CENTRE SYMMETRIC DIRECTIONAL LOCAL EDGE BASED PATTERN: A NEW TEXTURE DESCRIPTOR FOR IMAGE RETRIEVAL

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Abstract

In this paper, a new texture descriptor encodes the pixel intensity difference and directional information for content based image retrieval (CBIR).The proposed method Centre Symmetric Directional Local Edge based Pattern (CSDLEP) is similar to the existing LBP and includes edge information by taking forward difference of centre symmetric neighbour pixels and centre pixel in 0◦, 45◦, 90◦, and 135◦ directions in an image. Performance of this pattern is compared with LBP, LDP, LDP and DLEP transform domain methods by conducting five experiments on benchmark databases viz. Corel -10K, Brodatz, STex, MIT-VIS and AT&T databases. The results after being investigated show a significant improvement in terms of their evaluation measures as compared with other existing methods on respective databases.

Keywords: Texture descriptor, content based image retrieval, local binary pattern and Edge based directional information

1.Introduction

With the proliferation of digital devices and the fast development of Internet Technology, billions of people are projected to the Web sharing and browsing images. The ubiquitous access of online and offline images in various fields, e.g., education, news, entertainment, etc, sheds bright light on many emerging applications based on image search. Hence, image retrieval i.e. searching, browsing and retrieving similar images from a large collection of images has become a real challenge. The effectiveness of the image retrieval system mainly depends on feature extraction which is the technique adopted for extracting the features from a given image. The inherent contents of the image such as shape, color, texture, etc., are used to retrieve the images from the repository. An exhaustive and detailed description of image retrieval methods is available in Gai et al.[1], Shi et al.[2] , Smeulders et al.[3], Tang et al. [4], Rui and Huang [5]. Texture and color analysis are the major fields in the image retrieval process. Texture analysis and retrieval has gained wide attention in the field of medical, industrial, document analysis and many more. In the past few years, numerous researches have been done on content based image retrieval based on texture analysis. Texture is dependent on the local intensity of image, hence statistical features and local neighbourhood features are discovered for texture pattern. Many local patterns for image retrieval have been proposed by researchers, but most of the local patterns considered the frequency of each pattern in the image. And derived feature vector from its histogram. But probability gives information, only regarding to the occurrence of the pattern alone, and it does not reveal any information regarding the direction mutual occurrence of patterns in the image.

2. Related work

The recently proposed local binary pattern (LBP) [6] features are originally designed for texture description, which is advantageous for its computational simplicity and its efficacy in monotonic illumination changes. Later local binary patterns have been enhanced for rotational invariant texture classification [7]. Pietikainen et al. [8] proposed the rotational invariant texture classification using feature distributions. Zhao and Pietikainen [9] applied LBP in face recognition and analysis. Heikkil and Pietikainen [10] used LBP for background modelling and detection by using LBP. Li and Staunton [11] proposed a combination of LBP and Gabor filter for texture segmentation. By considering LBP as a non-directional 1st order spatial pattern, Zhang et al. [12] presented local derivative pattern for face recognition areas. A modified version of LBP called center-symmetric LBP, combined with scale invariant feature transform (SIFT) has been used to describe interest region in Heikkil et al. [13]. However, LBP is found to be sensitive to noise and uneven illuminations, as pointed out. LBP in nature represents the first-order circular derivative pattern of images, a micropattern generated by the concatenation of the binary gradient directions. However, the first-order pattern fails to extract more detailed information contained in the input object. In fact, the high-order operator can capture more detailed discriminative information. Some of the LBP variants tried to utilize the directions in order to improve it. Zhang et al [14] proposed a new descriptor based on the first order derivative of LBP called local derivative pattern (LDP) for face recognition application. While LDP has been shown to outperform LBP, it tends to produce inconsistent patterns in uniform and near-uniform regions due to its two-level discrimination coding scheme, and is heavily dependent on the number of prominent edge direction parameters. LBP can be conceptually considered as a nondirectional first order local pattern, which is the binary result of the first-order derivative in images. The second order LDP can capture the change of derivative directions among local neighbours, and encode the turning point in a given direction. The 1st-order LDP is a local pattern presented in a general form which captures detailed relationship in a local neighbourhood. Instead of centre pixel and neighbouring pixel relationship, center symmetric pixels were compared for pattern formation and called centre symmetric local binary pattern (CSLBP). Though it shows robustness to monotonic illumination, it is sensitive to nonmonotonic illumination variation. Jabid et al. utilized the relative magnitude’s strength of edge responses in eight directions to compute the local directional pattern (LDiP) [15]. A single eight bit code for a block is used to reduce the dimensionality of the local directional pattern. The local directional ternary pattern (LDTP) [16] converts the image into eight directional images using Robinson compass masks and then finds the primary and secondary directions to generate the feature vector. LDTP (Local Directional Texture Pattern) is another kind of local texture pattern, which includes both directional and intensity information. Again, in Directional Local Extrema Pattern DLEP [17], the feature was extracted by the edge information. DLEP captures more spatial information as compared with LBP. In Local Neighbourhood Difference Pattern(LNDP)[18], the feature is extracted by considering only the nearest element to a particular pixel and the final feature extraction for image retrieval is done by concatenating this LNDP feature with LBP feature. It has already been proved that the directional features are very valuable for image retrieval applications [19–21]. The versions of LBP in the open literature cannot adequately deal with the range of appearance variations that commonly occur in unconstrained natural images due to illumination, pose, facial expression, aging, partial occlusions, etc

