Rotated Local Binary Pattern (RLBP)
Rotation Invariant Texture Descriptor

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Abstract: In this paper we propose two novel rotation invariant local texture descriptors. They are based on Local Binary Pattern (LBP), which is one of the most effective and frequently used texture descriptor. Although LBP efficiently captures the local structure, it is not rotation invariant. In the proposed methods, a dominant direction is evaluated in a circular neighbourhood and the descriptor is computed with respect to it. The weights associated with the neighbouring pixels are circularly shifted with respect to this dominant direction. Further, in the second descriptor, the uniformity of the patterns is utilized to extract more discriminative information. The proposed methods are tested for the task of texture classification and the performance is compared with original LBP and its existed extensions.

1 INTRODUCTION

Texture classification is an important area of research in computer vision and pattern recognition. The texture based descriptors have been used for object, scene and face classification. A number of approaches can be found in literature based on filter banks (Salas and Hille, 1978), co-occurrence statistics (Haralick, 1979), local scale (Ojala et al., 2002) and more recently, on keypoints based setting (Ling and Soatto, 2007) and multi fractal schemes (Xu et al., 2009).

Among them, Local Binary Pattern (LBP) (Ojala et al., 2002) has gained a popularity due to computational simplicity and good performance. The original LBP operator is invariant to monotonic gray scale changes as it is computed by taking a difference of the pixels intensities. However, it is not invariant to image rotations. A number of extensions of LBP have been proposed to incorporate the rotation invariance property into it. Ojala et. al. proposed LBPROT which circularly shifts the binary code until it corresponds to one of the preselected rotation invariant patterns (Ojala et al., 2002). This approach, however, loses a discriminative information because of the non-uniformity of the pattern density in the image. To retain the global information Li et. al. proposed a circular shifting of the histogram bins with respect to the largest bin, since it corresponds to the most frequent pattern in the image (Li et al., 2012). Gou et. al. combined the information related to the magnitude and central pixel that is complementary to the sign values (Guo et al., 2010a). They also proposed to estimate the principle orientation and then align the LBP features with respect to this orientation (Guo et al., 2010b). Recently Zhao et. al. proposed LBP Histogram Fourier (LBP-HF) descriptor (Zhao et al., 2012), that computes the discrete Fourier transform over the histograms to achieve rotation invariance. The Fourier transform, however, completely ignores the structural arrangement of the histogram, thereby losing some discriminative information.

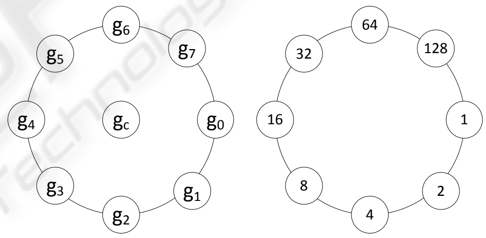

Figure 1: (a) The neighbourhood for LBP (b) Weights associated with the neighbours.

In all above mentioned approaches the rotation invariance is achieved at the expense of losses of some discriminative features extracted using original LBP. These losses occur due to the compact mapping (Ojala et al., 2002), transformation of histograms (Zhao et al., 2012) or shifting of the histograms bins (Li et al., 2012). In this paper we propose a framework which can incorporate the complete structural

