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# Some variants of spiral LBP in texture recognition

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**Abstract:** Texture classification is one of the recently popular study topics in pattern recognition. Local binary pattern (LBP) is a very efficient local texture descriptor and is used for feature extraction in texture recognition. There are five main steps in representation of texture images: neighbourhood topology and sampling, thresholding and quantisation, encoding and regrouping, combining complementary features. In this study, the authors used symmetric two spirals LBP to measure the grey-scale difference between the centre pixel and its neighbours. They also extended the proposed method by using four spirals LBP to generate the LBP code. For classification, linear regression classification method, which is generally used to solve the face recognition problems, is used. The authors tested the performance of their method on UIUC and CUReT texture image databases. It is experimentally demonstrated that the proposed method achieves the highest classification accuracy among the comparative methods on texture databases.

## 1 Introduction

Many researchers tried to define texture in the last 40 years. Formal or commonly accepted definition of the texture has not been found yet but it can be defined as a repeating pattern of local variations in image intensity. The diversity of texture definition in the literature leads to a variety of different approaches to analyse the texture such as statistical and structural methods [1]. In statistical approaches, each texture is described by a feature vector of properties, which represents a point in a multi-dimensional feature space. In structural approaches, the texture is represented by well-defined primitives and a hierarchy of spatial arrangements of those primitives.

Local binary pattern (LBP) is one of the method for texture representation which is a unifying approach to structural and statistical texture analysis [2]. The LBP, which was presented by Ojala *et al.* in 2002, is an efficient and powerful texture descriptor. It is widely used in image processing and computer vision areas such as object recognition [3], recognition of individual cattle [4], gender classification [5], text detection [6], image retrieval, classification [7] and especially face recognition problems [8, 9]. Owing to the great success of LBP in computer vision and pattern recognition, it has recently become one of the popular study areas. In [10], various LBP variants and their connections are provided. Based on these relations a taxonomy for the LBP variants is proposed. We are focused on neighbourhood topology and sampling step which is a second class according to their taxonomy.

The conventional LBP defines the neighbourhood on a circle around the reference pixel. This neighbourhood topology provides a solution to texture classification application which is the rotation invariance problem. In some applications, especially face recognition, anisotropic structural information is very important rather than rotation. Liao and Chung proposed new neighbourhood topology and a new feature to capture gradient information. Shape of the neighbourhood distribution is chosen as elliptical [elongated LBP (ELBP)] to extract anisotropic information from face [11]. At the end of the experiments, the highest recognition rate is obtained with combined new features.

Another variant of neighbourhood topology is studied by Nanni *et al.* [12]. In addition to circle and ellipse shapes, the neighbourhood around the reference pixel is distributed as a parabola, a hyperbola and an Archimedean spiral. The local grey-scale difference between the reference pixel and one of its neighbours is encoded by using five values unlike conventional LBP encoding. According to this work, the proposed quinary encoding and using elliptic neighbourhood topology performs the best with the medical image databases.

Texture classification is divided into two stages: extracting features and classification. Representation of texture is a major problem but selection of the classification method to achieve good result according to the features is very important. In the literature, statistical tests are used to measure the similarity of histograms for classification purposes [13]. Performance of subspace-based classification methods and statistical tests based on similarity measures are compared in [14]. As a result of the experiments, one of the subspace-based classification method called linear regression classification (LRC) that is generally used to solve the face recognition problems [15–17] gives better recognition rates than the statistical tests.

In this paper, we analyse spiral local binary pattern (S1LBP) which is firstly proposed in [12] and we focus our attention on increasing the performance of LBP by extending the S1LBP. Firstly, we used symmetric two spirals to measure the grey-scale difference between the centre pixel and its neighbours. We also extended the proposed method by using four spirals LBP (S4LBP) for the calculation of LBP code. At first, we compared the performances of some classifiers, namely chi-square, support vector machines (SVM), linear discriminant analysis (LDA) and LRC using LBP, S1LBP, two spirals LBP (S2LBP) and S4LBP features. According to the results of the comparison experiment we choose LRC in classification step for the rest of the experiments.

To evaluate the effectiveness of the proposed method, we conducted the experiments on UIUC texture database [18] which includes strong non-rigid deformations, illumination changes, viewpoint-dependent appearance variations and CURet texture database [19] which have different viewing and illumination conditions. In our experiments, we have found that the proposed neighbourhood topology is effective in representing textures.

The rest of this paper is organised as follows. In Sections 2 and 3, brief reviews of the LBP and the classifiers are given, respectively. Section 4 describes the details of our proposed

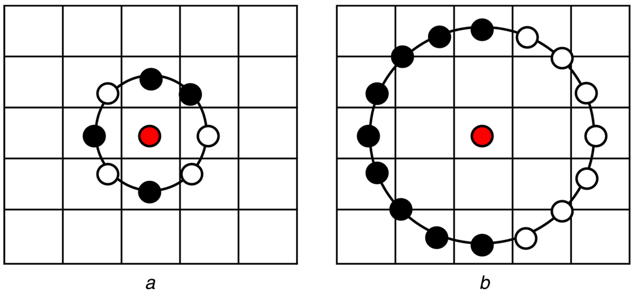

**Fig. 1** *Traditional LBP topology* ***(a)*** *Circular (8, 1) neighbourhood topology,* ***(b)*** *Circular (16, 2) neighbourhood topology*

method. Experimental results and analysis are given in Section 5. Section 6 gives conclusion.