To our knowledge, none of the previous methods considered the effect of the first order forward derivative of immediate adjacent neighbours with directional information in a 3×3 window of an image for encoding it. However, the work in DLEP and LDP considered second order derivative and mutual information of all eight neighbours of a particular pixel for its binary representation. In other words, the effect of neighbouring pixels to calculate a binary pattern has not yet been fully explored. In this work, we explore the information contained in the adjacent neighbours of a particular pixel for encoding it rather than considering just two of its neighbours. Following this, we developed a novel method to calculate the binary pattern which takes into account of first order derivative in four directions and included directional information based on position of neighbour pixels. This is motivated by the fact that neighbours of a particular pixel also contain a significant amount of texture information.

3. Local patterns

3.1. Local Binary Pattern (LBP)

As proposed by Ojala et al., Local Binary Pattern (LBP) was mainly invented for texture classification. Due to its computational ease and performance was reported in object tracking, facial recognition, medical imaging and finger print recognition. Given a center pixel in the 3×3 pattern, LBP value is computed by comparing its grayscale value with its neighbourhoods based on Eqns. (1) and (2) as explained in Fig.1.

$$\mathrm{LBP}P, R = \sum_{p=1}^{P} 2^{(p-1)} \ x \ f1\big(I(gp) - I(gc)\big) \qquad \text{--(1)}$$

$$f1(x) = \begin{cases} 1 & x \geq 0 \\ 0 & \text{else} \end{cases} \qquad \text{--(2)}$$

where *I (gc)* denotes the gray value of the centre pixel, *I (gp)* represents the grey value of its neighbours, *P* stands for the number of neighbours, and *R* the radius of the neighbourhood. Thus, a local binary map of the image is generated by replacing each pixel with its LBP value. The feature vector is derived by creating histogram of this Local binary map.

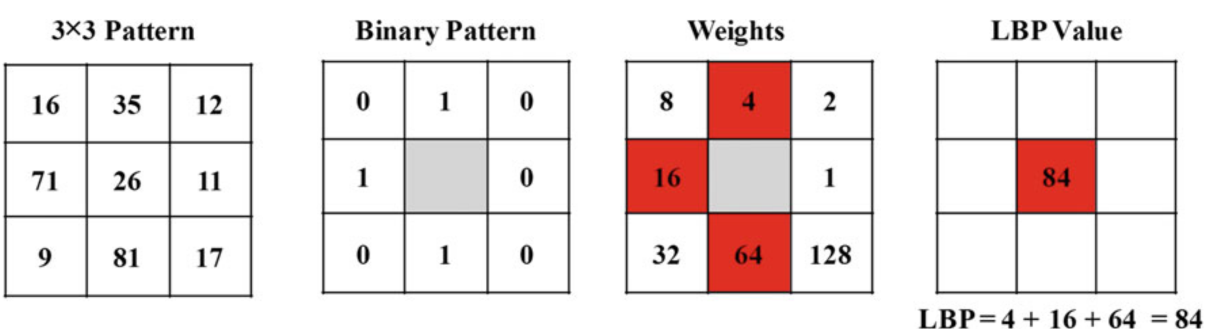

Fig. 1. LBP pattern

3.2. Centre-symmetric LBP (CS_LBP)

A centre symmetric LBP of pixels are considered instead of the existing centre pixel neighbour comparison by Heikkil and Pietikainen [13]. The computation of CS-LBP is done as per the Eqn. (3):

$$\textbf{CS-LBP}_{P,R} = \sum_{p=1}^{P} 2^{(p-1)} f1\left(I(gp) - I\left(gp + (P/2)\right)\right) \quad \text{--- (3)}$$

Subsequent to calculation of CS_LBP for each pixel, a histogram is built to represent the extracted data in a similar way to LBP. The histogram is considered as the feature vector for retrieval.

3.3. Directional local extrema patterns (DLEP)

Directional Local Extrema Pattern (DLEP) has been developed based on LBP. DLEP describes the spatial structure of the local texture using the local extrema of centre grey pixel g_c. In DLEP for a given image the local extrema in 0◦, 45◦, 90◦, and 135◦ directions are obtained by computing local difference between the centre pixel and its neighbours as given (4-7) below:

$$I`_{\alpha}(g_c) = I(g_c) - I(g_i);\ i = 1, 2, \ldots, 8 \quad \text{----(4)}$$

The local extrema are obtained by Eq. (5).

$$^{\wedge}I_{\alpha}(g_c) = f3(I`(g_j), I`(g_{j+4})); \qquad j = (1 + \alpha/45)\ \forall\alpha = 0^{\circ}, 45^{\circ}, 90^{\circ}, 135^{\circ} \quad \text{---(5)}$$

$$f3(I`(g_j), I`(g_{j+4})) = \begin{cases} 1 & \text{if } (I`(g_j) \times I`(g_{j+4})) \geq 0 \\ 0 & \text{else} \end{cases} \quad \text{---(6)}$$

