Review of local binary pattern operators in image feature extraction

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ABSTRACT

With the substantial expansion of image information, image processing and computer vision have significant roles in several applications, including image classification, image segmentation, pattern recognition, and image retrieval. An important feature that has been applied in many image applications is texture. Texture is the characteristic of a set of pixels that form an image. Therefore, analyzing texture has a significant impact on segmenting an image or detecting important portions of an image. This paper provides a review on LBP and its modifications. The aim of this review is to show the current trends for using, modifying and adapting LBP in the domain of image processing.

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1. INTRODUCTION

In the area of image processing and computer vision, texture indicates the duplication of basic texture elements, which are referred to as texels. This element consists of multiple pixels that are either intended to be randomly placed or intended to be placed in a periodic manner. According to [1], an image texture can be coarse, fine, smooth, granulated, rippled, regular, irregular or linear. Generally, texture reflects neighbor-surrounding points in the same way that a color reflects a point value [2]. Scale is a significant factor that is associated with texture, and a variant scale produces variant textures, even if the textures were equivalent [3]. Therefore, a single image can contain multiple levels of different textures that are located on different scales. One of the most common texture descriptors is the Local Binary Pattern (LBP), such descriptor is utilizing the structural and statistical features of the image in order to identify local characteristics. The literature showed great progress in the field of image feature extraction by using the LBP. Yet, LBP has encountered various challenges issues such as the rotation, uniformity and others. Therefore, researchers have contributed toward proposing adaptations, modification and alteration of the LBP descriptor. This paper aims to review these modifications of LBP and the current trend in using such descriptor.

2. LOCAL BINARY PATTERN

The LBP was introduced by Ojala et al. [4]; it has been demonstrated as a powerful grayscale invariant texture descriptor in the literature. An LBP operator integrates characteristics of structural and statistical texture analysis. The LBP illustrates texture using microprimitives and their statistical placement rules. The LBP performs on a pixel basis and illustrates the eight surrounding pixels in binary code. The LBP subsequently summarizes all codes into a histogram, which facilitates the extraction of a texture feature. Therefore, a 256-texture pattern for a 3 × 3 neighboring would be produced. Consider the following matrix:

$$B = \begin{pmatrix} g_8 & g_1 & g_2 \\ g_7 & g_{(0,0)} & g_3 \\ g_6 & g_5 & g_4 \end{pmatrix} \quad (1)$$

This matrix shows a 3 × 3 grayscale block of pixels, in which the center is located at (0,0). In this manner, LBP will subtract the coordinate from each neighbor as follows:

$$LBP1 = \begin{pmatrix} (g_8 - g_{center}) & (g_1 - g_{center}) & (g_2 - g_{center}) \\ (g_7 - g_{center}) & g_{center} & (g_3 - g_{center}) \\ (g_6 - g_{center}) & (g_5 - g_{center}) & (g_4 - g_{center}) \end{pmatrix} \quad (2)$$

To generate the binary code, the following equation should be considered:

$$LBP2 = \begin{pmatrix} s(g_8 - g_{center}) & s(g_1 - g_{center}) & s(g_2 - g_{center}) \\ s(g_7 - g_{center}) & g_{center} & s(g_3 - g_{center}) \\ s(g_6 - g_{center}) & s(g_5 - g_{center}) & s(g_4 - g_{center}) \end{pmatrix}$$

$$s(x) = \begin{cases} 1 & if\ x \geq 0 \\ 0 & if\ x < 0 \end{cases} \quad (3)$$

Consequentially, an eight-bit binary pattern will be encoded as follows:

$$LBP = \sum_{a=0}^{8} s_{(g_a - g_c)} 2^p \quad (4)$$

The possible 256-bit pattern that is produced by (3) will be used to construct a histogram, which will facilitate the process of texture description. Texture is a significant characteristic of different types of images and is involved in several images from multispectral images to microscopic images. The significance of texture is depicted in numerous computer vision and image analysis applications. Recently, different discriminative local texture descriptors have been proposed; the most common descriptor is local binary pattern. The local binary pattern (LBP) was originally presented as a texture descriptor [5]. The LBP has been utilized in several domains of computer vision, such as face recognition and facial expression recognition, to model motion and actions. Multiple modifications have been conducted on the original LBP to fit other tasks. The LBP has contributed toward significant progress in the area of texture analysis, where various applications that range from 2D texture to 3D texture have been examined. The LBP can be viewed as a unifying method for the classical divergent statistical and structural models of texture analysis. The key success factor behind the LBP is its accurate monotonic grayscale changes, such as illumination variations. In addition, the LBP has another advantage-simple computations-which renders it competitive in the area of real-time image analysis. The LBP depends on the assumption that emphasizes that texture has two complementary perspectives: pattern and strength. The pixels of an image are being annotated by a specific threshold that compares neighboring pixels with the center. The result will be represented as a binary number. This resulting value will be used as a texture descriptor.