## 2 Local texture descriptors: LBP review

LBP is a feature extraction method, proposed by Ojala *et al.*, for texture recognition problems [2]. It describes local features of image by comparing the pixel intensity values. A pixel is set as a reference and circularly symmetric neighbour pixels are chosen for comparison.

In Fig. 1, there are examples of patterns which have different radius and number of samples. Red circles demonstrate the centre pixels, black and white circles around of red ones are selected for neighbour pixels. Grey level values of neighbour pixels are used for comparison but some neighbours may not overlap to centre of a pixel. Interpolation is used for calculating grey value of the pixels. The process continues for all pixels in image. End of this, every pixel have a binary code generated depending on whether the central pixel intensity is smaller than or equal to its neighbours. For example, black circles are smaller than centre red pixel. Therefore, they are coded as 0 and white ones are coded as 1. Binary codes are converted to decimal values and related centre pixel is labelled with this relevant value. Histogram is created with these values.

Let $\mathrm{LBP}_{P,R}$ denote the LBP code of a pixel's circularly neighbourhood, where $P$ is the number of sample points on the circle of radius $R$, $g_c$ is the grey value of centre pixel and $g_p$ is the grey value of its $p$th neighbour. Then the $\mathrm{LBP}_{P,R}$ can be calculated as follows:

$$\mathrm{LBP}_{P,R} = \sum_{p=0}^{P-1} s\left(g_p - g_c\right)2^P, \quad s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{1}$$

As a result of calculation of LBP operator, decimal number is assigned to each pixel of image. After this process, a histogram is built to represent the image and is used for pattern recognition as feature.

Any pattern, named uniform pattern, is used to extract fewer feature of image texture [13]. After comparison grey values of pattern, bitwise transitions from 0 to 1 or vice versa are controlled. If the binary code comprises at most two bitwise transitions, the pattern is called uniform [uniform local binary pattern (ULBP)]. For example, binary code of the pattern given in Fig. 1*a* is 00110101.

This pattern consists of five bitwise transitions. For this reason, it is non-uniform pattern. The pattern in Fig. 1*b* that has 16 neighbours is uniform pattern because of two transitions. If each pixel in image has eight neighbourhoods, there are totally 58 uniform patterns. All non-uniform patterns correspond to one bin so the histogram consists of 59 bins.

## 3 Classifiers

In this section we briefly review classification algorithms used in this paper to compare the LBP and its spiral variants.

Chi-square ($\chi^2$) test is a non-Euclidean measure to compare the similarity of histograms. Assume that we have two histograms $S$ and $M$ for comparison. The similarity between $S$ and $M$ according to this test is computed as

$$d_{\chi^2}(S, M) = \sum_{i=1}^{B} \frac{(s_i - m_i)^2}{s_i + m_i} \tag{2}$$

where $B$ is the number of bins, $s_i$ and $m_i$ represent the value of $S$ and $M$ distributions at the $i$th bin, respectively. A simple nearest-neighbour rule is used for classification.

Another machine learning algorithm used in the classification problems is SVM. The aim of SVM is to select a hyperplane which separates input variable space by their class. To find the best separating hyperplane it solves the following objective function using quadratic programming:

$$\min \frac{1}{2} \| \boldsymbol{w} \| \quad \text{s.t.} \quad y_i(\boldsymbol{w}x_i + b) \geq 1, \quad \forall x_i \tag{3}$$

where $x_i$ is the $i$th data point and $y_i$ is the corresponding class label.

LDA is one of the most commonly used dimensionality reduction technique. It maximises the linear separability of the groups belonging to different classes in data by maximising the distance between distributions of classes and minimising the variation in each class. It reduces the dimension of the feature space and saves the information that is used in classification process at the same time. The objective function maximised in LDA is defined as

$$J(\boldsymbol{w}) = \frac{\boldsymbol{w}^{\mathrm{T}} S_{\mathrm{B}} \boldsymbol{w}}{\boldsymbol{w}^{\mathrm{T}} S_{\mathrm{T}} \boldsymbol{w}} \tag{4}$$

where $\boldsymbol{S}_{\mathrm{B}}$ is the between-class scatter matrix and $\boldsymbol{S}_{\mathrm{T}}$ is the within-class scatter matrix.