The DLEP is defined (α = 0◦, 45◦, 90◦, and 135◦) as follows:

$$DLEP\,(I(g_c))|\,\alpha = [^{\wedge}I_{\alpha}(g_c);\ ^{\wedge}I_{\alpha}(g_1);\ ^{\wedge}I_{\alpha}(g_2); \ldots\ ^{\wedge}I_{\alpha}(g_8)]; \quad \text{---(7)}$$

Eventually, the given image is converted to DLEP images with values ranging from 0 to 511. After calculation of DLEP, the whole image is represented by building a histogram supported by Eq. (8)

$$HDLEP|\,\alpha\,(l) = \sum_{k=1}^{M}\sum_{j=1}^{N} f2(\mathrm{DLEP}(j,k)|\alpha, l) \quad l \in [0, 511] \quad \text{---(8)}$$

where the size of input image is $N1 \times N2$. Further, these directions are utilized to obtain DLEP patterns in 0◦, 45◦, 90◦, and 135◦ directions. In the same fashion, DLEP patterns for centre pixel in the directions 45◦, 90◦, and 135◦ are also computed.

3.4. Centre Symmetric Directional Local Edge Pattern (CSDLEP)

Centre symmetric directional Local Edge pattern (CSDLEP) is an extension of popular LBP. In addition, to LBP the similar method related to our method is DLEP which also considers derivative of neighbouring pixels for binary pattern calculation. We consider a window of 3X3 to calculate our proposed binary pattern. Our proposed pattern intends to explore the mutual information with respect to centre pixel and centre symmetrical pixels in a particular direction. The definition of pattern in a 3×3 window is provided using a diagram in Fig. 2.

In proposed CSLDLEP for a given image is obtained by computing local forward difference at each pixel in 0◦, 45◦, 90◦, and 135◦ directions and its neighbours as given below:

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$$\boldsymbol{I^{`}(g_{c,\alpha}) = I(g_c) - I(g_{j,\alpha})}; \qquad \text{where } \alpha = 0^\circ, 45^\circ, 90^\circ, \text{ and } 135^\circ \quad \text{--(9)}$$

The local extrema are obtained by Eqns. (10)(a-b)

$$\boldsymbol{I_\alpha(gc) = f3(I^{`}(g_{j,\alpha}), I^{`}(g_{c,\alpha}), I^{`}(g_{j+4,\alpha}))}; \quad \textbf{where } \boldsymbol{j = (1 + \alpha/45)} \textbf{ and } \boldsymbol{\alpha = 0^\circ, 45^\circ, 90^\circ, \text{and } 135^\circ} \quad \text{---(10.a)}$$

$$\boldsymbol{I^{`}(g_{c,\alpha}) = \begin{cases} 1 & \text{if } I^{`}(g_{c,\alpha})>0 \\ 0 & \text{else} \end{cases}} \quad \text{--------------(10.b)}$$

The CSDLEP is defined as follows:

$$\textbf{CSDLEP } \boldsymbol{(I\alpha\,(gc)) = [\,\hat{I}_{0^\circ}(gc); \hat{I}_{45^\circ}(gc); \hat{I}_{90^\circ}(gc); \hat{I}_{135^\circ}(gc);]}; \text{ ------(11)}$$

Eventually, the given image is converted to CSDLEP images with values ranging from 0 to 4095. After calculation of CSDLEP, the whole image is represented by building a histogram supported by Eq. (12).

$$HCSDLEP|\,(l)=\sum_{j=0}^{N-1}\sum_{k=0}^{M-1} f2(CSDLEP(j,k)|,l); l \in [0, 4095] \quad \text{--(12)}$$

The local difference between the centre pixel and its eight neighbours are used to evaluate the directions as shown in Fig. 2. From Fig. 6, it is observed that the DLEP yields more directional edge information as compared with LBP, DLEP and LDP. The experimental results demonstrate that the proposed DLEP shows better performance as compared with other descriptors images, indicating that it can capture more edge information than LBP for texture extraction.

I_4	I_3	I_2
I_5	I_c	I_1
I_6	I_7	I_8

16	28	18
17	23	31
18	08	45

16	28	18
17	23	31
18	08	45

Fig. 4 Fig. 5 Fig. 6

Fig. 2

Fig.3

16	28	18	
17	23	31	67
18	08	45	

16	28	18
17	23	31
18	08	45

Thus, we use a 3×3 window to calculate our proposed binary pattern. The definition of neighbors in a 3×3 window is provided using a diagram in Fig. 2. As shown I_c is the center pixel and its 8 neighborhood pixels are I_1 to I_8. In this pattern, we first calculate the forward difference in four direction 0^0,45^0,90^0 and 135^0 at each pixel of the image as shown in Fig. 3. If the difference is positive then assign 1 other wise 0 in each direction. With this we get a M x N x 4 binary matrix, where M is number of rows and N is number of columns of image. For coding pattern at center pixel Ic, First we consider the neighbors of Ic(23) in 0^0 direction. As shown in Fig.3. ‘17’ and ‘31’ and we consider difference values at these pixels. Now these binary values are arranged as given in equ. 10.a. For 3x3 window in Fig.4. the binary value for ‘17’ is ‘0’ and for center pixel ‘23’ its value is’0’. similarly, for ‘31’ derivative value is ‘0’in 0^0

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direction. As in equ.10. a. we get a three-bit sequence for 00. In this way we compute the three-bit pattern for rest of directions ie., 45^0,90^0 and 135^0- directions. After that we concatenate all these four sequences as explained in equ.11 and we got a pattern of 12 bits. The final value corresponding to central pixel (I_c) is calculated using eqn. (11) which is replaced in place of it at the final binary pattern map. After getting this pattern map, the histogram is calculated using eqn. (12).

