Biomedical image retrieval using microscopic configuration with local structural information

G DEEP^{1,*}, L KAUR² and S GUPTA³

¹Department of Computer Science and Engineering, Chandigarh Engineering College (CEC), Landran, Punjab Technical University, Mohali 140307, India

²Department of Computer Engineering, Punjabi University, Patiala 147002, India

³Department of Computer Science and Engineering, University Institute of Engineering and Technology, Panjab University, Chandigarh 160014, India

e-mail: gaganpec@yahoo.com; mahal2k8@gmail.com; savita2k8@yahoo.com

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Abstract. This paper focusses on the use of microscopic configuration (MiC) for discriminative information to retrieve lung cancer images. Existing local binary pattern (*LBP*) detects the local structures, such as lighting spots and edges in images, whereas the local configuration pattern (*LCP*) explores multi-channel discriminative information of both the MiC and local structures of images. Both methods are used to extract the rotation- and scale-invariant features from all lung cancer images. The performance of these methods is tested by conducting experiments on benchmark biomedical database of Lung Image Database Consortium and Image Database Resource Initiative-computer tomography. The database includes CT images with region of interest. The results show that *LCP* yields significant improvement in terms of average retrieval precision and average retrieval rate as compared with *LBP* and other state-of-the-art texture descriptors.

Keywords. Image retrieval; local binary pattern; local configuration pattern; medical imaging; texture.

1. Introduction

Day by day, the importance of medical images is increasing in medical hospitals for patient diagnosis. The medical image data exist in different formats such as computer tomography (CT), magnetic resonance imaging (MRI), ultrasound (US) and X-ray. As we know that medical imaging is made up of dissimilar minor structures, there has been much interest of researchers in the development of well-structured techniques to work on huge image databases of biomedical images for efficient access, search and retrieval. To address this problem, content-based biomedical image retrieval came into existence. The content-based image retrieval (CBIR) uses the visual content features such as colour, texture, shape, spatial layout, etc. of regions or objects to represent and index the biomedical image database for efficient retrieval. The previously available image retrieval systems are presented by Giuliano *et al* [1], Michalis *et al* [2], An *et al* [3], Gianluca *et al* [4], Sihyoung *et al* [5] and Yue *et al* [6].

The main step of the CBIR is feature extraction, the effectiveness of which rests upon the method derived for extracting features from given images. The visual content descriptors are either global or local. A global descriptor

represents the visual features of the whole image, whereas a local descriptor represents the visual features of regions or objects to describe the image. These features are arranged as multi-dimensional feature vectors and stored in the feature database. The selection of feature descriptors affects the image retrieval performance.

In early years, Manjunath *et al* [7] used features based on intensity histogram for biomedical image retrieval. However, their retrieval performance is usually limited especially on large databases due to lack of discrimination power of such descriptors. To address this problem, texture-based features have been proposed for biomedical image retrieval. They are extensively used in the image processing applications to identify the visual patterns. Most of the biomedical images represented in greyscale are extensively textured in common. Hence, in clinical exams, the appearance of organ/tissue/lesion in the images is due to intensity variations laid on various texture characteristics. Thereafter, texture became very popular in biomedical image retrieval because of eminent significance of acquired texture. For the texture analysis, the local binary pattern (*LBP*) by Ojala *et al* [8] is proposed. *LBP* has low computational complexity and capacity of coding minute specifications. Ojala *et al* [9] advocated some more moderations in *LBP* for texture classifications. In the field of medicine, Oliver *et al* [10] used *LBP* descriptor for mammogram images and Unay and Ekin [11] introduced a

*For correspondence

Figure 1. Example of obtaining LBP for 3×3 neighbourhoods (adopted from Ojala *et al* [9]).

powerful search and retrieval method that used *LBP* with Support Vector Machines (SVMs) to find relevant slices in brain magnetic resonance volumes. Keramidas *et al* [12] have given texture representation on thyroid US images. Nanni and Lumini [13, 14] used *LBP* to automate the cell phenotype image classification. In the area of face classification, Nanni and Lumini [15] and Ahonen *et al* [16] have extensively worked on *LBP*. Guo *et al* [17] proposed the rotation-invariant *LBP* variance operator for texture classification. In some important works, Nanni and Lumini [18] and Shang and Veldhuis [19] have also successfully experimented *LBP* in other useful applications. More on *LBP* can be explored at http://www.ee.oulu.fi/mvg/page/lbp_bibliography#biomedical.