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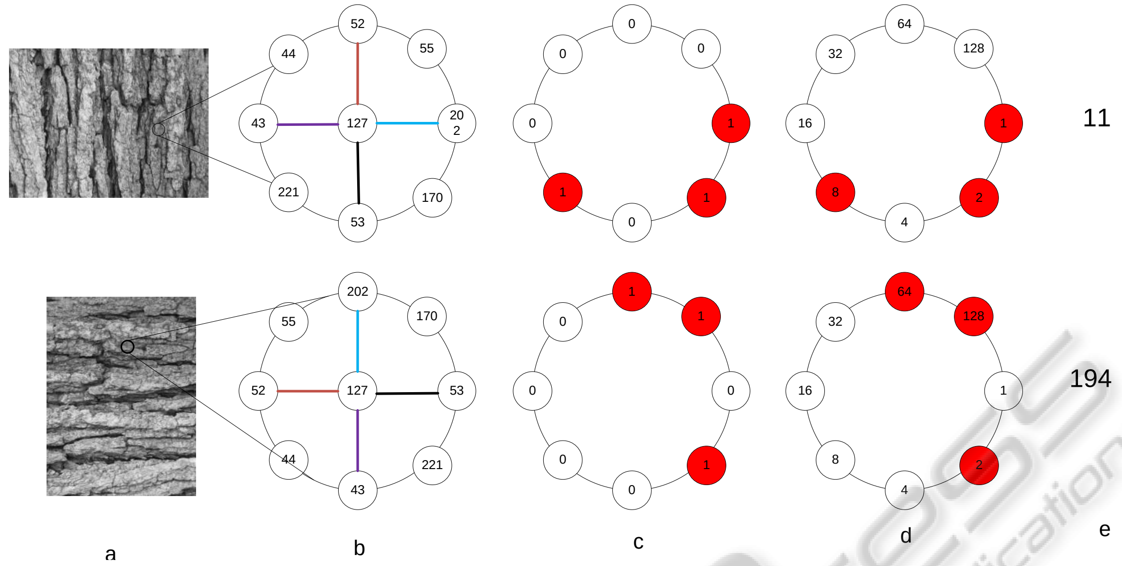

Figure 2: Effect of rotation on LBP operator (a) The image (top) and 90^0 counter-clockwise rotated image (bottom), (b) In the rotated images the neighbourhood is rotated counter-clockwise by 90^0, (c) Values above threshold are shown in red color, (d) The weights corresponding to the thresholded neighbours, (e) LBP values.

information extracted by LBP and, at the same time, achieve a rotation invariance. The main idea behind the paper is to set a local reference direction in every circular neighbourhood and compute the descriptor with respect to it. When the image is rotated, the local reference direction is also subjected to the rotation by the same degree, hence, the descriptor computed with respect to it remains the same. The choice of local reference, instead of a global one, is motivated by the fact that the texture is a local cue and is computed locally by LBP. Usage a single global reference for a whole image may lead to computation of LBPs which are misaligned.

This paper starts with a discussion on the reasoning behind the inability of LBP to deal with a rotation changes. Then we introduce the idea of dominant direction, which is used as the reference while computing the local descriptor. Based on this idea we propose novel descriptors RLBP and uRLBP. RLBP is computed by circularly shifting the binary code at each location based on the dominant direction. uRLBP is an extension of RLBP, utilizing the concept of uniform pattern. The proposed descriptors are easy to compute and with a relatively less number of neighbours they achieve a good performance.

The rest of the paper is organized as follow. In Section 2 we discuss the LBP operator on rotated images. In Section 3, we present the proposed approach for a texture classification based on two novel descriptors RLBP and uRLBP. The experiments are performed on the standard texture datasets to compare the performance of the proposed methods with the existed ones. The results are reported in Section 4 and, finally, the paper is concluded in Section 5.

2 LBP ON ROTATED IMAGES

LBP operator is computed in a local circular region by taking the difference of the center pixel with respect to its neighbours. It is defined as

$$LBP_{R,P} = \sum_{p=0}^{P-1} s(g_p - g_c) \cdot 2^p, \tag{1}$$

$$s(g_p - g_c) = \begin{cases} 1 & g_p \geq g_c \\ 0 & g_p < g_c \end{cases}. \tag{2}$$

where g_c and g_p denote the gray values of the central pixel and its neighbour, respectively, p is the index of the neighbour, R is the radius of the circular neighbourhood and P is the number of the neighbours. Fig. 1 shows the neighbours for $P = 8$ and the weights corresponding to these neighbours. If the coordinate of the central pixel is (x, y), then the coordinates of uniformly spaced circular neighbourhood are given as $(x + Rcos(2\pi p/P), y - Rsin(2\pi p/P))$ for $p = 0, 1, 2, ..., P - 1$. If the neighbouring coordinate does not correspond to integer values, then bilinear interpolation is used for estimation of pixel value.