4. Proposed image retrieval system

In this paper, we propose a novel feature descriptor for image retrieval by applying the concept on the extracted geometric structure. First, the image is loaded and converted into gray scale in case if it is RGB. Finally, the CSDLEP features are derived by constructing the histogram. The flowchart of the proposed technique and algorithm for the same is presented here:

- Take an image from the image database and convert it into gray scale image if the image is colored.
- Apply CSDLEP and compute the histogram for each image in database and create feature vectors database.
- Take the query image as input.
- Apply CSDLEP to extract the feature vector of the query image.
- Perform the similarity measure to compute the similarity index of the query image vector with every database image using D1 distance similarity measures.
- Sort the similarity indices from highest to lowest to get the set of similar images.
- Evaluate the performance using the metrics.

4.1 Similarity Measurement

To retrieve the images in a Content based image retrieval technique, alongside feature vector calculation, similarity measure also plays an important role. After calculating the feature vectors, this similarity measure gives the distance between the query image feature vector and feature of every image from the database. 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 query image and image in the database |DB|. In order to retrieve similar images, we used *d*1 similarity distance metric given by Eqn. (13).

$$D\,(Q, \mathrm{DB}) = \sum_{i=1}^{Lg} \left| \frac{f\mathrm{DB}ji - fQi}{1 + f\mathrm{DB}ji + fQi} \right| \qquad \text{---(13)}$$

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

5. Experimental results and discussions

The performance of the proposed method for image retrieval is analysed by conducting five experiments on four different databases (Corel-10K, MIT-Vis, STex and Brodatz database) and one face image database (AT&T database). The superiority of the proposed method has been analysed by comparing image retrieval in terms of the evaluation metrics precision and recall. In all experiments, each image in the database is used as the query image. For each query, the system collects *n* database images $X = (x1, x2, \ldots, x_n)$ with the shortest image matching distance computed using Eq. (13). If the retrieved image $xi = 1, 2, \ldots, n$ belongs to same category as that of the query image then we say the system has appropriately identified the expected image; else, the system fails to find the expected

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image. The performance of the proposed method is measured in terms of average precision, average recall, and average retrieval rate (ARR).

5.1 Experiment #1

In experiment 1, we have used 10,000 images to form database of Corel-10K. This database includes 100 different categories and each category contain 100 images. The performance of proposed method and all techniques in terms of average precision and ARR on Corel-10K database can be seen in Fig. 8 a, b, respectively. From Table 3, it is clear that the proposed method shows a significant improvement as compared with other existing methods in terms of them evaluation measures on Corel-10K database. Figure 7 illustrates the query results of proposed method on Corel-10K database. CSLBP,LBP,LDP,LDIP,CSLDP,LNDP,DLEPAND LOOP, 72.25%,14.98%,16.03%,61.72%,52.19%,4.2%,11.1%,23.75%

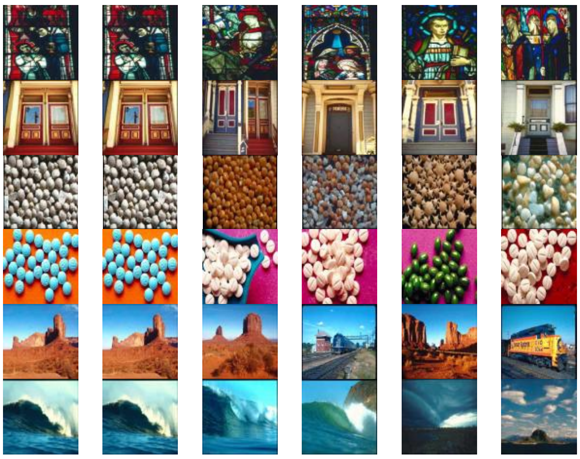

Figure 7 An example of image retrieval by proposed method (DLEP) on Corel-10K database