For richer and more detailed information from normal texture databases, Guo *et al* [20] proposed local configuration pattern (*LCP*) by integrating the microscopic configuration (*MiC*) information with local structural information of *LBP* descriptor. Image *MiC* contains robust and reliable discriminative information, which has improved the classification performance. The robustness of *LCPs* against illumination variations and image rotation is strongly implied. In literature, Murala *et al* [21–24] and Murala and Jonathan [25, 26] had proposed many extended versions of *LBP* to derive new image features for biomedical image indexing and retrieval. In this paper, discrimination power of *LBP* and *LCP* has motivated us to use the biomedical images for image retrieval.

The organization of the paper is as follows. In section 1, a brief review of medical image retrieval and related work is given. A concise review of local patterns can be further visualized in section 2. The retrieval system analysis and framework of the existing descriptors are presented in section 3. Experimental results and discussion are presented in section 4. Finally, the concluding remarks are given in section 5.

2. Local patterns

2.1 LBP formulation

The *LBP* was first introduced by Ojala *et al* [9] for rotation-invariant texture classification. The *LBP* is a very efficient texture descriptor due to its discriminative power and computational simplicity. I is a greyscale image of size $n \times m$ pixels and $I(g)$ denotes the grey level of the g th pixel in the image I . The *LBP* operator is calculated at each pixel by evaluating the binary differences of the values in a small circular neighbourhood (with radius R) around the value of a central pixel, g_c . Mathematically, the *LBP* value of current pixel is

$$LBP_{P,R} = \sum_{p=0}^{P-1} f_1(g_p - g_c) 2^p, \quad f_1(x) = \begin{cases} 1 & \text{if } x \geq 0; \\ 0 & \text{otherwise;} \end{cases} \quad (1)$$

where g_c is the grey value of the central pixel, g_p are the grey values of the circularly symmetric neighbourhood g_p ($p = 0, \dots, P-1$), P is the image pixels in the circle of radius R ($R > 0$) and 2^p is the binomial factor for each sign $f_1(g_p - g_c)$.

A histogram is generated to represent the texture image after finding the *LBP* code of each pixel in the image. Figure 1 shows how a texton and *LBP* code are derived; the *LBP* takes the 3×3 neighbourhood of a central pixel and generates a binary 1 if the neighbour of that pixel has a larger value; otherwise, it produces a binary 0. An *LBP* code for a neighbourhood is produced by multiplying the threshold values with weights given to the corresponding pixels, and summing up the result. Thus, each *LBP* is regarded as a micro-texton in Ojala *et al* [9].

Local textons include spots, flat areas, edges, line ends and corners. Figure 2 shows the different texture primitives

Figure 2. Different texture primitives (spot, spot/flat, line end, edge and corner) detected by the uniform patterns of *LBP* (Ojala *et al* [9]).

Figure 3. Sample patterns to analyse the performance: intensity variations ($g_c - g_i$) between the central pixel and neighbourhood. Here, g_c denotes the intensity of the central pixel and g_i ($i = 0, \dots, 7$) denotes the intensities of neighbourhood pixels.

detected by the uniform patterns of *LBP*. In the figure, grey circle indicates the central pixel, black and white circles correspond to bit values of 0 and 1 in the different patterns of the operator.

2.1a Rotation invariance [9]: To remove the effect of rotation, each *LBP* code must be rotated back to a reference position, effectively making all rotated versions of a binary code the same. This transformation is defined as follows:

$$LBP_{P,R}^{ri} = \min \{ROR(LBP_{P,R}, i) | i = 0, \dots, P-1\} \quad (2)$$

where the superscript ‘*ri*’ stands for ‘rotation invariant’; the function $ROR(x, i)$ performs ‘*i*’ times bit-wise circular right shift on the P -bit binary number, x . In terms of image pixels, this simply corresponds to rotating the neighbour set clockwise so as to get maximum number of zeros in the beginning of the binary string; ‘min’ operator will just take the minimum decimal values from different patterns.