Example

6	5	2
7	6	1
9	8	7

Threshold

1	0	0
1		0
1	1	1

Weights

1	2	4
128		8
64	32	16

The first table contains a 3×3 pixel, which represents an image portion. The LBP focuses on the center, in which all surrounding pixels will be compared against the center. This comparison attempts to identify the smaller and greater values. Thus, the pixels that have greater values than the center will be encoded as 1, and the pixels that have values smaller than the center will be encoded as 0, as shown in the second table (i.e., threshold). The pattern can be extracted as ‘10001111’ and will be utilized as a texture feature for learning purposes. The third table provides an assumption by assigning weights to all pixels (which are powers of 2). The LBP is computed by summing all corresponding pixels in the second table as follows:

$$LBP = 1+128+64+32+16 = 241$$

C, which is the contrast measure, is computed by summing all corresponding pixels of '1' divided by their number and then subtracting them from the corresponding pixels of '0' divided by their number as follows:

$$C = \frac{6+7+9+8+7}{5} - \frac{5+2+1}{3} = 4.7$$

Note that if all pixels have the same values of '1' or '0', the results of C will be zero. The C and 2D distributions of the LBP codes are employed as a features vector in texture analysis, such as recognition.

2.1. Uniform local binary pattern

Ojala et al. [6] have identified some frequent patterns, such as edges, curves and spots. These patterns can be represented by the transition from '1' to '0' in the matrix as follows:

1	0	0
1		0
1	1	1

Based on these patterns, uniform local binary patterns (U-LBP) were introduced. The key advantage of the U-LBP is that it minimizes the number of patterns, which reduces the length of the feature vector. Generally, binary patterns are considered significant properties of texture; they usually have the majority of the frequency. This pattern is uniform and can be determined using a uniformity measure that identifies the spatial transition. Figure 1 depicts an image, in which the left side shows the non-uniform changes and the right side shows the uniform changes. The uniformity pattern can be computed as:

$$LBP_{p,r}^{riu2} = \int \begin{matrix} \sum_{p=0}^{p-1} s(g_p - g_c) & if & U(LBP_{P,R}) \leq 2 \\ P+1 & otherwise & \end{matrix} \quad (5)$$

Where,

$$U(LBP_{p,r}) = |s(g_p - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{p-1} |s(g_p - g_c) - s(g_0 - g_c)|$$

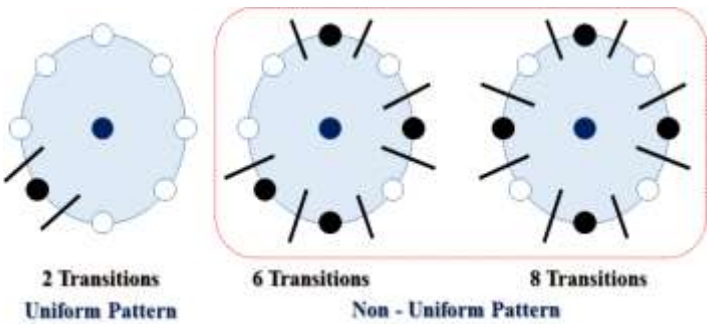

Figure 1. Uniform and non-uniform pattern

A critical expansion is the uniform local binary pattern, which has been presented to diminish the dimensionality of the highlighted feature vector and scrutinize the rotation invariant. This premise is spurred by the hypothesis that some of the binary patterns in texture images occur more commonly than other patterns. LBP can be uniform in the event that the double design contains at most two—0-1 or 1-0—transitions. For example, the feature vector '11101111' is a uniform pattern because it has two transitions, whereas the feature vector '101010' is not uniform because it has five transitions. The pattern 00010000 has 2 transitions and is known as a uniform pattern, whereas the pattern 01010100 has 6 transitions. To compute the LBP histogram, the histogram has a separate bin for every uniform pattern, and all non-uniform patterns are assigned to a single bin. The uniform local patterns and length of the feature vector will be used for a single cell to reduce from 256 to 59.

