

LETTER

Reflection and Rotation Invariant Uniform Patterns for Texture Classification

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SUMMARY In this letter, we propose a novel texture descriptor that takes advantage of an anisotropic neighborhood. A brand new encoding scheme called Reflection and Rotation Invariant Uniform Patterns (riu2) is proposed to explore local structures of textures. The proposed descriptor is called Oriented Local Binary Patterns (OLBP). OLBP may be incorporated into other varieties of Local Binary Patterns (LBP) to obtain more powerful texture descriptors. Experimental results on CURET and Outex databases show that OLBP not only significantly outperforms LBP, but also demonstrates great robustness to rotation and illuminant changes.

key words: Oriented Local Binary Patterns (OLBP), LBP, Completed LBP, texture classification

1. Introduction

Texture classification is a fundamental topic in computer vision. Texture descriptors have been widely used in image retrieval, image segmentation, face recognition, etc. As textures can occur in any orientation, rotation invariance is very important for texture descriptors. Local Binary Patterns (LBP) [1] is one of the most famous rotation invariant texture descriptors, and there are hundreds of variations of LBP.

The basic idea of LBP is to construct a histogram of binary patterns of each pixel. For each pixel, LBP utilizes the signs of differences between the neighbor pixels and the central pixel to construct a binary pattern. The neighbor pixels are sampled evenly on a circle. Completed LBP (CLBP) [2] extends LBP by using two more kinds of binary patterns: the magnitudes of differences, and the global thresholding using the mean value of the image. To achieve rotation invariance, both LBP and CLBP utilize Rotation Invariant Uniform Patterns (riu2) encoding scheme [1]. LBP Histogram Fourier features (LBP-HF) [3] improves riu2 encoding by introducing discrete Fourier transform to histograms of uni-

form patterns. Both riu2 encoding and LBP-HF are based on circular neighborhood. Different from LBP and LBP-HF, Elongated LBP (ELBP) [4] samples neighbors on an ellipse rather than on a circle. ELBP is not rotation invariant, but it is more suitable for face recognition than LBP. Although ellipse is anisotropic, ELBP continues to use the riu2 encoding scheme. Therefore, two problems need to be addressed to make an elliptic neighborhood suitable for making a rotation invariant texture descriptor. The first one is that the ellipse is anisotropic, which makes it impossible for a single ellipse to be rotation invariant. The second one is that riu2 encoding scheme is designed for circular neighborhood, the circular shift operation in riu2 encoding scheme is not proper for elliptic neighborhood.

In this letter, the authors propose a rotation invariant descriptor called Oriented LBP (OLBP). OLBP samples neighbor pixels on multiple ellipses. A brand new encoding scheme called Reflection and Rotation Invariant Uniform Patterns (riu2) is introduced to discriminate different local structures. Moreover, we propose Completed OLBP (COLBP) which is more powerful but with higher dimensional feature space than OLBP's.

2. The Proposed Feature

The idea of OLBP is derived from the receptive field of human visual system. The receptive field in Lateral Geniculate Nucleus (LGN) is a circle, while the receptive field in Primary Visual Cortex (V1) area is bar-like. LBP can be viewed as the corresponding part of LGN, while OLBP is designed to simulate the reaction of V1 neurons. V1 area is on a higher level of human visual system than LGN, and bar-like features prove to be more efficient to represent natural image patches [5].

As there are bar-like receptive fields in all directions to detect lines in different directions in V1 area, we prefer to utilize multiple ellipses in OLBP. The coordinates of the i^{th} neighbor pixel on the n^{th} ellipse are given by

$$x_{i,n} = x_c + a \cos\left(\frac{2\pi i}{P}\right) \cos\left(\frac{n\pi}{N}\right) - b \sin\left(\frac{2\pi i}{P}\right) \sin\left(\frac{n\pi}{N}\right) \quad (1)$$

$$y_{i,n} = y_c + a \cos\left(\frac{2\pi i}{P}\right) \sin\left(\frac{n\pi}{N}\right) + b \sin\left(\frac{2\pi i}{P}\right) \cos\left(\frac{n\pi}{N}\right) \quad (2)$$

where x_c and y_c are the x and y coordinates of the central pixel, a and b are the lengths of the semi-major axis and the semi-minor axis, P is the number of neighbor pixels