2.1b Uniform pattern [9]: Sometimes, rotation-invariant patterns cannot give good discrimination. Some patterns among rotation-invariant patterns are dominant, and are fundamental properties of texture. The patterns are considered uniform if the number of transitions between 0 and 1 is less than or equal to two in the circular binary code. This operator is called $LBP_{P,R}^{riu2}$. Patterns are considered non-

uniform if they contain the main part of the noise of the images. A region with no transitions is considered as a background or a flat region of the image. The *LBP* feature vector is extracted from each cell and is the histogram of dimension $P + 2$ (a single bin for non-uniform patterns). $LBP_{P,R}^{riu2}$ operator is formally defined as follows:

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c) & \text{if } U(LBP_{P,R}) \leq 2, \\ P + 1 & \text{otherwise,} \end{cases} \quad (3)$$

where

$$U(LBP_{P,R}) = |s(g_{P-1} - g_c) - s(g_0 - g_c)| + \sum_{p=0}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)| \quad (4)$$

where superscript ‘*riu2*’ denotes the rotation-invariant ‘uniform’ patterns that have U values that are at most 2. Therefore, mapping from $LBP_{P,R}$ to $LBP_{P,R}^{riu2}$ results in only $p + 1$ distinct groups of patterns, leading to a much shorter histogram representation for the whole image. To achieve rotation invariance, a Look-Up Table (LUT) is used. The LUT stores all the possible uniform patterns along with their unique $LBP_{8,R}^{riu2}$ code.

In conventional *LBP* the central pixel is discarded (despite the implicit use of the intensity of the central pixel as the threshold to achieve local grey-scale invariance), and only the joint distribution of the neighbourhood around each pixel is considered. The *LBP* oversimplifies local structure and loses textural information. Therefore, Ojala *et al* [9] made a correction by including the local contrast of each pattern and proposing a complementary local descriptor called $VAR_{P,R}$. Using the joint histogram of $LBP_{P,R}^{riu2}$ and $VAR_{P,R}$, denoted as $LBP_{P,R}^{riu2}/VAR_{P,R}$ (aka *LBPV*), a powerful tool for rotation-invariant texture classification is

$$VAR_{P,R} = \frac{1}{P} \sum_{p=0}^{P-1} (g_p - \mu)^2, \text{ where } \mu = \frac{1}{P} \sum_{p=0}^{P-1} g_p \quad (5)$$

2.2 LCPs [20]

Guo *et al* [20] proposed an *LCP* descriptor for texture image description by combining information with *LBP*. The descriptor provides the information of images in two parts: (1) local structural information and (2) MiC information that involves image configuration and pixel-wise interaction relationships. *LBP* is used to extract the local structural information and construct pattern occurrence histograms of images, whereas MiC information is explored by encoding linear relationships among neighbouring pixels. However, *LBP*-based local features show the same pattern type of figure 3a and b while their textural surfaces are totally different from each other.

By incorporating *LBP* with local variance information [9], patterns could be distinguished, while patterns in figure 3b and c would still be considered as the same pattern type because of the same variance. However, they are actually two patterns with different textural properties. Therefore, higher discriminator power than local variance is included by encoding both the magnitude information and pixel-wise interaction relationships for effective image representation in the retrieval framework.

2.2a Discriminative representation by microscopic information (adopted from Guo *et al* [20]): We aim to model pixel-wise interaction relationships with respect to each rotation-invariant uniform pattern. To be specific, we estimate optimal weights associated with intensities of neighbouring pixels to linearly reconstruct the central pixel intensity for each pattern type. This is expressed by the relation

$$E(a_0, \dots, a_{P-1}) = \left| g_c - \sum_{i=0}^{P-1} a_i g_i \right| \quad (6)$$

In this formula, a_i ($i = 0, \dots, P-1$) are weighting parameters associated with g_i , and $E(a_0, \dots, a_{P-1})$ is the reconstruction error regarding model parameters a_i ($i = 0,$

$\dots, P-1$). To minimize the reconstruction error for each pattern, optimal parameters are determined by the least squares estimation as presented by Roweis and Saul [27].