Further, to extract the most fundamental structure from the LBP, the idea of uniform pattern is utilized. A local binary pattern is called uniform if binary code contains at most two transitions from 0 to 1 or vice versa. For example, the patterns 00011100, 01000000 are uniform as both consist of 2 transitions, while 00101000 and 00011010 are non-uniform as they contain 4 transitions. In practice, this is implemented using a lookup table of elements where the table maps the non-uniform patterns into a single bin and all others separately. For P neighbours, the number of uniform LBP patterns is given by $P(P-1)+3$.

The LBP operator takes the difference of the central pixel with the neighbouring pixels and combines the signs of these differences using unique weights. The order of the weights is fixed in the circular neighbourhood, i.e. the weight corresponding to g_0 is always 1 and so on, as it is shown in Fig. 1. If the image undergoes a rotation, the arrangement of the pixel around the center undergoes a shift. Since the order of the weights is fixed, the LBP computed on the rotated images is unable to deal with the rotation changes. Thus, even for a simple image rotation the LBP operator provide very different values. Fig. 2 shows the effect of rotation on the LBP operator. In this illustration LBP is computed at some location in image and on a rotated version of the same image. As image is rotated counter-clockwise by 90^0, the neighbours around each pixel also undergo a counter-clockwise rotation of the same angle as shown in Fig. 2(b). The pixels in the circular neighbourhood are thresholded with respect to the central pixel and those above the threshold are shown in red color in Fig. 2(c). The weights corresponding to these pixel values are also highlighted in red color in Fig. 2(d). The thresholded pixels and weights in both images correspond to very different locations and when summed up this results in distinct output values. It is due to the fact that the arrangement of the weights in LBP does not depend on the values of the neighbours. In order to overcome this problem we propose to adaptively select the arrangement of the weights based on the values of pixels in the neighbourhood.

3 TEXTURE CLASSIFICATION USING RLBP

In this section we present the proposed approach for the task of texture classification. First, we introduce RLBP operator obtained by circularly shifting the weights of LBP operator. Further, the intrinsic structure of the patterns is utilized by incorporating the principle of uniform patterns to generate uniform RLBP (uRLBP). Finally, two classifiers (nearest neighbour (NN) and support vector machine (SVM)) are discussed along with their choice of parameters.

3.1 Rotated Local Binary Pattern (RLBP)

LBP only considers the signs of the differences to compute the final descriptor. The information related to the magnitude of the differences is completely ignored. The magnitude provides a complimentary information that has been utilized (Guo et al., 2010a) to increase the discriminative power of the operator. Especially in the neighbourhood with strong edges the magnitude of the differences can provide an important information. Here we utilize the magnitude of the difference to find the dominant direction in a neighbourhood. The dominant direction is defined as the index in the circular neighbourhood for which the difference is maximum. As an image undergoes a rotation the dominant direction in a neighbourhood also undergoes the rotation by the same angle. In the proposed descriptor the dominant direction is set as the reference and the weights for the neighbourhood are arranged with respect to it.

In order to make the LBP invariant to rotation we circularly shift the weights according to the dominant direction. The dominant direction (D) in a neighbourhood is the index of neighbour whose difference to the central pixel is maximum; it is defined as

$$D = \underset{p\in(0,1\ldots P-1)}{\arg\max} |g_p - g_c|. \tag{3}$$

The rotation of neighbourhood with respect to its center shifts the direction D by the same angle. For example, if we consider a neighbourhood [23 25 28; 167 35 31; 56 67 72], after the thresholding its binary code is [0111**1**000], the index of D is 4 (shown in bold) corresponding to the pixel value 167 . If the image is rotated by 45^0 counter-clockwise, then the neighbourhood also rotates by the same angle and the binary code shifts to [00111**1**00]. D index still corresponds to the same value (167) but it shifts by one step. However, the circular arrangement of the pixels in the neighbourhood remains the same with respect to the direction D. Therefore the lowest weight is associated with the index corresponding to D and is subsequently increased in the counter-clockwise direction.