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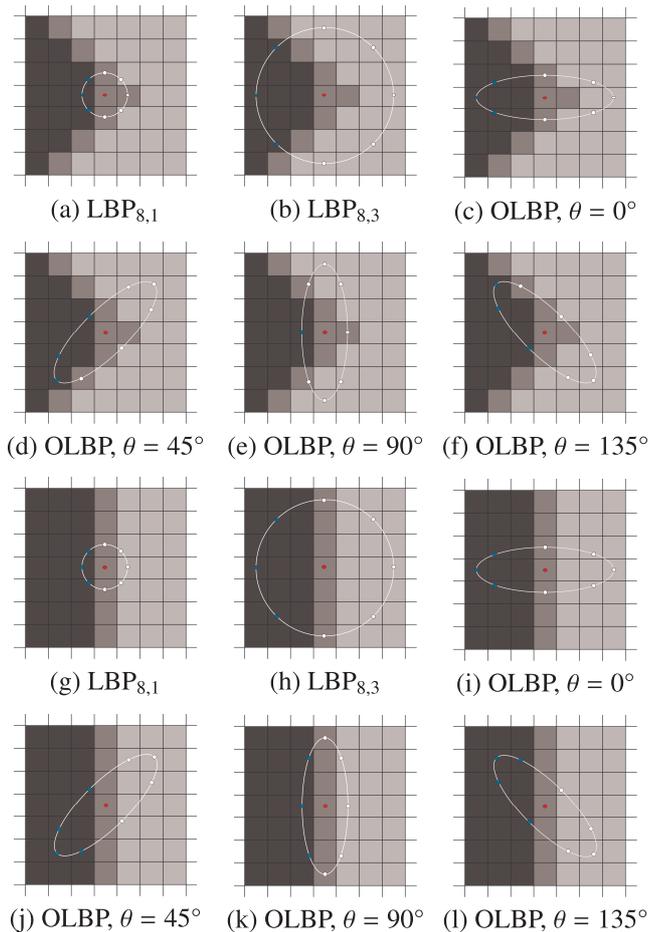


Fig. 1 Comparison between LBP and OLBP. We show binary patterns of an angle in the top two rows, and show binary patterns of a vertical line in the bottom two rows. Gray values of white points are greater than gray values of corresponding red points, while gray values of blue points are less than gray values of corresponding red points. The LBP codes of the angle and the line are the same, while their OLBP codes are different.

sampled on each ellipse, and N is the number of ellipses. We denote OLBP under these parameters $OLBP_{p,a,b,N}$. The four ellipses of $OLBP_{8,3,1,4}$ and pixels sampled on them are shown in Fig. 1 (c)~(f).

For each of the N ellipses, we obtain a binary pattern. The binary pattern is encoded using our proposed rriu2 encoding scheme rather than riu2 encoding scheme. Because the pixels sampled on an ellipse are not equidistant from the central pixel, an ellipse may be not superposition with itself after rotation. Hence, the circular shift operation in riu2 encoding scheme is not proper for ellipse. In rriu2 encoding scheme, we only utilize the symmetry of ellipse to reduce the dimension of feature space. We define reflection and rotation transform (RRT) as follows:

$$RRT(c, l, O, \theta) = \text{rot}(\text{relf}(c, l), O, \theta)$$

where c is a curve, e.g. the ellipse in Fig. 2 (a), $\text{relf}(c, l)$ is the reflection of curve c in line l , and $\text{rot}(c, O, \theta)$ is the rotation of curve c about point O given the angle of rotation θ . We define $RRT(c, \phi, O, \theta) = \text{rot}(c, O, \theta)$.

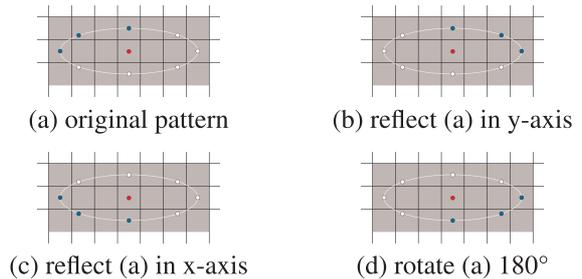


Fig. 2 Four patterns that are encoded to the same bin after rriu2 encoding. The patterns in (b), (c) and (d) are obtained through reflection and rotation of the pattern in (a).