LRC is a subspace-based classification method which is generally used in face recognition problems. Assume that we have $C$ classes with $N$ training images. The matrix $\boldsymbol{W}_i$ contains all feature vectors from $i$th class. Thus

$$\boldsymbol{W}_i = [\boldsymbol{x}_i^1 \vdots \cdots \vdots \boldsymbol{x}_i^j \vdots \cdots \vdots \boldsymbol{x}_i^N] \tag{5}$$

where $\boldsymbol{x}_i^j$ represents the $j$th feature vector of the $i$th class. $\boldsymbol{W}_i$ is called the regressor of the $i$th class. Let $\boldsymbol{y}$ is an unknown query to be classified. Firstly, the predictions $\widehat{\boldsymbol{y}_i} = \boldsymbol{W}_i\left(\boldsymbol{W}_i^{\mathrm{T}}\boldsymbol{W}_i\right)^{-1}\boldsymbol{W}_i^{\mathrm{T}}\boldsymbol{y}$, $i = 1, 2, \ldots, C$, are calculated. The minimum distance between the query $\boldsymbol{y}$ and the predictions $\widehat{\boldsymbol{y}_i}$ gives the correct class of the $\boldsymbol{y}$.

## 4 Spiral local binary pattern (SLBP)

In this section, firstly we analyse S1LBP previously introduced for texture recognition and define two extensions, named S2LBP and S4LBP. We aim to increase the recognition rate by describing local texture pattern by using spiral topology.

The type of the spiral used in this study is Archimedean spiral. It is a plane curve generated by a point moving away from or towards a fixed point at a constant rate while the radius vector from the fixed point rotates at a constant rate. The equation of the Archimedean spiral is expressed in terms of polar coordinates. It can be described as follows:

$$r = a + b\theta \tag{6}$$

Here $a$ and $b$ are real numbers, $r$ is the radial distance and $\theta$ is the polar angle.

In our work, we tested various values for $b$ within the range [0.2 0.5] to generate spiral shape. Eight sampling points on one spiral neighbourhood topology (S1LBP) is implemented for the decision of optimum parameter value. Also, we set $a = 0$ to start spiral from origin.

For the classification of the features, the LRC method is used. To assess the impact of parameter $b$, 30 training images from each class in UIUC texture dataset are used for training and the remaining images are chosen for testing purposes. The average accuracy over ten randomly splits is listed in Fig. 2. It can be observed from Fig. 2 that the highest classification accuracy is achieved at 0.3 using both basic and uniform S1LBP (S1ULBP), so we set parameter $b$ as 0.3.

In traditional LBP, every pixel of an image is selected as a centre of neighbourhood circle. The limitation of LBP is to ignore the sampling point which is inside the reference pixel. To overcome this problem, the neighbours of reference pixel are designated on spiral shape (see Fig. 3). Therefore, we are motivated to propose spiral topologies.

One spiral shape includes a certain area for the computation grey-scale difference. For this reason, symmetric two spirals are used. By using two spirals, since we cannot scan horizontal neighbours, we cannot describe local pattern ideally. We used four spirals around the pixel to scan vertical and horizontal directions. Consequently, S4LBP is proposed.

Fig 3*a* shows an example of S1LBP pattern where the spiral starts from the reference pixel and stops after $2\pi$ radians. The neighbour points are assigned by choosing $\theta$ intervals of $\pi/4$ for the eight neighbourhoods. For 16 neighbourhoods, this value becomes $\pi/8$. If the coordinates of the neighbour pixels on the spiral do not overlap exactly with the centre of a pixel in the image, intensity value of the neighbour pixel is calculated by using bilinear interpolation.

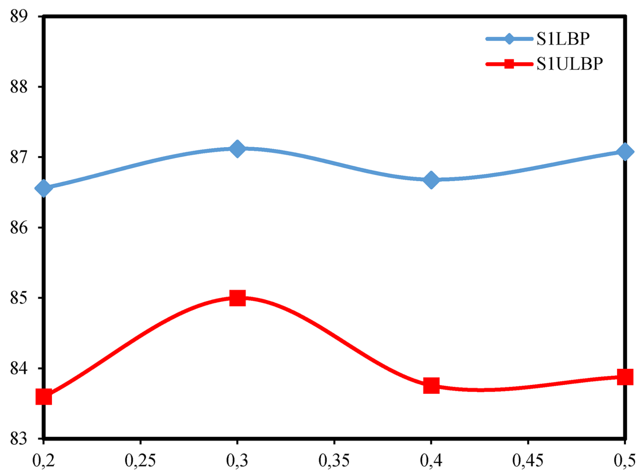


**Fig. 2** *Accuracy rates with using different b values*

The grey-scale difference for the S1LBP is calculated in the same way as the traditional LBP. If the reference pixel is equal or smaller than the neighbours' intensity value binary code is 1, otherwise 0. Binary code size changes according to the numbers of neighbours. The LBP code is generated by converting the binary code to decimal value. The obtained LBP code is labelled to centre pixel. Finally, the histogram of decimal values is created.

S1ULBP code of a pixel is calculated depending on the number of 0–1 or 1–0 bitwise transitions similar to uniform LBP. Also, non-uniform patterns correspond to one bin in histogram. The final feature vector extracted from the S1LBP is used to represent the texture image.

Archimedean spiral equation is defined at the beginning of this section. Symmetric two spirals are generated by adding $\pi$ to $\theta$ in (6).

