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ResearchArticle

Rotation Invariant Features Based on Regional Rank for Texture Classification#

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Abstract: In this paper, we present rotation invariant descriptors using regional rank for texture classification. The regional rank presents the rank of the gray level of each pixel in a region whose size and shape depend on the gray level of the treaty pixel and its neighbors. Rotation invariant features are obtained by combining the rank which is found and the treaty pixel code. This latter is calculated by global thresholding. Eight discriminates and rotation invariant features are then obtained. The features size don’t increase with scale and kept constant. Tests are performed on the well known Outex database. Compared to LBP method using different schemes, the proposed method achieves good texture classification performance while enjoying a compact feature representation.

1. Introduction

Texture analysis is an active research topic in image processing and pattern recognition. However, arbitrary rotation could occur in real-world textures. It will affect the performance of the texture analysis methods. Thus, extracting texture features that are rotation- invariant is an important issue to be addressed.
Many methods were proposed for rotation invariance [1].Early ones focus on the statistical analysis of texture images. This starts with the co-occurrence matrix method [2].Later, many model-based methods were proposed for rotation invariance, such as circular autoregressive model [3] and markov random fields [4-6]. Rotation invariant features obtained through filter bank responses are also used [7-9]. Recently, Ojala et al. [10] proposed a local binary pattern (LBP) histogram for rotation invariant texture classification. LBP is a simple yet efficient operator to describe local image pattern, and it has achieved impressive classification results on representative texture databases [11].Many extensions of LBP were presented [12-14].
In [15], we introduced regional rank coding method. In order to extract more discriminate texture pattern, some modifications were conducted. First, to acquire more precision,regional rank ratio is portioned in four intervals and not two. Second, the gray level information is used for coding after global thresholding. Thus, eight rotation invariant patterns are obtained. Third, different neighbourhood search space dimension are exploited. Also, the features histogram has the same size in different scales. So, they can be easily fused to improve the texture classification accuracy.
The rest of the paper is organized as follows. Section 2 reviews briefly LBP. Section 3 presents the proposed features. Section 4 reports the experimental results on large public texture database. Finally, Section 5 concludes the correspondence.

2. Brief review of Local binary Pattern (LBP)

LBP is initially proposed by Ojala et al. [16] to support the local contrast measure of image. The spatial structure of a local image texture is characterized by thresholding a 3×3 square neighbourhood with the value of the center pixel. To allow multi-resolution analysis and rotation invariance a more general formulation defined on circular symmetric neighborhood was proposed in [10] .The LBP pattern is computed by comparing the value of the center pixel x_c with those of its P neighbors that are evenly distributed on a circle of radius R centred at center x_c , such that the LBP response is calculated as

$$LBP_{R,P} = \sum_{i=0}^{P-1} s(x_i - x_c)\, 2^i, \quad s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \qquad (1)$$

The major problem of LBP is the exponential growth of the number of patterns with respect of the neighborhood size. In order to address this problem, Ojala et al. [10] defined three mapped patterns,which are uniform, rotation invariant and rotation invariant ones, respectively.
The uniform value of an LBP pattern, which is the number of circular spatial transition (bitwise 0/1 or 1/0 changes), can be mathematically computed by

$$U(LBP_{R,P}) = \sum_{i=0}^{P-1} |s(x_i - x_c) - s(x_{i+1} - x_c)| \qquad (2)$$

When $U(LBP_{R,P})$ is less than or equal to 2 i.e U≤2, the pattern is called uniform pattern, denoted as $LBP_{R,P}^{u2}$. Uniform patters have P× (P-1) +3 different output values; these patterns are one of the fundamental patterns within image textures [10].
To achieve rotation invariance, a locally rotation invariance and pattern is defined as follows:

$$LBP_{R,P}^{ri} = \min(ROR(LBP_{R,P}, i) \quad i = 0,1, \ldots P-1) \quad (3)$$

Where($ROR(x, i)$) denotes bit-wise right shift on the number x i times. By introducing the definition of rotation invariance, LBP not only has prominent performance for image rotation, but also has fewer patterns[10].
In order to obtain improved rotation invariance and to further reduce the dimensionality of the LBP histogram feature, building on $LBP_{R,P}^{ri}$, Ojala et al [10] proposed the rotation invariant uniform patterns $LBP_{R,P}^{riu2}$, the collection of those rotation invariance patterns having a U value of at most 2.

$$LBP_{R,P}^{riu2} = \begin{cases} \sum_{i=0}^{p-1} s(x_i - x_c), & if \quad U(LBP_{R,P}) \leq 2 \\ P+1 & otherwise \end{cases} \qquad (4)$$

If P and R are respectively set to 8 and 1 the histogram dimensions of uniform pattern, rotation invariant pattern and rotation invariant uniform pattern are 59, 36 and 10 respectively.

3. Regional Texture descriptors

The regional rank coding is based on the rank of pixel gray scale defined on regional neighborhood. The size and shape of each region depend on the gray level of the treaty pixel.
For each pixel x of the image, we determine the set of pixels forming the tray or plateau containing x noted Pt (x). A plateau is a set of pixels of the same gray level and which are 8 connected (Figure.1). The regional rank coding assigns the same value to all the pixels of the plateau Pt (x), based on gray levels of its neighbors. The set of neighbors of a plateau Pt (x) be the set V (Pt (x)) defined as follows:

$V(Pt(x))=\{y \in (Pt(x))^c \ /B8 \ (y) \ \cap \ ((Pt(x)) \ \neq \varnothing\}$
(5)

Figure.1 represents a partition of an image, we can see two plateau whose gray level equal to 7 (gray color) surrounded by all relevant neighbors (blue color). One of the plateau is composed of five pixels surrounded by sixteen neighbors, while the other plateau is composed of three pixels surrounded by nine neighboring pixels.