Since the dominant direction is taken as the reference in the circular neighbourhood, the weights are assigned with respect to it. Thus the RLBP operator is defined as

$$RLBP_{R,P} = \sum_{p=0}^{P-1} s(g_p - g_c) \cdot 2^{mod(p-D,P)}, \tag{4}$$

where *mod* indicates the modulus operation. In the above definition the weight term $2^{mod(p-D,P)}$ depends

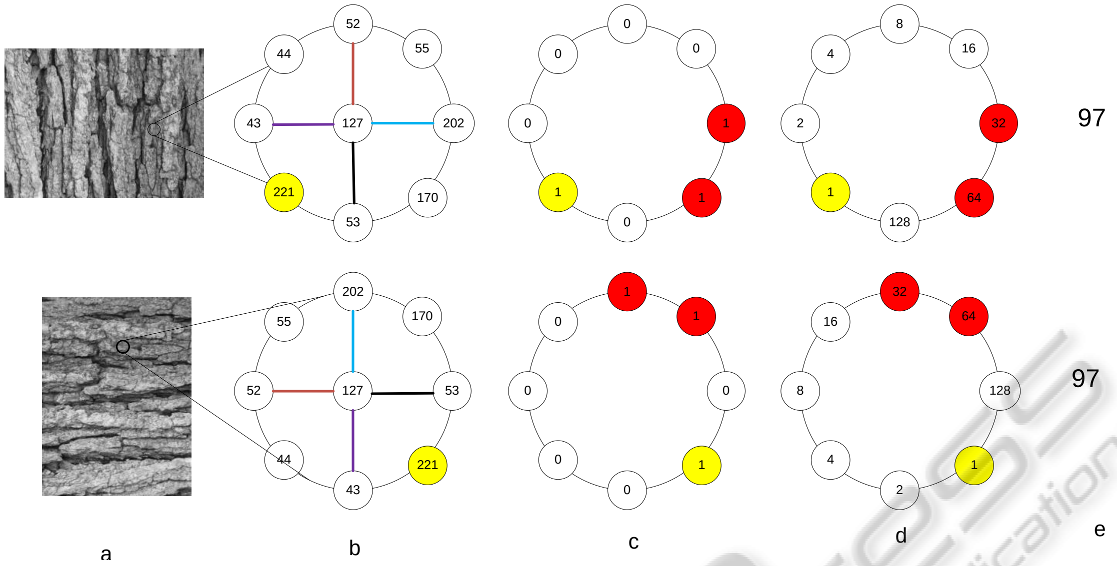

Figure 3: Effect of rotation on RLBP operator (a) The image (top) and 90^0 counter-clockwise rotated image (bottom), (b) Yellow color pixel indicate the dominant direction, (c) Values above threshold are shown in red color, (d) The weights are circularly shifted with respect to dominant direction, (e) RLBP values.

on D. The weights are circularly shifted with respect to the dominant direction. The shift results in a rotation invariance, as the weights now depend on the neighbourhood and not on a preselected arrangement. Fig. 3 shows the effect of rotation on the RLBP features. For clear understanding we use the same scenario as was used in Fig. 2 for LBP. As before, the red color indicate the pixels above the threshold, yellow color indicate the pixel corresponding to the dominant direction D. The bit corresponding to index D always takes the lowest weight of 1 and other weights are circularly shifted with respect to it. In Fig. 3(d) it can be seen that the weight corresponding to the dominant position is the same for original and rotated images, although these pixels are at different locations. Thus the RLBP values obtained for two different rotated neighbourhood are similar in this case.

3.2 Uniform Rotated Local Binary Pattern

To utilize the intrinsic structure of the binary patterns the idea of uniform patterns is applied on the LBP. The uniform LBP (uLBP) achieves better performance compared to LBP due to the statistical properties of these patterns. Experiments carried out on large image datasets showed that up to 90% of the total patterns are uniform while the remaining small percentage are non uniform. This small portion of non-uniform patterns are distributed in large number of histogram bins which cannot be estimated reliably. The accumulation of large number of uniform patterns into relatively small number of histogram bins provides the discriminative information, which is utilized by uLBP. Thus, if the distribution of the patterns obtained by the operator is preserved, the uniformity of the pattern can be utilized to enhance the discriminative power.