Obtained spiral topology is used when the LBP code is calculated. LBP histograms are created for each spiral in S2LBP separately. For example, the centre pixel is firstly compared with its neighbours on the green spiral of S2LBP structure in Fig. 3*b*. As a result of this process, 8 bit binary code is generated. Then, one more binary code is generated by comparing the reference pixel with its neighbours on the red spiral. Both binary codes are converted to a decimal value. Consequently, each centre pixel has two labels so the total label numbers are obtained from image twice as much as number of pixels. The final histogram is generated by concatenating two histograms evaluated from the green and red spirals. In this way, feature vector size of the texture image is $2^8 + 2^8 = 512$ for the S2LBP topology which uses 8–8 neighbours. In the uniform S2LBP (S2ULBP), feature vector size is $59 + 59 = 118$.

S4LBP topology is used four spirals neighbourhood to measure grey-scale differences. We add $\pi/2$, $\pi$ and $3\pi/2$ to $\theta$ in (6) to generate three more spirals. We assume that one spiral neighbourhoods of each pixel in the image has $k$ neighbours. Feature size is defined as follows:

$$B = n \times 2^k \tag{7}$$

where $n$ is the total number of spirals and $B$ is the bins of the histogram. Each spiral is represented with different colours in Fig. 3*c* and LBP codes are computed separately. By concentrating all the histograms evaluated from each spirals, global information of texture image is obtained. Fig. 4 shows the example of proposed S4LBP. According to given example in Fig. 3*c*, feature vector size is $4 \times 2^8 = 1024$. For the uniform S4LBP (S4ULBP), its size is reached to $59 \times 4 = 236$.

The computational complexity of S1LBP can be described as follows. Assume that we have $m$ sample points on the circle with respect to the centre pixel and input image have $N$ pixels. The time complexity of traditional LBP is $O(mN)$. Since circular mask is

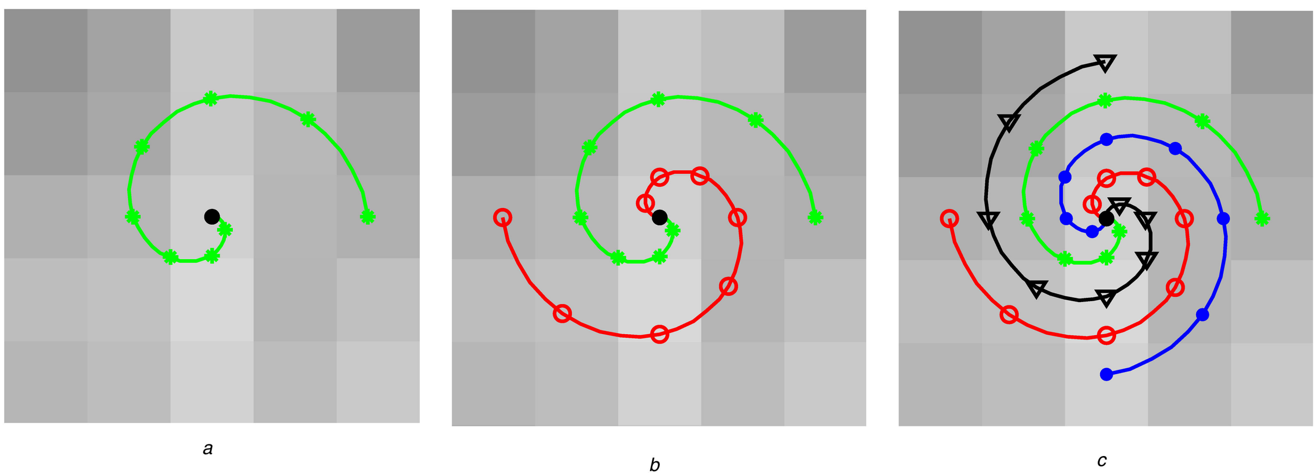


**Fig. 3** *Example of proposed spiral topologies* ***(a)*** *One spiral,* ***(b)*** *Two spirals,* ***(c)*** *Four spirals*