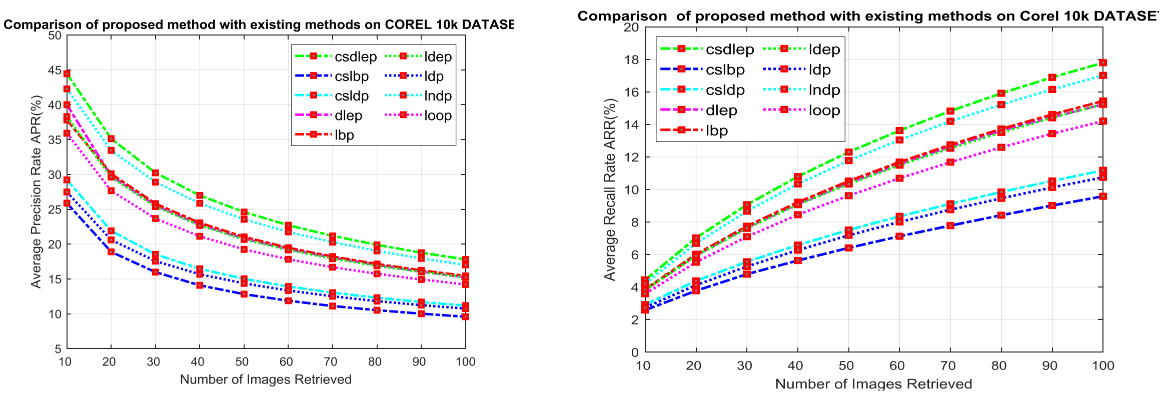

Fig. 8 (**a**) Precision vs number of images retrieved (**b**) Recall vs number of images retrieved

5.2 Experiment 2

The Brodatz texture dataset has 112 texture images each of size 640 x 640. The images are divided into 25 sub images each of size 128×128, which gives a database of 112 categories and each category contains 25 images. The results obtained using our proposed method on this dataset have been shown in Fig.9 (a) and Fig. 9(b). Images are retrieved in a group of 25,30, 35, ..., 70 to measure the performance of system for different numbers in images. The performance of the proposed method is better than those obtained with state-of-the-art methods such as CSLBP, LBP, LDP, LDIP, CSLDP, LNDP, DLEP AND LOOP, by 37.3%, 5.65%, 11.4%, 34.1%, 24.8%, 5.06%, 12.9% and 7.9% on Average Retrieval Rate as shown in Table 3. In Fig. 10, the first image of each row represents the query image and the remaining images show the retrieved images for each query image.

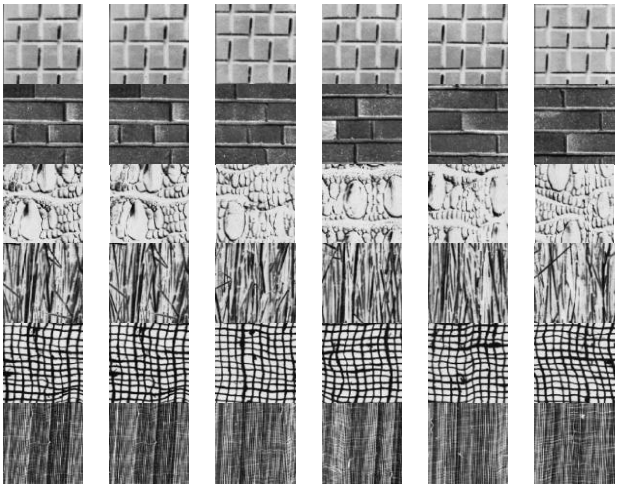

Figure 10 An example of image retrieval by proposed method (DLEP) on Brodatz database

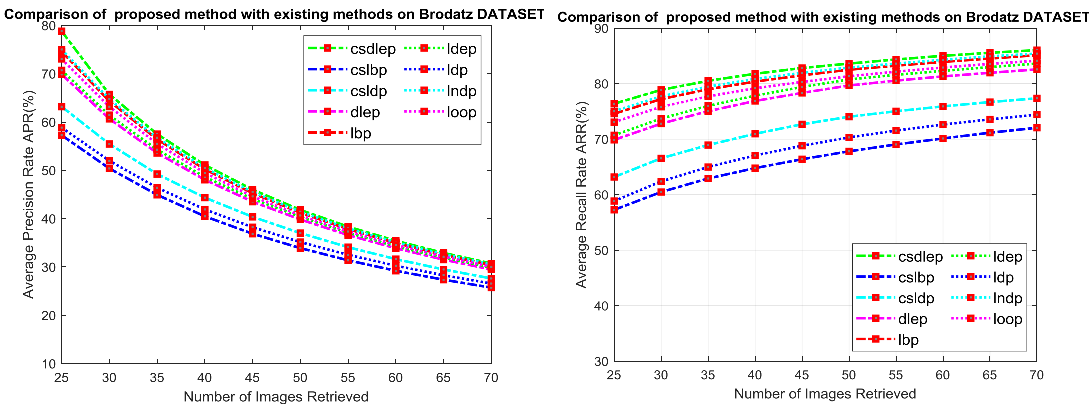

Fig. 9 (**a**) Precision vs number of images retrieved (**b**) Recall vs number of images retrieved

5.3. Experiment # 3

In third database has been considered from Computational Visual Cognition Laboratory, MIT [26]. It is formed by selecting eight categories of urban and natural scenes, e.g., coast & beach, forest, highway, city center, mountain, open country, streets and tall buildings of size 256×256. In this experiment, 200 images per category are selected. Hence, a group of 10, 20, .., 200 images are retrieved in each experiment. In Fig. 11 precision and recall graphs of retrieved images have been shown. The performance in precision and recall is better than other methods as visible in graphs. In terms of precision the proposed method performance is significantly increased from CSLBP, LBP,

LDP, LDIP, CSLDP, LNDP, DLEP AND LOOP BY 22.9%, 6.2%, 6.38%, 19.43%, 18.6%, 5.83%, 10.7% and 9.74%. Precision and recall graphs with different descriptors are presented in Fig. 11. In the most of the categories, the proposed method outperforms other methods. For six query images in leftmost column are denoted in Fig.12, and first five images retrieved images are shown as results.