2.2. Completed modeling local binary pattern

Guo et al. [7] introduced a new operator and a texture classification scheme for the local binary pattern. This operator is referred to as completed modeling, where the local variances have been decomposed into two main parts: the first part for the sign and the second part for the magnitude.

The CLBP_M is defined by the following operator:

$$CLBP\_M_{P,R} = \sum_{p=0}^{P-1} t(m_p, c)2^p, t(x,c) \begin{cases} 1, x \geq c \\ 0, x < c \end{cases} \tag{6}$$

The CLBP_C is defined by the following operator:

$$CLBP\_C_{P,R} = t(g_c, c_I) \tag{7}$$

The 3D joined histogram is generated from the three components and denoted by:

$$CLPB\_S_{P,R}^{riu2} / M_{P,R}^{riu2} / C. \tag{8}$$

Instead of the contrast measure of the standard LBP, the completed modeling local binary pattern (CLBP) aims to utilize the magnitude as an alternative. The authors have also added information related to the intensity of an image in their representation. In their work, all pixel values have been subtracted from the center's value as follows:

Sample

6	5	2
7	6	1
9	8	7

Local difference

0	-1	-4
1		-5
3	2	1

The sign has been implemented by representing the negative values as '-1' and the positive values as '1' as follows:

Local difference

0	-1	-4
1		-5
3	2	1

Sign

1	-1	-1
1		-1
1	1	1

Consequentially, the authors have used the magnitude of the sign matrix as follows:

Sign

1	-1	-1
1		-1
1	1	1

Magnitude

0	1	4
1		5
3	2	1

The threshold binary values of the magnitude will be presented as follows:

Magnitude

0	1	4
1		5
3	2	1

Threshold binary

-1	-1	-1
-1		-1
-1	-1	-1

2.3. Volume local binary pattern (VLBP)

The LBP has faced a new challenge, which is represented by motion analysis. Pietikäinen [8] has introduced an extension of the LBP, which has the ability to analyze dynamic texture in a spatiotemporal manner. The proposed extension is known as the volume local binary pattern (VLBP). This method treats texture in three dimensions: two spatial dimensions and one dimension that represents time.

$$VLBP = \sum_{q=0}^{3p+1} v_q 2^q \tag{9}$$

To simplify the expression of V we use $V = v\left(v_0,...,v_q,...,v_{3p+1}\right)$ and q corresponds to the index of values in V orderly. By assigning a binomial factor 2^q, for each sign $s\left(g_{t,p} - g_{t_c,c}\right)$ we transform (4) into a unique $VLBP_{l,p,r}$ number that characterizes the spatial structure of the local volume dynamic texture:

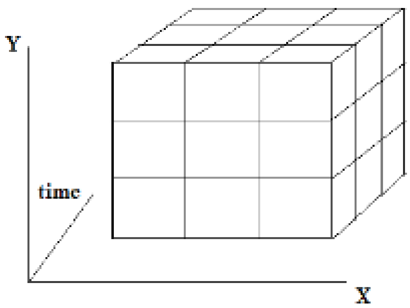

Figure 2. Volume LBP

Where V in a local neighborhood of a monochrome dynamic texture sequence as the joint distribution of the gray levels of $3p+3\left(p \succ 1\right)$ image pixels.

$$V = v(gt_C - L, c, gt_C - L, 0, \cdots, gt_C - L, P-1, gt_C, c, gt_C, 0, \cdots, gt_C, P-1, gt_C + L, 0, \cdots, gt_C + L, P - 1, gt_C + L, c) \tag{10}$$

Where the gray value gt_C,c corresponds to the gray value of the center pixel of the local volume neighborhood, $gt_C - L,c$ and $gt_C + L,c$ correspond to the gray values of the center pixels in the previous and posterior neighboring frames with time interval L; $g_{t,p}(t = t_c - L, t_c, t_c + L; P = 0,..., P-1)$ correspond to the gray values of P Equally spaced pixels on a circle of radius $R\left(R \succ 0\right)$ in image t, which form a circularly symmetric neighbor set.