If there exists l, O and θ , so that one curve can be totally superposition with itself after $RRT(c, l, O, \theta)$, and the transformed binary pattern is the same as the original one, then rriu2 encodes the two binary patterns into the same bin. For instance, the four binary patterns in Fig. 2 are encoded to the same bin. Moreover, we follow rriu2 encoding scheme that all nonuniform patterns are encoded to the same bin.

The rriu2 encoding is more discriminative than riu2 encoding. The binary patterns in Fig. 1 (c), (d), and (k) are visually different to each other, they should be encoded to different bins. The riu2 encoding scheme codes them into the same bin as they all have five successive ones and three successive zeros, while rriu2 encoding scheme can distinguish between them because the five successive ones are located at different positions of an ellipse. Meanwhile, binary patterns in (d) and (f) are visually the same and they are encoded into the same bin in rriu2 encoding scheme.

After rriu2 encoding, OLBP is only partially rotation invariant because ellipse has only two axes of symmetry. To make OLBP fully rotation invariant, we combine the binary patterns of the N ellipses together. For each of the N elliptic neighborhoods, a histogram is generalized. And then the corresponding bins of these histograms are summarized to form the $OLBP^{rriu2}$ descriptor. $OLBP^{rriu2}$ can distinguish more local structures than LBP^{riu2} does. As we can see in Fig. 1, LBP^{riu2} results in the same binary pattern for the angle and the line. $OLBP^{rriu2}$ results in three kind of binary patterns for the angle and three different kinds of binary patterns for the line, so that $OLBP^{rriu2}$ can distinguish the angle and the line.

OLBP improves LBP by distinguishing more local structures, while CLBP improves LBP through utilizing three kinds of thresholds. OLBP and CLBP improves LBP through different ways and can be combined together. If we replace the circular neighborhood and riu2 encoding scheme in CLBP with N elliptical neighborhoods and rriu2 encoding scheme, we obtain Completed OLBP (COLBP). COLBP is expected to take the advantages of both OLBP and CLBP.

3. Experiments and Discussion

To evaluate the effectiveness of OBLP and COLBP, we tested them on CURET database [6] and Outex database [7].

Table 1 Comparison of feature dimensions

descriptor	number of neighbors	encoding	feature dimension
LBP	8	riu2	10
LBP-HF	8	-	38
OLBP	8N	riu2	10
OLBP	8N	riu2	21
CLBP	8	riu2	200
COLBP	8N	riu2	200
COLBP	8N	riu2	882

Table 2 Classification rate (%) on CURET database

descriptor	number of training samples			
	46	23	12	6
$LBP_{8,1}^{riu2}$	79.94	73.99	66.83	57.88
$LBP_{8,5}^{riu2}$	73.00	67.52	61.34	53.54
$LBP-HF_{8,1}$	89.74	84.24	77.01	67.20
$LBP-HF_{8,5}$	89.90	84.60	77.64	68.26
$OLBP_{8,5,1,8}^{riu2}$	84.86	78.50	70.99	61.60
$OLBP_{8,5,1,8}^{riu2}$	91.28	85.80	78.64	69.03
$CLBP_{8,1}^{riu2}$	95.04	90.66	84.01	74.17
$CLBP_{8,5}^{riu2}$	91.70	85.86	78.08	67.60
$COLBP_{8,5,1,8}^{riu2}$	94.37	89.24	81.88	71.54
$COLBP_{8,5,1,8}^{riu2}$	95.73	91.41	84.77	74.77

In all of our experiments, the parameters for OLBP and COLBP are set to $a = 5$, $b = 1$, and $N = 8$. To compare with LBP and CLBP, the radius of neighborhood for LBP, LBP-HF, and CLBP are set to 1 and 5. The riu2 and rriu2 encoding scheme are also compared in the following experiments. Table 1 lists the feature dimensions of all the descriptors we compare. In all settings, we classify the textures with a nearest neighbor classifier and utilize chi-square distance as the metric.