Similar to the LBP operator, the RLBP operator computes the binary patterns based on pixel neighbourhood. The final values obtained by these operators are different because the weights are circularly shifted in RLBP operator. Since the binary patterns are same for both operators, the distribution of the patterns is similar. To capture an additional discriminative information, we apply the idea of the uniform patterns to RLBP operator. The uniform RLBP operators is given as $U(RLBP_{R,P})$, where $U()$ is the lookup table that defines a mapping from a binary pattern to a uniform pattern. For a neighbourhood of P pixels, the lookup table $U()$ consist of 2^P elements and $P(P-1)+3$ different output values corresponding to the uniform patterns.

3.3 Classifiers

The performance of the descriptor is tested by two different classifiers: Nearest Neighbour (NN) and Support Vector Machine (SVM). The nearest neighbour classifier is used with a number of different distance metrics such as chi-square, log-likehood, cosine distance, etc. In this study we use the histogram intersection which is given as

$$d(H,K) = 1 - \frac{\sum_i min(h_i,k_i)}{\sum_i k_i} \quad (5)$$

where H is the histogram of the test sample, K is the histogram of the training sample, i represent the bin number and h_i, k_i are the values of the the i^{th} bin in the histogram H and K respectively. The test sample is assigned to the class of the training sample which minimizes this distance.

Nearest neighbour is a simple classifer which can deal with easy rotational variations. However it cannot effectively model the texture with more difficult viewpoint and scale variations. Thus, to deal with these difficult conditions, SVM classifier is utilized. The SVM classifier is tested with different kernels and the linear kernels provided the best numerical results.

4 EXPERIMENTS

The proposed method is tested on three different texture datasets: Outex-10, Outex-12 and UIUC texture datasets. Outex-10 and Outex-12 have only rotational variation while the UIUC is much more difficult dataset with rotation, scale and viewpoints variations. The performance of the proposed algorithm is compared with LBP, uniform LBP (*uLBP*), rotation invariant LBP (*riLBP*), uniform rotation invariant LBP (*uriLBP*) and LBP-HF.Three of these methods ((*riLBP*),(*uriLBP*) and LBP-HF) are rotation invariant version of LBP. To keep the complexity low we set the number of neighbours to 8 in all the tests.

4.1 Outex-12

Outex-12 dataset consists of 9120 images representing 24 different textures under different lighting and rotations. In our experiments, 20 images from each class are used for training and the rest are used for testing. Thus, the testing set consists of 8640 images and training set consists of 480 images. The results of comparison are shown in Table 1. It can be observed that the methods proposed specifically to deal with the rotation changes, such as riLBP, LBP-HF and the proposed descriptor, achieve much better accuracy than the original LBP. LBP-HF preforms better than earlier proposed descriptors riLBP and uriLBP. However, the proposed descriptor outperforms this state-of-the-art rotation invariant LBP-HF. The radius parameter is increased from 1 to 3 for LBP-HF and RLBP. It is interesting to observe that for both descriptors the performance improves with an increase in the radius. At smaller radius the operator captures pixel related information while at the larger radius the region based information is captured. For radius 3 the operator captures the directional information from the circular regions of diameter 7. As the radius is increased further the accuracy decreases, which implies that for large region (radius > 3) binary patterns cannot effectively capture the structure.

Table 1: Test results for Outex-12 dataset.