As shown in Figure 2, addressing 3 dimensions involves a cube of pixels, where the center will be compared with every neighbor. The result is 2^{26} possibilities. For this reason, the authors have focused on three orthogonal planes rather than the whole cube to decrease the possibilities, as shown in Figure 3.

The result is 3×2^8, which is substantially smaller than 2^{26} [9]. The original applications, which were based on VLBP, have been intended to detect faces, facial expressions, and facial gender and to perform lip-reading. As previously mentioned, the eight surrounding pixels will be used to construct the histogram. In this manner, four neighbors will be located at different distances than the other neighbors. To overcome this issue, a circular neighborhood can be utilized. Figure 4 depicts this utilization, in which the neighbors that are not be located exactly at the center can be interpolated. Two parameters—P and R—should be considered, where R indicates the distance between each neighbor and the center, and P indicates the number of samples at this distance.

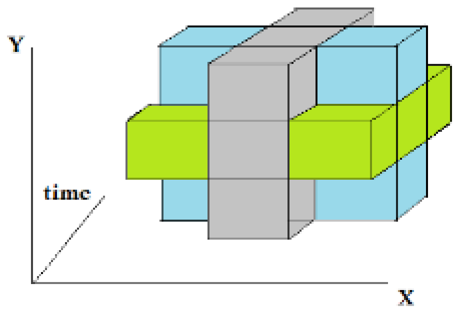

Figure 3. 3-orthogonal planes

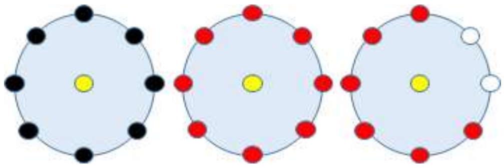

Figure 4. Circular LBP

2.4. Rotation invariant local binary pattern

This type of LBP is concentrated on the rotation of an image, where the values of neighbors that surround the centers will change. The rotation invariant LBP has the ability to overcome this issue by shifting the binary structure using the following equation:

$$LBP_{p,r}^{ri} = \min\left\{ROR\left(LBP_{p,r}, i\right) \middle| i = 0,1,.....,P-1\right\} \tag{11}$$

where ROR (x,i) performs a circular bitwise right shift on the P bit number. Figure 5 depicts a rotation of an image, where the values of the neighbors change. Assume that the black dot indicates the 1's and the white dots indicate the 0's. The pattern of the image before the rotation is different compared with the pattern after rotation. By applying the rotation invariant LBP, the patterns can be identical.

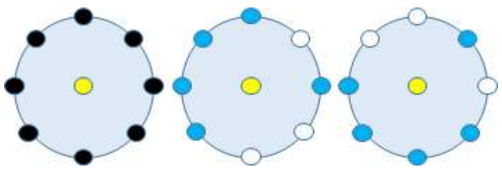

Figure 5. Different patterns of a rotated image

Guo et al. [10] adapted the standard local binary pattern by combining the directional statistics from the invariant rotation. This statistical information has been used to enhance the classification of the LBP, in which specific information, such as the deviation of the local differences, is utilized. Other information, such as the least squares, has been utilized to decrease the local variances that contribute to stabilizing the directional features. Garcia et al. [11] have modified the adapted LBP, in which the standard deviation has been oriented rather than utilized within the matching process. This modification has shown competitive results in some domains of interests. Guo et al. [12] have proposed a variance LBP, in which the gray contrast has been utilized as a weight for pruning the computations of the LBP histogram. The proposed variance features have been utilized to predict the principal orientations. The proposed variance features have been utilized to identify the nondominant patterns for the sake of dimensionality reduction. Zhang et al. [13] have proposed a modified rotation invariant LBP by combining a new operator with the rotation measures included in the standard operator. This operator was a monogenic tensor that aimed to identify the information related to the local surface, which has been performed using Riesz transforms. Zhao et al. [14] determined the information related to the gray contrast without the need to identify the structural information. This step has been performed by utilizing an operator referred to as the completed local binary count. According to the authors' assumptions, identifying some structural information for accommodating classification based on a rotation invariant is not necessary in some cases. Zhao et al. [15] presented a method for extracting features related to a rotation-invariant using a histogram of patterns that are not invariant based on Fourier transforms, in which the histogram of the LBP has been involved. The proposed method enhancing the classification of rotation-invariant and shown competitive results in terms of the classification accuracy compared with the state of the art.