Least squares estimation: For a given image I , suppose the occurrence of a particular pattern type L is N_L , which means there are N_L pixels in I with the pattern type L . The label code is calculated by Eq. (1) or (3), depending on what kind of patterns is of interest. We denote the intensities of these N_L pixels as $c_{L,i}$ ($i = 0, \dots, N_L - 1$), and organize them into a vector:

$$C_L = \begin{pmatrix} C_{L,0} \\ C_{L,1} \\ \vdots \\ C_{L,N_L-1} \end{pmatrix}. \quad (7)$$

The intensities of their neighbouring pixels $v_{i;0}, \dots, v_{i;P-1}$ ($i = 0, \dots, N_L - 1$) can thus be organized as follows:

$$V_L = \begin{pmatrix} v_{0;0}v_{0;1} \dots v_{0;P-1} \\ v_{1;0}v_{1;1} \dots v_{1;P-1} \\ \vdots \\ v_{N_L-1;0}v_{N_L-1;1} \dots v_{N_L-1;P-1} \end{pmatrix} \quad (8)$$

In order to minimize the reconstruction error in Eq. (6), the unknown parameters a_i ($i = 0, \dots, P-1$) are constructed as a column vector:

$$A_L = \begin{pmatrix} a_0 \\ a_1 \\ \vdots \\ a_{P-1} \end{pmatrix} \quad (9)$$

In this way, the problem becomes a least-square problem $C_L = V_L A_L$. When the system is over-determined, optimal parameter vector A_L is determined by the relation

$$A_L = (V_L^T V_L)^{-1} V_L^T C_L. \quad (10)$$

Otherwise, when $N_L \leq P$, the pattern L rarely occurs; hence, it would be considered as a non-reliable pattern to serve as a feature. In this case, each entry of the parameter vector will be set to zero. By considering the pixel-wise interaction, the parameter vectors of different patterns shown in figure 3b and c would not be the same since each entry of A_L changes according to the relative neighbourhood positions. Therefore, the obtained feature is capable of capturing both the information of magnitude and pixel-wise interactions, which makes it more discriminative than the previous representation.

Rotation-invariant analysis: In the area of texture analysis, rotation-invariant analysis is a widely studied problem, which aims at providing texture features that are invariant to rotation angle of the input image. To produce

Figure 4. (a) Two sample images. (b, c) Comparison of various features on two sample images from LIDC-IDRI-CT database.

rotation-invariant features, we apply 1D Fourier transform to the estimated parameter vector A_L . The transformed vector is expressed by the relation

$$H_L(k) = \sum_{i=0}^{P-1} A_L(i) e^{-\frac{j2\pi ki}{P}} \quad (11)$$

where $H_L(k)$ is the k^{th} element of H_L and $A_L(i)$ is the i^{th} element of A_L . Although image rotation would lead to cyclic translations of A_L , Fourier transform is invariant to this kind of translations so that H_L can achieve rotation-invariant property. The magnitude part of vector H_L is taken as the MiC feature, which is defined by the relation

$$|H_L| = [|H_L(0)|; |H_L(1)|; \dots; |H_L(P-1)|]. \quad (12)$$

Considering that $|H_L|$ encodes the image configuration and pixel-wise interaction relationship of each specific pattern, it together with pattern occurrences of *LBP*s would construct a complementary feature for both the discrimination of MiC and local structures. In this way, the final feature is

$$LCP = [|H_0|; O_0]; [|H_1|; O_1]; \dots; [|H_{q-1}|; O_{q-1}] \quad (13)$$

where $|H_i|$ is calculated by Eq. (12) with respect to the i^{th} pattern of interest, $|O_i|$ is the occurrence of the i^{th} local

pattern of interest (i.e., the *LBP*) and q is the total number of patterns of interest. Moreover, multi-scale analysis is achieved by combining *LCP*s with different radii and neighbouring samples.

3. Retrieval analysis and framework

In the literature, it is observed that the pattern-based features are analysed on normal texture databases. Hence, in this paper, the effectiveness of *LCP* over *LBP* and other existing texture patterns is analysed by conducting experiments on biomedical databases.