The CURET database contains 61 classes of textures. Each class has 92 images with 200*200 pixels. These images are acquired at different illumination orientations and the the viewing angles are less than 60°.

Table 2 lists the experimental results on CURET database. The results are divided into two parts. We compare LBP, LBP-HF, and OLBP in the first part. LBP, LBP-HF, and OLBP only use the signs of the differences between the neighbor pixels and the central pixel. Although it is not so reasonable for elliptic neighborhood to use the riu2 encoding scheme, $OLBP_{8,5,1,8}^{riu2}$ still gets better results than $LBP_{8,1}^{riu2}$ and $LBP_{8,5}^{riu2}$. These results demonstrate that elliptic neighborhood is better than circular neighborhood. The feature dimension of $LBP-HF_{8,1}$ is higher than $OLBP_{8,5,1,8}^{riu2}$, but $OLBP_{8,5,1,8}^{riu2}$ outperforms $LBP-HF_{8,1}$ in all cases. The reason is that $LBP-HF_{8,1}$ only samples 8 neighbors on a circle, while $OLBP_{8,5,1,8}^{riu2}$ retains more discriminative information via sampling 64 neighbors on 8 ellipses. In the second part, we compare COLBP and CLBP. $COLBP_{8,5,1,8}^{riu2}$ achieves the highest classification rates in all cases. The results show that elliptic neighborhood is superior to circular neighbor-

Table 3 Classification rate (%) on TC10 and TC12

descriptor	TC10	TC12 t184	TC12 horizon
$LBP_{8,1}^{riu2}$	85.05	66.13	64.05
$LBP_{8,5}^{riu2}$	71.20	63.96	63.47
$LBP-HF_{8,1}$	83.23	76.53	78.31
$LBP-HF_{8,5}$	75.44	71.69	71.74
$OLBP_{8,5,1,8}^{riu2}$	96.41	86.00	80.76
$OLBP_{8,5,1,8}^{riu2}$	98.18	91.18	85.95
$CLBP_{8,1}^{riu2}$	96.67	90.19	92.87
$CLBP_{8,5}^{riu2}$	94.38	88.24	90.12
$COLBP_{8,5,1,8}^{riu2}$	98.88	92.64	92.96
$COLBP_{8,5,1,8}^{riu2}$	99.24	94.86	94.75

hood and rriu2 encoding scheme is superior to riu2 encoding scheme and the discrete fourier transform used in LBP-HF.

We also compare these descriptors on Outex database. The Outex database contains 24 classes of textures. These textures are taken on three illuminants and with nine rotation angles. The TC10 test case contains 20 training samples and 160 testing samples for each class. The training samples and testing samples are acquired at different rotation angles under illuminant “inca”. TC12 test case have the same training samples as TC10, while the testing samples for TC12 “horizon” and TC12 “t184” are acquired under illuminants “horizon” and “t184”, respectively.

Table 3 lists the experimental results on Outex database. The results are similar to those on CURET database except that $OLBP_{8,5,1,8}^{riu2}$ outperforms $LBP-HF_{8,1}$ and $LBP-HF_{8,5}$. In TC12 “t184” and “inca” test cases, the training samples and testing samples are acquired under different illuminants, and the classification rates of $OLBP_{8,5,1,8}^{riu2}$ outperform $LBP_{8,1}^{riu2}$ and $LBP_{8,5}^{riu2}$ by more than 20%, which demonstrates that OLBP is robust under different illuminants. In all settings, $COLBP_{8,5,1,8}^{riu2}$ still achieves the highest recognition rates. These results once again demonstrate that OLBP and CLBP improves LBP in different ways, and their combination (COLBP) is better than each one of them.

4. Conclusion

In this letter, we propose OLBP to sample neighbors on multiple ellipses. A brand new encoding scheme (rriu2) is proposed to explore the local structures more accurately that riu2 does. Experiments on CURET database and Outex database show that OLBP is superior to LBP and LBP-HF. Moreover, OLBP can be embedded in the CLBP scheme to obtain a more powerful descriptor called COLBP. COLBP takes advantage of both OLBP and CLBP and exceeds OLBP and CLBP in all experiments.

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