2.5. Rotation invariant uniform local binary pattern (RIULBP)

Similar to the rotation invariant, this pattern can be obtained in the same way. Figure 6 shows a pattern of rotation invariant uniform, where eight neighbors and 9 rotation invariant uniform LBP codes have been depicted. Two rotations are depicted without any changes to the 0's and 1's (i.e., 0 and 8), while the remaining rotations showed a sequence of changes (i.e., 1-7).

$$LBP_{(P,R)}^{riu2} = \begin{cases} \sum_{p=1}^{p-1} s\left(g_p - g_c\right), & if\, U\left(LBP_{P,R}\right) \leq 2 \\ p = 1, & otherwise \end{cases} \quad (12)$$

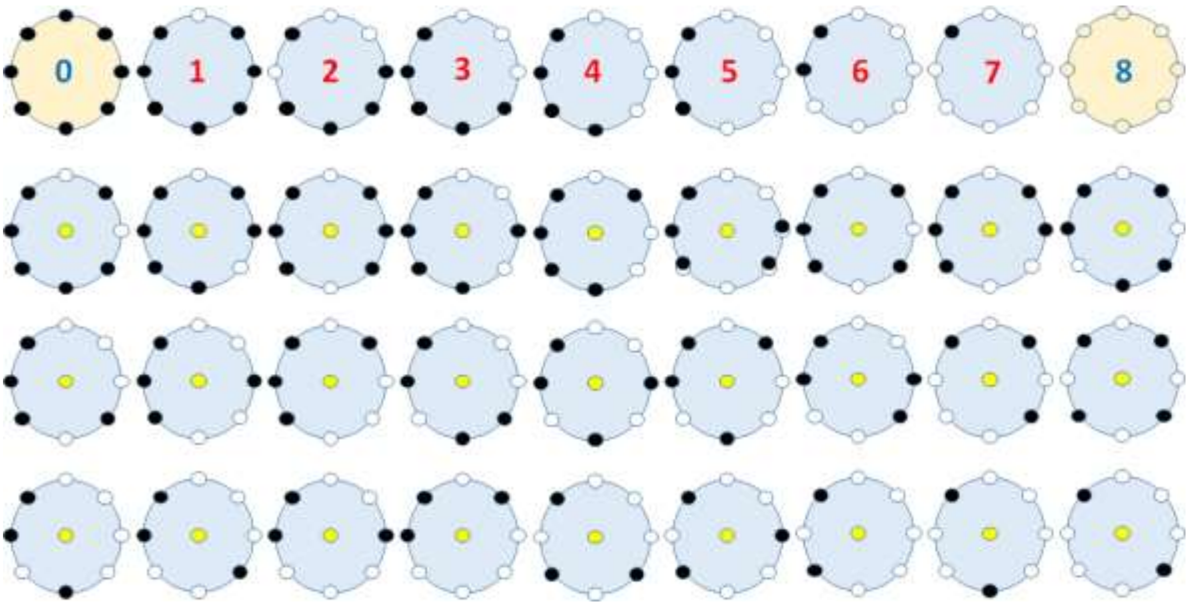

Figure 6. Uniform rotation invariant LBP

2.6. Current Trends of Using LBP

The local binary pattern is an effective texture feature analysis method that has been examined for several domains in the literature. For instance, Liu et al. [16] have addressed the problem of the sensitivity of the LBP regarding noisy data, which hinder the capturing of macrostructure information. The authors have proposed a novel texture classification method that is based on a median robust extended LBP. Unlike the traditional method, the proposed method constrains the regional image medians instead of the raw image intensities. Using benchmark data, the authors have demonstrated that the performance of their proposed method is superior regarding the grayscale variations and noise-resistance. Khaleefah et al. [17] have utilized texture classification method by using LBP descriptors for the task of paper texture identification or fingerprinting, which are well-known technique, in the texture classification that shown superior performance in authenticating documents. Wan et al.[18] have proposed an enhanced LBP, namely, average-LBP, for the process of texture analysis of human breast tissue images. These images are obtained by optical coherence microscopy (OCM), which is a technology to capture microscopic images of human tissue. The proposed averaged-LBP has outperformed the original LBP in terms of encoding the texture structure.