3.1 Analysis

Figure 4 illustrates the comparison between the various features on two sample images as shown in figure 4a, which are selected from the different categories of Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI)-CT database. By visualization we can identify that the sample images are not similar. The histograms of both images (two sample images) using *LBP* methods as in figure 4b are almost similar. However, the histograms of both images using *LCP* are not similar, which

Figure 5. Retrieval framework.

can be seen in figure 4c. From figure 4, it is clear that the *LCP* method is able to differentiate the two sample images as compared with *LBP*.

3.2 System framework

Figure 5 illustrates the framework of the proposed analysis system and algorithm for the same is given as follows.

Algorithm.

Input: Query image;

Output: Retrieval results

1. Load the query image.
2. Calculate the *LBP* features at R and $R + 1$ with respect to the central pixel.
3. Also calculate the *LCP* features at R and $R + 1$ with respect to the central pixel.
4. Form feature vectors of calculated values from *LBP* and *LCP*.
5. First, using *LBP* feature vectors of images, compare the query image with the images in the database using similarity measure.
6. Second, using *LCP* feature vectors, compare the query image with the images in the database using similarity measure.
7. Retrieve the images based on the best matches.

This algorithm is applied on the database LIDC-IDRI-CT for best matches. Finally, results from these two methods are compared.

3.3 Similarity measure

The representation of feature vector of query image Q is $f_Q = (f_{Q_1}, f_{Q_2}, \dots, f_{Q_{L_g}})$ acquired after the feature extraction. Likewise, dataset $|DB|$ of all medical images is represented with feature vectors $f_{DB_j} = (f_{DB_{j1}}, f_{DB_{j2}}, \dots, f_{DB_{jL_g}}); j = 1, 2, \dots, |DB|$. However, the only purpose here is to obtain n top match images by measuring the distance between query image and image in the dataset $|DB|$. Finally, n best images are displayed that are similar to the query image.

In this paper, Euclidean distance measure is used as similarity distance metrics and this is shown as follows:

$$D(Q, DB) = \left(\sum_{i=1}^{L_g} (f_{DB_{ji}} - f_{Q_i})^2 \right)^{\frac{1}{2}} \quad (14)$$

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

3.4 Evaluation measures (adopted from Murala and Jonathan [25])

For performance evaluation, the average retrieval precision (ARP) and average retrieval rate (ARR) are used. Murala and Jonathan [25] defined the precision (P) and recall (R) for the query image I_q , as follows:

$$\text{precision} : P(I_q) = \frac{\text{number of relevant images retrieved}}{\text{total number of images retrieved}} \quad (15)$$

$$ARP = \frac{1}{|DB|} \sum_{i=1}^{|DB|} P(I_i) |_{n \leq 10} \quad (16)$$

$$\text{recall} : R(I_q) = \frac{\text{number of relevant images retrieved}}{\text{total number of relevant images in the database}} \quad (17)$$

$$ARR = \frac{1}{|DB|} \sum_{i=1}^{|DB|} R(I_i) |_{n \geq 10}. \quad (18)$$

3.5 Abbreviations

The abbreviations used in the analysis are the following:

<i>LBP</i>	local binary patterns as defined in Ojala <i>et al</i> [8, 9]
$LBP_{1,8}^{u2}$	<i>LBP</i> with uniform patterns at (1, 8) neighbourhood size
$LBP_{1,8}^{u2}/VAR_{1,8}$	<i>LBP</i> with uniform patterns at (1, 8) neighbourhood size with variance information
$LBP_{1,8}^{riu2}$	<i>LBP</i> with rotation-invariant uniform patterns at (1, 8) neighbourhood size

$LBP_{1,8}^{riu2}/VAR_{1,8}$

LPQ

LQP

BGP

BSIF

WLD

SIFT

GLCM

LCP

$LCP_{1,8}^{riu2}$

$LCP_{2,8}^{riu2}$

$LCP_{2,16}^{riu2}$

LBP with rotation-invariant uniform patterns at (1, 8) neighbourhood size with variance information

local phase quantization as defined in Ojansivu and Heikkila [28]

local quinary patterns as defined in Nanni *et al* [29]

binary Gabor patterns as defined in Zhang *et al* [30]

binarized statistical image features as defined in [31]

Weber law descriptor as defined in Chen *et al* [32]

scale-invariant feature transform as defined in Lowe [33]

Grey level co-occurrence matrix as defined in Haralick *et al* [34]

Local configuration patterns as defined in Guo *et al* [20]

LCP with rotation-invariant uniform patterns at (1, 8) neighbourhood size

LCP with rotation-invariant uniform patterns at (2, 8) neighbourhood size

LCP with rotation-invariant uniform patterns at (2, 16) neighbourhood size

Table 1. Data acquisition details of LIDC-IDRI-CT image database.