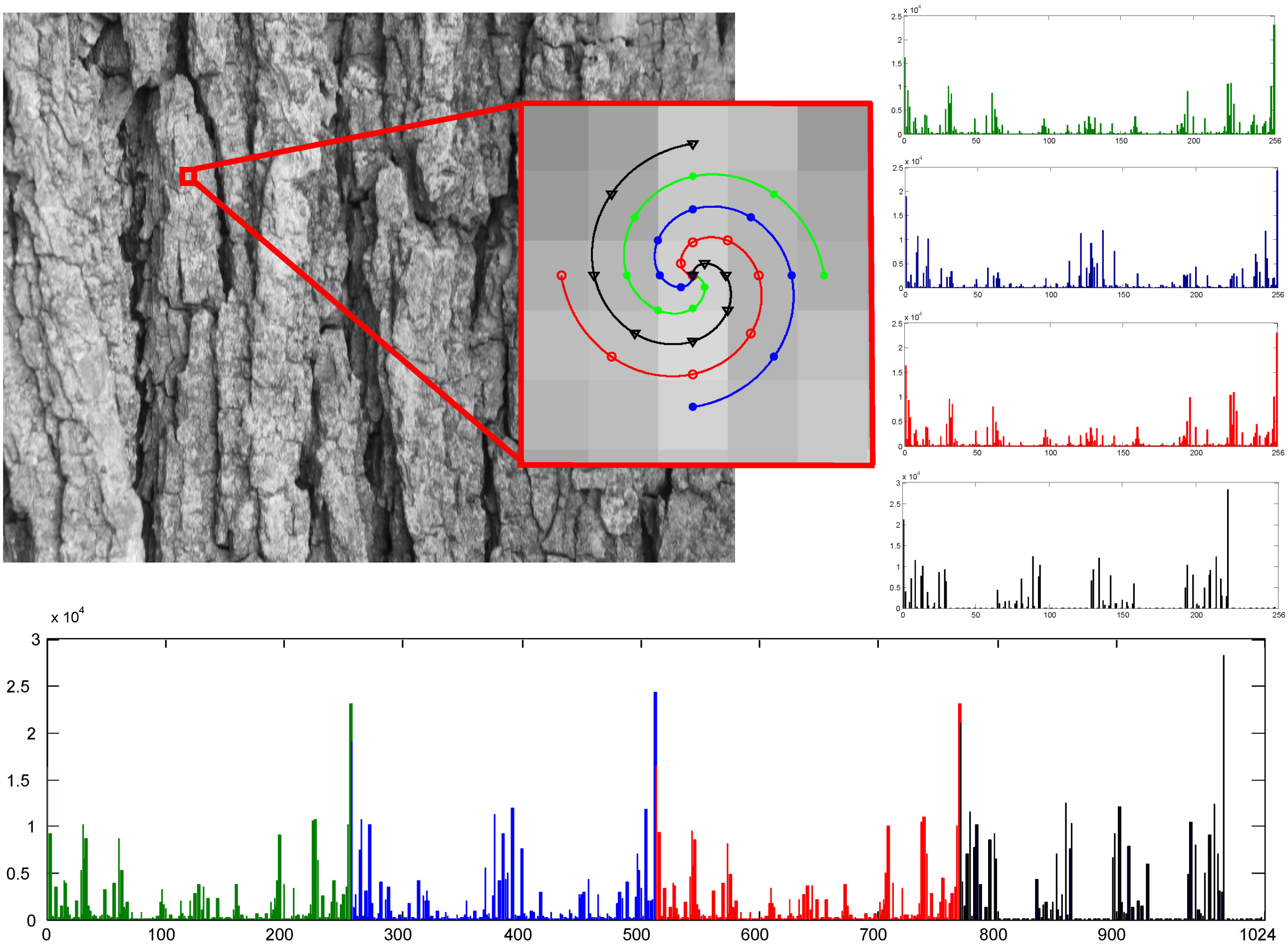


**Fig. 4** *Illustration of S4LBP feature extraction*

used for each pixel to generate LBP code and there are $N$ pixels in total, a similar result can be reached for the spiral mask, then the time complexity of S1LBP is $O(mN)$. S2LBP and S4LBP have two and four spirals, respectively. Since $O(mN) = O(2mN) = O(4mN)$ is the same time complexity then the time complexity of the proposed methods is $O(mN)$.

## 5 Experimental results

In order to test the efficiency of the proposed spiral neighbourhood topologies in the texture recognition problem, we use UIUC [18] and CURet [19] texture databases.

UIUC texture database involves 40 texture images from each of 25 texture classes. The resolution of the each sample is $640 \times 480$ pixels. Fig. 5*a* shows example images from each class. Samples of each class have significant viewpoint and scale differences. Furthermore, the dataset includes non-rigid deformations, illumination changes and viewpoint-dependent appearance variations.

CURet texture database contains 61 samples. Each class has 205 images which acquired at different viewpoints and illumination conditions. Ninety-two images from which a sufficiently large region could be cropped $(200 \times 200)$ across all texture classes are selected [20]. We converted all the cropped regions to a grey scale. Fig. 5*b* shows the example images from each class.

In proposed S2LBP and S4LBP, Archimedean spirals start in a centre pixel and make a curve with one round $(2\pi)$. Sampling points on the spirals are computed with $2\pi/N$ angular intervals where $N$ denotes the number of neighbours. If a sampling point does not overlap with a pixel's centre, we use bilinear interpolation to compute the value of the point.

In the first experiment, we compare the performances of the classifiers given in Section 3 in the both databases. We randomly choose 30 images for training and the rest of the images are used for testing purposes on UIUC database. Similarly, we randomly choose 46 images for training and the rest of the images are used for testing on CURet database for each class. The experiments are executed ten times and the results are obtained by averaging each run. It is obviously seen in Figs. 6*a* and *b* that LRC outperforms the other classifiers in the both databases independent of the feature type. For this reason, we use LRC in classification stage for the following experiments.