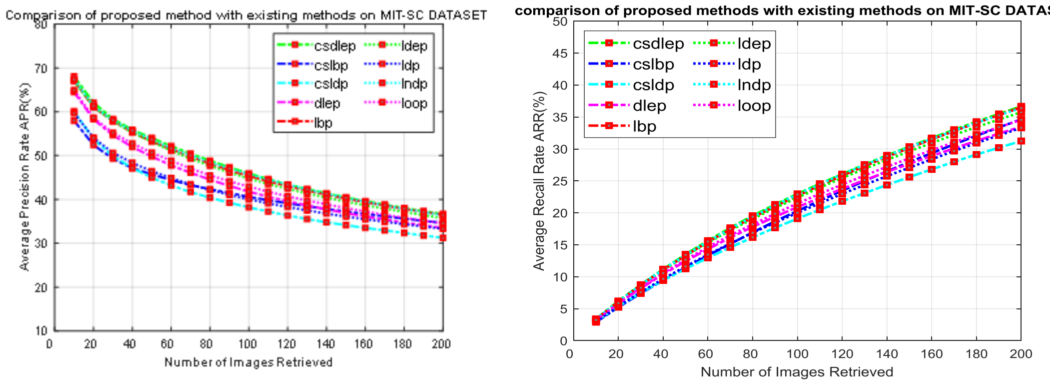

Fig. 11. (**a**) Precision vs number of images retrieved (**b**) Recall vs number of images retrieved

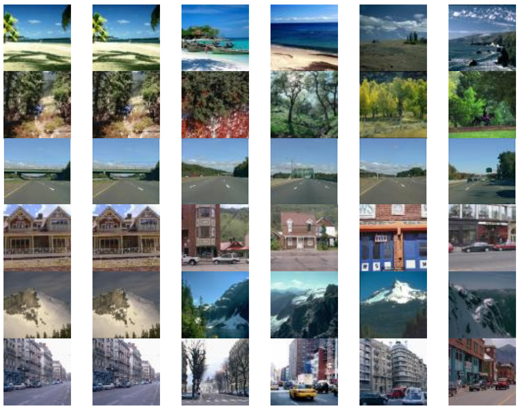

Figure 12. An example of image retrieval by proposed method (DLEP) on MIT-SC database

5.4. Experiment # 4

AT &T face dataset is considered as fourth set of images for comparative study of our method with several recently developed methods. It includes images of 40 different types with 10 sample images of each person and a total of 400 images. The size of each image in the database is 92×112. For this database, initially one image is retrieved and then increased insteps of 1 upto10. The query and related retrieved images are shown in Fig. 14. The left most column represent query images and rest retrieved images. The proposed method outperforms the existing methods like CSLBP, LBP, LDP, LDIP, CSLDP, LNDP, DLEP and LOOP by 20.06 %, 7.36%, 4.04%, 27.75%, 27.87%, 5.34%, 4.58%,11.47% when performance is compared using Average Retrieval Rate as a metric. The precision and recall curves have been shown with the help of graphs in Fig. 13(b) and 13(a).

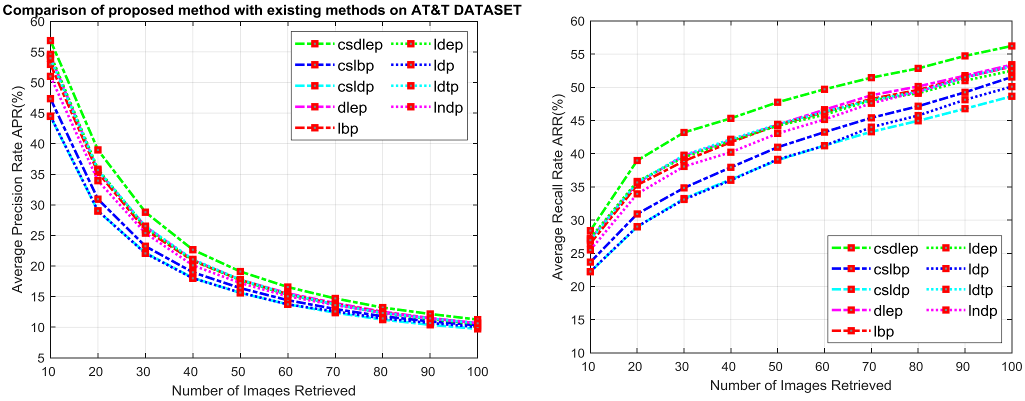

Fig. 13. (**a**) Precision vs number of images retrieved (**b**) Recall vs number of images retrieved

5.5. Experiment # 5

The Salzburg[4] texture Database contains images of size 128×128. There are a total of 7616 images. There are a total of 476 categories and each category contains 16 images. Different types of textures like wood, rubber, etc. are presented in the database. Each image of the database is treated as a query image. Fig. 15 shows some query images and their corresponding retrieved image. The number of images retrieved for each category for this experiment is initially considered as 16. This is increased in small steps of 16 images. The maximum number of images for this dataset retrieved in our experiment is 112. The proposed method clearly shows an improvement on Average retrieval rate (ARR) over the recently developed methods for content-based image retrieval such as CSLBP, LBP, LDP, LDIP, CSLDP, LNDP, DLEP and LOOP by 56.81 %, 8.52%, 11.37%, 53.5%, 29.4%, 4.94%, 13.54%,12.37%. The precision and recall curves are shown in Fig. 16(a) and Fig. 16(b).