Case no.	Data	No. of slices	No. of images	Resolution	Slice thickness (mm)	Tube voltage (kV)	Tube current (mA)
1	LIDC-IDRI-0002	20	40	512 × 512	1.3	120	440
2	LIDC-IDRI-0003	10	40	512 × 512	2.5	120	300
3	LIDC-IDRI-0006	20	80	512 × 512	1.3	120	440
4	LIDC-IDRI-0007	21	84	512 × 512	1.3	120	440
5	LIDC-IDRI-0010	15	60	512 × 512	1.3	120	401
6	LIDC-IDRI-0011	27	108	512 × 512	2.5	120	265
7	LIDC-IDRI-0012	20	80	512 × 512	2.5	120	300
8	LIDC-IDRI-0013	18	72	512 × 512	2.5	120	320
9	LIDC-IDRI-0014	07	28	512 × 512	2.5	120	300
10	LIDC-IDRI-0015	19	76	512 × 512	1.3	120	361
11	LIDC-IDRI-0016	26	104	512 × 512	2.5	120	265
12	LIDC-IDRI-0017	26	104	512 × 512	2.5	120	265

Figure 6. Sample images from LIDC-IDRI-CT image database.

4. Experimental results and discussion

The performance of the various methods is analysed for biomedical image retrieval by conducting experiments on medical database. The database includes CT images with region of interest (ROI). The results show that *LCP* yields significant improvement in terms of *ARP* and *ARR* as compared with *LBP* and other existing texture descriptors. In all the experiments, each image in the database is chosen as the query image. For each query image, the system collects n database images $X = (x_1, x_2, \dots, x_n)$, with the shortest image matching distance (Eq. (14)). If x_i ; $i = 1, 2, \dots, n$ are associated with the same category of the query image, we can say that the system has correctly matched the desired.

4.1 Experiment set 1

Due to high robustness and reliable discriminative information of *LCP*, it has given overwhelming retrieval performance over *LBP*. To evaluate the performance of *LCP* method, experiments are conducted on the images collected from Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI), which is a public lung image database of CT scans provided by Kascic [35] and NEMA-CT online image database [36]. The database is separated into 84 cases, each containing around 100–400 Digital Imaging and Communication (DICOM) images and an XML data file containing the physicians' annotations. The database contains 143 nodules having size range of 3–30mm (to be manually

segmented by radiologists). The CT lung images (512×512) from the database are converted into 'tif' image format for rapid processing with the use of Lamport's LIDC 2 image toolbox [37] (available online). Radiologists detected the locations of nodules, which have also been provided. Furthermore, ROIs were annotated manually from each slice from some patients to construct the ROI CT image database. For the experiment, 12 patient cases consisting of 75 nodules (26 benign and 49 malignant) and 229 slices have been selected. The CT scan data acquisition details are given in table 1. Figure 6 depicts the sample lung nodule images of LIDC-IDRI-CT database (one image from each patient scan).