The grey-scale differences between centre and neighbour pixels are computed using 8 and 16 sampling points on a circle of 1 and 2 radii in LBP and ULBP. For the proposed method, 8 and 16 sampling points are used on each spiral. The features obtained by different topologies in the literature i.e. circularly symmetric topology in LBP [2], elliptic topology in ELBP [11] and spiral topology in [12] are compared with proposed methods. The extracted features are classified with the LRC method. To assess the classification performance, $N$ training images are randomly selected from each class of the database while the remaining $(40 - N)$ images per class for UIUC and $(92 - N)$ images per class for CURet are used as the validation sets. The average accuracies over ten randomly splits are listed in Table 1 for UIUC texture database and in Table 2 for CURet database.

All experiments in this paper have been implemented on a PC with 2.7 GHz Intel Quad CPU, 8 GB RAM, Windows 10 and MATLAB version 7.14 (2014a). Several findings can be noted from Tables 1 and 2. Firstly, basic patterns can get better results than uniform patterns for all conditions in feature extraction methods. This is mainly because significant information about texture is lost, so uniform patterns cannot achieve high performance in difficult databases. Secondly, when the number of training images are increased, the recognition rates also increase in every case as expected. Thirdly, compared to smaller number of neighbouring samples, using 16 neighbour samples can reach higher classification results. It should be noticed that image representation is more successful by using more neighbouring samples to evaluate the difference between pixels. The last

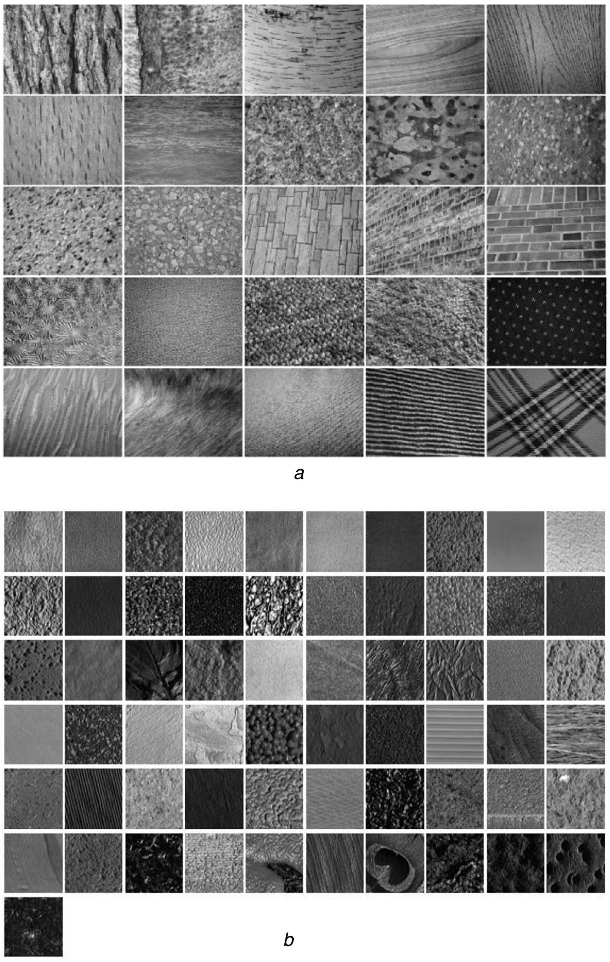


**Fig. 5** *Sample images from* ***(a)*** *UIUC texture dataset,* ***(b)*** *CURet texture dataset*

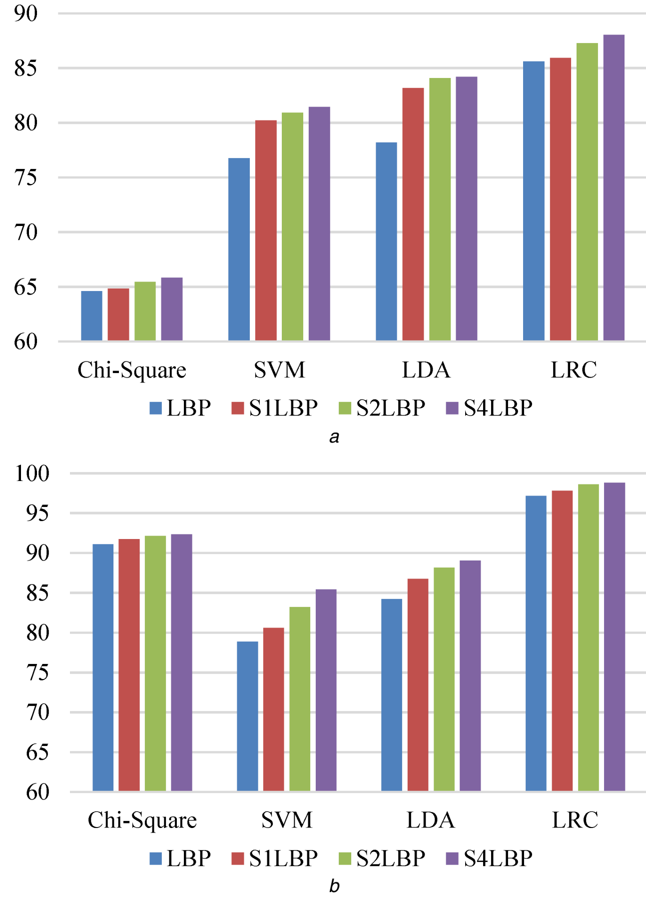


**Fig. 6** *Classification accuracies of Chi-square, SVM, LDA and LRC for LBP, S1LBP, S2LBP and S4LBP* ***(a)*** *on UIUC database,* ***(b)*** *on CURet database*