Method	Accuracy	Dimensionality
LBP	54.8	256
uLBP	54.54	59
riLBP	66.40	36
uriLBP	62.23	10
$LBP-HF_{1,8}$	75.48	38
$LBP-HF_{2,8}$	80.30	38
$LBP-HF_{3,8}$	82.97	38
$RLBP_{1,8}$	72.35	256
$RLBP_{2,8}$	80.88	256
$RLBP_{3,8}$	85.68	256
$uRLBP_{1,8}$	74.86	59
$uRLBP_{2,8}$	83.19	59
$\mathbf{uRLBP_{3,8}}$	**88.01**	59

4.2 Outex-10

The Outex-10 dataset consists of 4320 images belonging to 24 different textures classes. The images are rotated at nine different angles $(0^0, 5^0, 10^0, 15^0, 30^0, 45^0, 60^0, 75^0, 90^0)$ and the illumination is kept constant. In our experiments, 20 images from each class are used for training and the rest 3840 images are used for testing. The results are shown in Table 2. LBP and uLBP perform poorly because they are not designed to deal with any rotational variations. Their rotation invariant versions, riLBP and uriLBP, provide much better results. The best accuracy is again achieved by the uRLBP with radius 3. The proposed method again achieves higher accuracy than the recently proposed LBP-HF which can be attributed to the fact that the structural information is retained in the RLBP while in the LBP-HF rotation invariance is achieved at the loss of the structural information of the binary patterns.

4.3 UIUC Dataset

In order to test descriptor against more difficult conditions we have used the UIUC texture dataset. This dataset consist of 1,000 uncalibrated unregistered images: 40 samples each of 25 different textures. Significant rotation, viewpoint changes and scale differences are present within each class and illumination

Table 2: Test results for Outex-10 dataset.

Method	Accuracy	Dimensionality
LBP	52.66	256
uLBP	54.19	59
riLBP	83.15	36
uriLBP	84.01	10
$LBP-HF_{1,8}$	78.46	38
$LBP-HF_{2,8}$	83.46	38
$LBP-HF_{3,8}$	87.81	38
$RLBP_{1,8}$	86.41	256
$RLBP_{2,8}$	89.82	256
$RLBP_{3,8}$	90.39	256
$uRLBP_{1,8}$	88.07	59
$uRLBP_{2,8}$	92.94	59
$\mathbf{uRLBP_{3,8}}$	**95.96**	59

Table 3: Test results for UIUC Texture dataset.

Method	Accuracy	Dimensionality
LBP	50.40	256
uLBP	49.2	59
riLBP	58.00	36
uriLBP	56.13	10
$LBP-HF_{1,8}$	59.73	38
$LBP-HF_{2,8}$	70.00	38
$LBP-HF_{3,8}$	66.40	38
$RLBP_{1,8}$	67.06	256
$RLBP_{2,8}$	73.60	256
$\mathbf{RLBP_{3,8}}$	**77.47**	256
$uRLBP_{1,8}$	67.06	59
$uRLBP_{2,8}$	72.53	59
$uRLBP_{3,8}$	74.53	59

conditions are uncontrolled. In our experiments we use 10 images from each class for training and rest of the images for testing. The results of the comparison are shown in Table 3. Although the descriptor is not specifically designed to deal with viewpoint and scale changes, it achieves best performance among the rotation invariant LBP versions. It can be observed that the performance of other rotation invariant LBP (uLBP, riLBP and LBP-HF) decreases considerable on this dataset. Proposed descriptor achieves highest accuracy because it retains the structural information captured by the original LBP in addition the rotation invariance helps to deal with the viewpoint changes. Also it is interesting to note the role of uniform pattern in this dataset; for all three descriptors LBP, riLBP and RLBP where uniform patterns are utilized, the accuracy drops by few percent for their uniform counterpart. In the difficult rotation, scale and viewpoint variations the small number of uniform patterns are not sufficient to model the neighbourhood of the pixels.

5 CONCLUSIONS

In this paper we have presented rotation invariant local descriptors for texture classification. The operators utilize information from the local neighbourhood to achieve a rotation invariance. Under any rotation transformation the local circular neighbourhood also undergoes the rotation around its center. However, if the descriptor is computed by using the local dominant direction as the reference, then it becomes invariant to a rotation. Based on this idea we proposed two rotation invariant descriptors RLBP and uRLBP. The experiments performed on the standard texture datasets show that the proposed method performs better than a number of state-of-the-art LBP based rotation invariant descriptors.

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