Table 2 shows the performance of various methods on LIDC-IDRI-CT database in terms of *ARP* by passing different query images. Figure 7a shows the retrieval performance in terms of *ARP* of all the methods ($LBP_{1,8}^{u2}$, $LBP_{1,8}^{u2}/VAR_{1,8}$, $LBP_{1,8}^{riu2}$, $LBP_{1,8}^{riu2}/VAR_{1,8}$, $LCP_{1,8}^{riu2}$, $LCP_{2,8}^{riu2}$, $LCP_{2,16}^{riu2}$) as a function of number of top matches. Comparison performance of the $LCP_{2,16}^{riu2}$ over other methods as a function of number of top matches is also given in figure 7b in terms of *ARR* on the database. In the results, $LCP_{2,16}^{riu2}$ and $LCP_{2,8}^{riu2}$ show better performance than that of *LBP* on different values of P , R because *LCPs* also extract more microscopic pattern information from this database. Figure 7b and table 3 summarize the performance of *LCP* with *LBP* on different values of P and R . From here, it is observed that *LCP* values on the specific radius $R = 2$ and $P = 16$ show overwhelming response than $LCP_{1,8}^{riu2}$, $LCP_{2,8}^{riu2}$. Figure 8 illustrates three query results of *LBP* and *LCP* by considering 10 top matches on LIDC-IDRI-CT database. In each result, top row presents the query image.

4.1a LCP over other existing methods on LIDC-IDRI-CT: Further, the results of *LCP* method over other existing methods (*LPQ*, *LQP*, *BGP*, *BSIF*, *GLCM*, *WLD*, *SIFT*) are compared and it is observed that it gives outstanding

Table 2. Performance of various methods by passing different query images in terms of *ARP* on LIDC-IDRI-CT database.

Query images	ARP						
	$LBP_{1,8}^{u2}$	$LBP_{1,8}^{u2}/VAR_{1,8}$	$LBP_{1,8}^{riu2}$	$LBP_{1,8}^{riu2}/VAR_{1,8}$	$LCP_{1,8}^{riu2}$	$LCP_{2,8}^{riu2}$	$LCP_{2,16}^{riu2}$
Query image 1	0.7032	0.7036	0.7823	0.7823	0.7462	1.0000	1.0000
Query image 2	0.8274	1.0000	0.9765	0.9765	1.0000	1.0000	1.0000
Query image 3	0.7143	0.4585	0.5022	0.5022	1.0000	0.7917	0.5423
Query image 4	0.6111	0.3674	0.5889	0.5889	0.7226	0.7481	1.0000
Query image 5	1.0000	0.6428	1.0000	1.0000	0.2111	0.7024	1.0000
Query image 6	0.9468	0.6188	0.7972	0.7972	0.7885	0.7024	1.0000
Query image 7	0.8553	0.5954	0.7167	0.7167	0.8357	0.9107	1.0000
Query image 8	1.0000	0.7889	0.9283	0.9283	0.1944	0.7254	1.0000
Query image 9	0.3696	0.2917	0.2897	0.2897	0.8486	0.2500	0.8523
Query image 10	0.1000	0.2500	0	0	0.8972	1.0000	1.0000

(a)

(b)

Figure 7. (a) Graphical performance analysis of various methods as function of number of top matches (1–10) in terms of ARP and (b) comparison of the $LCP_{2,16}^{riu2}$ over other methods as function of number of top matches (1–10) in terms of ARR on LIDC-IDRI-CT database.

Table 3. Performance analysis of various methods in terms of ARR on LIDC-IDRI-CT database.

Method	ARR
$LBP_{1,8}^{u2}$	0.7128
$LBP_{1,8}^{u2}/VAR_{1,8}$	0.5717
$LBP_{1,8}^{riu2}$	0.6582
$LBP_{1,8}^{riu2}/VAR_{1,8}$	0.6582
$LCP_{1,8}^{riu2}$	0.7244
$LCP_{2,8}^{riu2}$	0.7831
$LCP_{2,16}^{riu2}$	0.9395

performance. The performance of LCP over other existing texture descriptors is shown in tables 4 and 5 and figure 9.

4.2 Feature vector length V/S performance

Table 6 shows the feature vector length for a given query image using $LBP_{1,8}^{u2}$, $LBP_{1,8}^{u2}/VAR_{1,8}$, $LBP_{1,8}^{riu2}$, $LBP_{1,8}^{riu2}/VAR_{1,8}$, $LCP_{1,8}^{riu2}$, $LCP_{2,8}^{riu2}$, $LCP_{2,16}^{riu2}$. The experimentation is carried out on a core2 Quad computer with 2.66 GHz, 4 GB of memory and all methods are implemented on the MATLAB software. From table 6, it is clear that the feature vector length of

Figure 8. Query results on LIDC-IDRI-CT database (a–c) through *LBP* and *LCP*, respectively.

