precision, recall, ARP and ARR.

The category-wise performance of the various methods in terms of average precision and average recall is illustrated in Fig. 14a and b respectively on Corel-10K database. Further, the performance of the various methods is also evaluated in terms of ARP and ARR on Corel-10K database. The ARP and ARR results are illustrated in Fig. 15a and b respectively. From Fig. 14 and Fig. 15, it is evident that the proposed method shows a significant development as compared to the state-of-the-art methods in terms of their evaluation measures on Corel-10K database.

5. Conclusions

A new feature descriptor named, local texton XOR patterns (LTxXORP) for content-based image retrieval was proposed. The proposed method collects the texton XOR pattern which gives the structure of the query image or database image. The feature vector is constructed based on the LTxXORPs and HSV histograms. The performance of the proposed method is evaluated by testing on benchmark database, Corel-1K, Corel-5K and Corel-10K in terms of precision, recall, average retrieval precision (ARP) and average retrieval rate (ARR). The results after investigation show a significant improvement as compared to the state-of-the-art features for image retrieval.

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