**Table 1** Classification accuracies for UIUC (P_N denotes Number of neighbours_Number of training images)

| P_N | LBP | ULBP | ELBP | UELBP | S1LBP | S1ULBP | S2LBP | S2ULBP | S4LBP | S4ULBP |
|---|---|---|---|---|---|---|---|---|---|---|
| **8_30** | 85.60 ± 2.01 | 83.28 ± 1.45 | 84.12 ± 3.04 | 78.72 ± 2.57 | 85.92 ± 1.76 | 84.32 ± 2.26 | 87.28 ± 2.56 | 87.20 ± 1.92 | 88.04 ± 1.88 | **88.08 ± 1.67** |
| **16_30** | 85.08 ± 3.40 | 85.08 ± 3.38 | 84.88 ± 2.27 | 84.44 ± 2.21 | 87.24 ± 2.51 | 87.48 ± 2.59 | 87.80 ± 2.70 | 87.76 ± 2.37 | **89.52 ± 2.59** | 88.84 ± 2.46 |
| **8_20** | 78.14 ± 2.36 | 77.22 ± 1.98 | 77.66 ± 2.09 | 74.06 ± 1.94 | 80.08 ± 2.20 | 78.76 ± 2.32 | 81.48 ± 1.96 | 81.44 ± 1.64 | **81.92 ± 2.39** | 81.74 ± 1.91 |
| **16_20** | 77.44 ± 2.11 | 76.60 ± 2.17 | 78.52 ± 1.91 | 77.86 ± 1.82 | 80.20 ± 1.66 | 79.58 ± 1.63 | 80.86 ± 1.75 | 80.72 ± 1.89 | **81.16 ± 1.89** | 81.12 ± 1.62 |
| **8_15** | 72.59 ± 2.42 | 71.92 ± 2.43 | 69.26 ± 2.87 | 65.93 ± 2.34 | 74.48 ± 2.24 | 73.50 ± 2.54 | 75.47 ± 1.89 | 74.75 ± 2.17 | **75.72 ± 2.19** | 75.26 ± 2.29 |
| **16_15** | 71.18 ± 1.98 | 70.89 ± 2.01 | 71.36 ± 2.84 | 70.16 ± 2.63 | 74.84 ± 1.80 | 74.27 ± 1.55 | 75.16 ± 1.99 | 74.91 ± 2.15 | **75.29 ± 2.02** | 75.12 ± 1.52 |
| **8_10** | 61.94 ± 2.06 | 61.96 ± 2.17 | 56.16 ± 1.47 | 53.16 ± 1.59 | 64.01 ± 1.77 | 63.25 ± 2.08 | 64.44 ± 1.89 | 63.73 ± 1.71 | **64.61 ± 2.08** | 64.22 ± 2.16 |
| **16_10** | 60.98 ± 2.26 | 60.18 ± 2.03 | 58.34 ± 1.57 | 56.01 ± 1.49 | 63.92 ± 1.56 | 63.29 ± 1.36 | 64.36 ± 1.45 | 64.02 ± 1.29 | **64.61 ± 1.39** | 64.08 ± 1.27 |

**Table 2** Classification accuracies for CURet (P_N denotes Number of neighbours_Number of training images)

| P_N | LBP | ULBP | ELBP | UELBP | S1LBP | S1ULBP | S2LBP | S2ULBP | S4LBP | S4ULBP |
|---|---|---|---|---|---|---|---|---|---|---|
| **8_46** | 97.14 ± 0.36 | 87.59 ± 0.88 | 97.64 ± 0.34 | 79.41 ± 0.93 | 97.80 ± 0.17 | 88.45 ± 0.70 | 98.61 ± 0.13 | 98.17 ± 0.11 | **98.82 ± 0.17** | 98.68 ± 0.17 |
| **16_46** | 98.45 ± 0.41 | 98.40 ± 0.21 | 97.71 ± 1.02 | 88.11 ± 0.78 | 98.74 ± 0.33 | 97.81 ± 0.24 | 98.84 ± 0.48 | 97.97 ± 0.28 | **99.61 ± 0.24** | 98.86 ± 0.27 |
| **8_23** | 95.26 ± 0.52 | 94.38 ± 0.55 | 95.53 ± 0.51 | 92.73 ± 0.71 | 95.98 ± 0.36 | 95.20 ± 0.44 | 96.68 ± 0.49 | 96.53 ± 0.39 | **96.83 ± 0.40** | 96.82 ± 0.38 |
| **16_23** | 96.12 ± 0.70 | 95.98 ± 0.42 | 94.75 ± 0.52 | 94.71 ± 0.50 | 96.44 ± 0.36 | 95.28 ± 0.33 | 96.95 ± 0.52 | 95.50 ± 0.46 | **97.11 ± 0.42** | 95.89 ± 0.50 |
| **8_12** | 89.52 ± 0.92 | 89.00 ± 0.88 | 89.39 ± 0.64 | 87.23 ± 0.65 | 90.54 ± 0.93 | 90.19 ± 0.98 | 91.14 ± 0.88 | 90.98 ± 0.86 | **91.32 ± 0.86** | 91.31 ± 0.91 |
| **16_12** | 90.33 ± 0.77 | 89.82 ± 0.80 | 71.36 ± 2.84 | 87.82 ± 0.93 | 90.12 ± 0.82 | 88.57 ± 1.02 | 90.46 ± 0.39 | 88.80 ± 0.94 | **92.45 ± 0.80** | 89.92 ± 0.74 |