Figure 14. An example of image retrieval by proposed method (DLEP) on AT & T database

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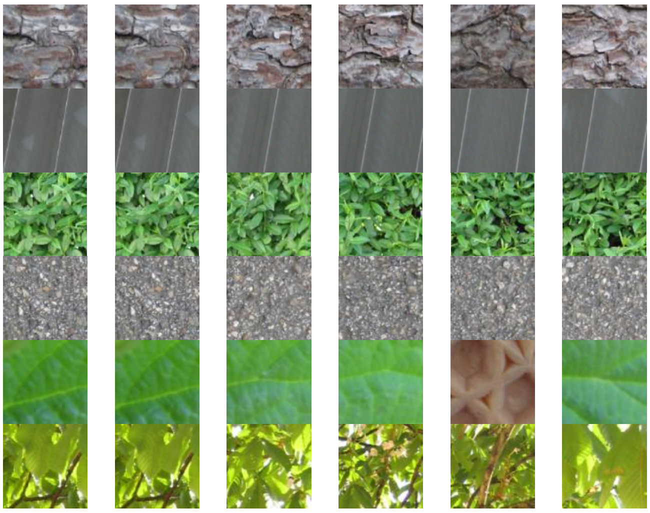

Figure 15. An example of image retrieval by proposed method (DLEP) on STex database

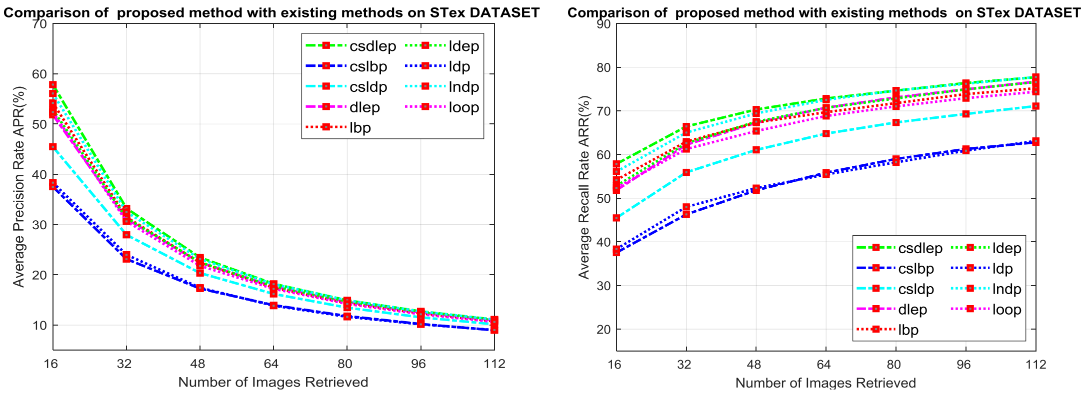

Fig. 16 (**a**) Precision vs number of images retrieved (**b**) Recall vs number of images retrieved

Table 3: Average Retrieval Rate for different datasets

Different Feature	Brodatz	MIT-Vistex	AT&T	STex	Corel 10k
CSLBP	57.26	57.98	47.35	37.53	25.8
LBP	74.58	67.11	52.95	54.23	38.65
LDP	70.71	67.03	54.64	52.84	38.3
LDIP	58.8	59.68	44.5	38.34	27.48
CSLDP	63.18	60.1	44.46	45.48	29.2
LNDP	75.03	67.35	53.97	56.08	42.65
DLEP	69.87	64.48	54.36	51.83	40.1
LOOP	73.07	64.95	51.0	52.37	35.91
CSDLEP(Proposed)	78.8	71.28	56.85	58.85	44.44

6. Conclusions and future work

A novel feature descriptor CSDLEP is proposed for texture image retrieval. It extracts edge information in 0◦, 45◦, 90◦, and 135◦ directions in an image like LBP. Performance of the proposed method is tested by conducting four experiments on benchmark image databases (Corel-10k, MIT VisTex, BrodatZ, STex database and AT & T face database.) and retrieval results show a significant improvement in terms of their evaluation measures as compared with other existing methods on respective databases.The results for the proposed method and previous methods are explained using graphs with evaluation measures, and results show that the proposed method outperforms other methods. Due to the effectiveness of the proposed descriptors, it can also be suitable for other pattern recognition applications such as face recognition, fingerprint recognition, etc.