With the availability of real-time 3D sensors, such as Kinect, the efforts of gesture recognition have extensively progressed. Since the 2D LBP utilizes texture information, it cannot be applied for gesture recognition, which usually does not have texture information. Therefore, Kim et al. [19] have proposed an adaptive LBP for 3D hand tracking. The proposed method has the ability to be invariant to both rotation and the depth distance in range images. Khaleefah et al. [20] have employed $\left(LBP_{p,r}^{basic}, LBP_{p,r}^{u2}, LBP_{p,r}^{riu2}\right)$ for the automated paper fingerprinting (APF) method. The results of the experiments showed that the proposed method can identify deformed paper fingerprinting. Similarly, Dey et al. [21] have addressed the problem of word spotting, in which the digital libraries usually store their books as images. Therefore, a vital demand exists to process these images to detect words, which would offer a great opportunity for information retrieval, where the user can search using some keywords and obtain accurate results. Thus, the authors have proposed a combination of LBP and spatial sampling for the process of detecting or spotting handwritten words using large-scale historical documents. Comparing the results of texture analysis features with other methods, the proposed method has demonstrated better performance. Additionally, Almezoghy et al. [22] have proposed a method for human palm print detection using the LBP. The proposed method utilizes different morphological features, and the LBP will use this feature to perform the detection. Using real data collected from 500 people, the proposed method has been applied and compared with other methods, such as principle component analysis. The experimental results showed that the performance of the proposed method is superior to PCA.

Bian et al. [23] have proposed an extension of the LBP, which is referred to as multistructure LBP, for the process of classifying high-resolution images. The proposed method utilizes three coupled descriptors with multistructure sampling to identify complementary features. The results revealed that the proposed method has the ability to effectively capture local spatial pattern and local contrast compared with other methods. Jia et al. [24] have improved the classification of hyperspectral images using a novel LBP, namely, LBP superpixel-level. The proposed method utilizes a uniform LBP to identify local features. Consequentially, a support vector machine classifier has been used to classify the description of every pixel that belongs to every class. Using real data of hyperspectral images, the proposed method showed superior performance in terms of classification. Due to the limitation of the traditional LBP when capturing spatial structures, Yuan et al. [25] have proposed a Hamming-distance approach to the LBP for texture classification and material recognition. The experiments demonstrate the efficacy of the proposed method. Another study by Xu et al. [26] has addressed the problem of averaging the underlying smooth surface in an image when using the original LBP. Therefore, the authors have proposed a polynomial contrast binary pattern (PCBP) to efficiently estimate the underlying local surface information that can be depicted as a linear projection of the local patch. The authors have examined the proposed method for the facial recognition task. Kou et al. [27] have examined the limitation of the inability to capture the macro and micro structure of an image when using the traditional LBP. The authors have proposed the principal curvatures local binary pattern (PCLBP) to capture consecutive rotation invariance, which can improve the extraction of micro and macro structure texture information. Table 1 summarizes all LBP texture analysis related work that has been illustrated in subsequent paragraphs.

Table 1. Summary of current trends for the LBP

Reference	Method	Problem	Task
Liu et al. [16]	Extended LBP	Structure	Image classification
Wan et al. [18]	Average-LBP	Averaging	Medical image classification
Kim et al. [19]	Adaptive LBP	Structure	Image classification for handwritten recognition
Dey et al. [21]	LBP and spatial sampling	Structure	Image segmentation for handwritten recognition
Almezoghy et al. [22]	PCA-LBP	Averaging	Image classification for palm recognition
Bian et al. [23]	Multistructure LBP	Structure	High-resolution image classification
Jia et al. [24]	LBP superpixel-level	Structure	Image classification for hyperspectral images
Yuan et al. [25]	HDLBP for spatial structure	Structure	Image classification for material recognition
Xu et al. [26]	PCBP	Averaging	Face recognition
Kou et al. [27]	PCLBP	Structure	Image texture classification
Khaleefah et al. [17,20,28]	LBP, ULBP	Parameter tuning	Paper fingerprinting

3. CONCLUSION

This paper provided a review on LBP as a texture descriptor along with its modifications. Most of the proposed modifications of LBP were intended to solve specific problems such as structural and averaging information. Future work shall consider the application of different combinations of LBP and other descriptors.

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