findings, two symmetric spirals topology can get much better classification rate than LBP which uses one spiral topology. Also, elliptic neighbourhood topology performs worse than the other topologies. When the number of spirals is increased to four, proposed S4LBP achieves the highest classification rates as shown in Tables 1 and 2. In other words, performance can be improved as the number of spirals is increased. However practically this may have a limitation. Increased computational time is the disadvantage of adding new spirals to topology. Each additional spiral increases the running time. Also, the addition of new spirals may add redundant information which not only increases the computation time but also may decrease the recognition performance of the system.

The proposed LBP-based spiral topology descriptors are compared with the other state-of-the-art methods: binarised statistical image features (BSIF) [21], local energy pattern (LEP) [22], noise-resistant LBP ($NRLBP^{riu2}$) [23], multi-scale joint encoding of LBP (MSJLBP) [24], pairwise rotation invariant

**Table 3** Recognition performance comparison of various descriptors in UIUC and CURet databases

| | LBP | ELBP | BSIF | LEP | NRLBP$^{riu2}$ | MSJLBP | PRICoLBP | ELGS | DRLBP | S1LBP | S2LBP | S4LBP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **UIUC** | 78.14 | 77.66 | 73.39 | 81.80 | 81.10 | **83.00** | 80.38 | 78.18 | 71.40 | 80.08 | 81.48 | 81.92 |
| **CURet** | 97.14 | 97.64 | 96.83 | 88.31 | 94.00 | 97.20 | 96.25 | — | 91.23 | 97.80 | 98.61 | **98.82** |

**Table 4** Feature extraction time and dimensionality comparison of various descriptors

| | LBP | ELBP | BSIF | LEP | NRLBP$^{riu2}$ | MSJLBP | PRICoLBP | ELGS | DRLBP | S1LBP | S2LBP | S4LBP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| feature extraction time, ms | 3.4 | 3.5 | 55.6 | 1088.9 | 356.9 | 854.6 | 380.4 | — | 17.2 | 4.7 | 9 | 18.5 |
| feature dimension | 256 | 256 | 1024 | 520 | 50 | 3540 | 3540 | 256 | 44 | 256 | 512 | 1024 |

cooccurrence LBP (PRICoLBP) [25], extended local graph structure (ELGS) [26] and dominant rotated LBP (DRLBP) [27] in Table 3. The number of neighbour samples $P$ is set to 8 for comparisons. Classification accuracies of the methods are reported with randomly chosen 20 images from each class in the UIUC and 46 images for the CURet database in training phase. The results show that the proposed LBP-based spiral topology outperforms the other state-of-the-art methods in CURet texture database. The proposed method is reached better results than all methods except MSJLBP in the UIUC database.

Feature extraction time and feature vector dimension are two parameters for computational complexity comparison. We compare the computational performances of several descriptors in Table 4. In the experiments, the average computation time taken per image for each descriptor is measured by using an image dataset that contains $128 \times 128$ dimensional 480 images. LBP is the best descriptor in terms of feature extraction time. However the computational cost difference of ELBP, DRLBP, S1LBP, S2LBP, S4LBP, BSIF and LBP is negligible. LEP and MSJLBP are the most computationally expensive methods, followed by PRICoLBP and NRLBP$^{riu2}$. MSJLBP and PRICoLBP have the highest feature vector dimensions.

## 6 Conclusion

In this paper, we deeply analysed uniform and basic LBP with Archimedean spiral neighbourhood topology (S1LBP) for sampling step of LBP. The difference between centre pixel and its neighbours is computed by using symmetric two spirals (S2LBP). We also extended the proposed method to four spirals (S4LBP) for the calculation of LBP code. We tested the performances of proposed descriptors in UIUC and CURet databases. In the classification stage we used the LRC method which is generally used to solve face recognition problems. Experimental results show that the S4LBP features are more effective in representing textures and achieve better recognition performance than the other descriptors. Additionally, we achieved comparable results using S2LBP and S4LBP with other methods in terms of computational cost. Results of our work also demonstrate that LRC is an efficient classifier and choosing topology of neighbourhood is very important in texture recognition. As a future work, we plan to focus on efficiently reducing the feature vector size to decrease the computation time and to increase the recognition performance by removing the redundant information.

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