Table 4. Performance of various methods by passing different query images in terms of *ARP* on LIDC-IDRI-CT database.

Query images	<i>ARP</i>									
	$LBP^{u2}_{1,8}$	$LBP^{u2}_{1,8}/VAR_{1,8}$	$LBP^{riu2}_{1,8}$	$LBP^{riu2}_{1,8}/VAR_{1,8}$	LQP	BGP	$BSIF$	$GLCM$	WLD	$SIFT$
Query image 1	0.7032	0.7036	0.7823	0.7823	0.8073	1	0.8	0.9095	0.7608	0
Query image 2	0.8274	1.0000	0.9765	0.9765	0.8783	1	0.3407	0.725	1	0.7036
Query image 3	0.7143	0.4585	0.5022	0.5022	0.5709	1	0.225	0.3562	1	0
Query image 4	0.6111	0.3674	0.5889	0.5889	0.8835	0	0.8803	0.5271	0.4083	1
Query image 5	1.0000	0.6428	1.0000	1.0000	0.6185	1	0.6718	0.7327	0.9318	1
Query image 6	0.9468	0.6188	0.7972	0.7972	0.7261	1	0.875	0.6079	0.8339	0.8084
Query image 7	0.8553	0.5954	0.7167	0.7167	0.7608	1	1	0.6185	0.9318	1
Query image 8	1.0000	0.7889	0.9283	0.9283	0.7233	1	0.5444	0.8264	1	1
Query image 9	0.3696	0.2917	0.2897	0.2897	0.7327	0	0.9765	0.7071	0.1111	0.3556
Query image 10	0.1000	0.2500	0	0	0.9526	0	1	0.8667	0.1111	0.6079

Table 5. Performance analysis of various methods in terms of *ARR* on LIDC-IDRI-CT database.

Method	<i>ARR</i>
$LBP^{u2}_{1,8}$	0.7128
$LBP^{u2}_{1,8}/VAR_{1,8}$	0.5717
$LBP^{riu2}_{1,8}$	0.6582
$LBP^{riu2}_{1,8}/VAR_{1,8}$	0.6582
LQP	0.8046
LQP	0.7654
BGP	0.7000
$BSIF$	0.7314
$GLCM$	0.6877
WLD	0.7089
$SIFT$	0.6475
$LCP^{riu2}_{1,8}$	0.7244
$LCP^{riu2}_{2,8}$	0.7831
$LCP^{riu2}_{2,16}$	0.9395

Table 6. Feature vector length of query image using various methods.

Method	Feature vector length
$LBP^{u2}_{1,8}$	59
$LBP^{u2}_{1,8}/VAR_{1,8}$	59
$LBP^{riu2}_{1,8}$	38
$LBP^{riu2}_{1,8}/VAR_{1,8}$	38
$LCP^{riu2}_{1,8}$	81
$LCP^{riu2}_{2,8}$	81
$LCP^{riu2}_{2,16}$	289

$LCP^{riu2}_{2,16}$ is more as compared with LBP , as it outperforms in terms of *ARP* and *ARR* on biomedical database.

5. Conclusions

In this paper, the applicability of existing *LCP* image indexing and retrieval algorithm is analysed. The *LCP* explores multi-channel discriminative information of both the MiC and local structures of an image. The performance of the *LCP* method is also analysed with different configuration pattern values on different radii and neighbourhood sizes. The performance improvement has been compared with the *LBP* on benchmark biomedical image database. The result shows a significant improvement in terms of precision, recall, *ARR* and *ARP* as compared with *LBP* and other existing texture descriptors on LIDC-IDRI-CT database.

The generality of the *LCP* descriptor is validated across one benchmark biomedical database. In future experiments, the same descriptor can be compared in other biomedical or ordinary datasets against state of the art descriptors.

(a)

(b)

Figure 9. (a) Graphical performance analysis of various methods as function of number of top matches (1–10) in terms of ARP and (b) comparison of the $LCP_{2,16}^{riu2}$ over other existing texture descriptors as function of number of top matches (1–10) in terms of ARR on LIDC-IDRI-CT database.

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