References

[1]. Gai S, Yang G, Zhang S (2013) Multiscale texture classification using reduced quaternion wavelet transform. Int J Electron Commun (AEÜ) 67:233–241

[2]. Shi F, Wang J, Wang Z (2011) Region-based supervised annotation for semantic image retrieval. Int J Electron Commun (AEÜ) 65:929–936

[3]. Smeulders AWM, Worring M, Santini S, Gupta A, Jain R (2000) Content-based image retrieval at the end of the early years. IEEE Trans Pattern Anal Mach Intell 22(12):1349–1380

[4]. Tang Z, Zhang X, Dai X, Yang J, Wu T (2013) Robust image hash function using local color features. Int J Electron Commun (AEÜ) 67:717–722

[5]. Rui Y, Huang TS (1999) Image retrieval: current techniques, promising directions and open issues. J Vis Commun Image Represent 10:39–62

[6]. T. Ojala, M. Pietikainen, D. Harwood, A comparative study of texture measures with classification based on feature distributions. Pattern Recogn. 29(1), 51–59 (1996)

[7]. Pietikainen M, Ojala T, Scruggs T, Bowyer KW, Jin C, Hoffman K, Marques J, Jacsik M, Worek W (2000) Overview of the face recognition using feature distributions. J Pattern Recogn. 33(1):43–52

[8]. T. Ojala, M. Pietikainen, T. Maenpaa, Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans. Pattern Anal.Mach. Intell. 24(7), 971–987 (2002)

[9]. Zhao G, Pietikainen M (2007) Dynamic texture recognition using local binary patterns with an application to facial expressions. IEEE Trans Pattern Anal Mach Intell 29(6):915–928

[10]. Heikkil M, Pietikainen M (2006) A texture-based method for modeling the background and detecting moving objects. IEEE Trans Pattern Anal Mach Intell 28(4):657–662

[11]. Li M, Staunton RC (2008) Optimum Gabor filter design and local binary patterns for texture segmentation. J Pattern Recognit 29:664–672

[12]. Zhang B, Gao Y, Zhao S, Liu J (2010) Local derivative pattern versus local binary pattern: face recognition with higher order local pattern descriptor. IEEE Trans Image Proc 19(2):533–544

[13]. Heikkil M, Pietikainen M, Schmid C (2009) Description of interest regions with local binary patterns. Pattern Recognition 42:425–436

[14]. Zhang, B., Gao, Y., Zhao, S., & Liu, J. (2010). Local derivative pattern versus local binary pattern: Face recognition with high-order local pattern descriptor. *IEEE Transactions on Image Processing*, *19*(2), 533–544.

[15]. Zhang, B., Gao, Y., Zhao, S., & Liu, J. (2010). Local derivative pattern versus local binary pattern: Face recognition with high-order local pattern descriptor. *IEEE Transactions on Image Processing*, *19*(2), 533–544.

[16]. Jabid T, Kabir MH, Chae OS (2010) Local directional pattern (LDP) for face recognition. In: IEEE international conference on consumer electronics, pp 329–330

[17]. A. R. Rivera, J. R. Castillo, and O. Chae, "Local directional texturepattern image descriptor," Pattern Recognition Letters, vol. 51, no. 1, pp. 94–100, 2015.

[18]. Murala, S., Maheshwari, R. P., & Balasubramanian, R. (2012a). Directional local extrema patterns: a new descriptor for content based image retrieval. *International Journal of Multimedia Information Retrieval*, *1*(3), 191–203.

[19]. KoteswaraRao L, Venkata Rao D (2015) Local quantized extrema patterns for content-based natural and texture image retrieval. Hum Cent Comput Inf Sci 5:26.

[20]. Subrahmanyam M, Maheshwari RP, Balasubramanian R (2012b) Local maximum edge binary patterns: a new descriptor for image retrieval and object tracking. Signal Process 92:1467–1479

[21]. T. Chakraborti et al., "LOOP descriptor: local optimal oriented pattern," IEEE Signal Process. Lett., 25 (5), 635 –639 (2018)

[22]. Verma, M., & Raman, B. (2016). Local tri-directional patterns: A new texture feature descriptor for image retrieval. *Digital Signal Processing: A Review Journal*, *51*, 62–72. https://doi.org/10.1016/j.dsp.2016.02.002

[23]. Verma, M., & Raman, B. (2016). Local tri-directional patterns: A new texture feature descriptor for image retrieval. *Digital Signal Processing: A Review Journal*, *51*, 62–72. https://doi.org/10.1016/j.dsp.2016.02.002

[24]. Verma, M., & Raman, B. (2017). Local neighborhood difference pattern: A new feature descriptor for natural and texture image retrieval. *Multimedia Tools and Applications*. https://doi.org/10.1007/s11042-017-4834-3

[25]. Corel5k and Corel10k Database, Available online: ⟨http://www.ci.gxnu.edu. cn/cbir/⟩.

[26]. MIT Vision and Modelling Group, Cambridge, "Vision texture", Available online: ⟨http://vismod.media.mit.edu/pub/⟩.

[27]R.Kwitt,P.Meerwald, Salzburg TextureImageDatabase,September2012, Available online: ⟨http://www.wavelab.at/sources/STex/⟩.

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Vol-10 Issue-10 No.02 October 2020

[28]. Brodatz P (1996) Textures: a photographic album for artists and designers. Dover, New York