12	11	5	4	7	4	4	12
8	4	7	2	2	1	0	11
2	7	7	7	4	2	7	7
11	6	7	4	6	6	7	1
4	6	4	5	7	6	5	8

Figure1.*Representation of plateau and its neighbors*

The gray level of the plateau Pt (x) and all its neighbors are classed in ascending order . If | | V | | is the number of neighbors, the values of possible rank be included in the closed discrete interval [0,. . ., | | V | |].The rank is found according to equation 5.
Considers $V(pt(x)) = [x_1, x_2, \ldots, x_V]$ a set of neighbors of Pt(x) . Let I be the image gray level.

$$rank(x) = \sum_{v=1}^{V} F(x, x_v) \qquad (5)$$
$$F(x, x_v) = \begin{cases} 1 & if \ I(x) \geq I(x_v) \\ 0 & if \ I(x) < I(x_v) \end{cases}$$

The found rank will not be used directly to encode the texture because it varies depending on the number of neighbors, then we consider the ratio P0 = rank / | | V | |.

Noting that the plateau Pt(x) and the set of neighbors V(Pt(x)) remains the same even if image is rotated, so ratio P0 is invariant to rotation.

P0 has a continuous value ranging between 0 and 1, hence a quantization is needed; this was done by adding to gether P0 which belonging to the same intervall :[0; 0.25], [0.25;0.5], [0.5;0.75]and [0.75; 1]. P0 aquires an important information , for example, if P0 ∈[0; 0.25], the Pt(x) posseds the minima gray level but if P0 ∈ [0.75. 1] , the corresponded plateau Pt(x) gray level is the maxima amoung its neigbors.

The image gray level has discriminate information. So, to calculate the final coding, a value corresponding to global thresholding of the gray level of the treaty pixel is combined with P0 according to Table 1 .Thus, eight rotation invariant features are extracted.

M represents the average gray level of the whole image I.

I(x) is the gray level of the treaty pixel.

Table1. Regional rank Pattern in function of gray level and ratio P0

	P0 values			
	[0- 0.25[	[0.25 -0.5[	[0.5- 0.75[	[0.75- 1]
I(x)<M	0	1	2	3
I(x)>=M	4	5	6	7

To acquire more information, other scales can be used: features are extracted by extending the search space around each pixel in square neighbourhood of S×S pixel size . The case explained in this section corresponds to S=3.

Figure.2 represents a partition of an image using a square neighborhood of 5×5 pixel size (S=5). We can see plateau whose gray level equal to 7 (graycolor) surrounded by all relevant neighbors (blue color).

The features sizes don’t increase with scale and kept constant and equaling to 8.RRC_S corresponds to the features extracted using S× S neighborhood size.

The use of different search space dimension can improve the discriminative power of texture descriptors. So, features extracted from each scale are concatenated in a single feature histogram with n*8 feature dimension where n is number of scales.

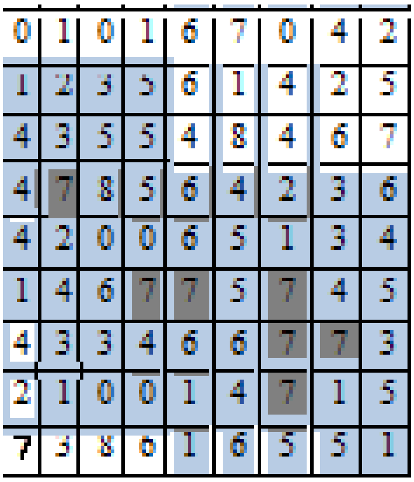

Figure2. *Representation of plateau (green) and its neighbors (blue) using 5× 5 search space .*

4 Experiments and results

The classification performance of the proposed descriptor is compared with state LBP methods on the well known texture databases Outex[11].The Outex database include two test suites: Outex_TC_00010(TC10)andOutex_TC_00012(TC 12).The two suites contain the same 24 classes of textures as shown in Figure.3.Each texture class was collected under three different illuminants(“horizon”, ”inca”, and “t184”) and nine different rotation angles (0° ,5° ,10° ,15° ,30° ,45° ,60°, 75° ,90°),there are 20non-overlapping 128*128 texture samples for each class under each situation .The experiment setups are as follows: for TC10, samples of illuminant “inca” and angle 0° in each class were used for classifier training and the other eight rotation angles with the same illuminant were used for testing. Hence, there are 480(24*20) models and 3840(24*8*20) validation samples. For TC12, the classifier was trained with the same training samples as TC10, and it was tested with all samples captured under illuminant “t184” or “horizon”.Hence, there are 480(24*20) models and 4320(24*20*9) validation samples for each illuminant.

These databases are challenging due to the large number of texture classes, significant rotation and illumination changes. Each texture image is converted into gray scale and normalized to zero mean and unit standard deviation . The nearest-neighborhood classifier χ^2 distance is adopted for the classification task[14].

The proposed method is compared to rotation invariant uniform patterns $LBP_{R,P}^{riu2}$ using different combination. $LBP_{R,P}^{riu2}$feature size are 10, 18 and 26 for R= 1, 2 and 3 respectively.

Table 2 lists the experimental results by different schemes. Under TC12,"t"represents the test setup of illuminant " t184" and "h" represents "horizon".The best results acquired by the proposed methods and LBP are in bold. From the produced results, we can make the following remarks:

First, the RRC_3 classification rate exceeds $LBP_{1,8}^{riu2}$considerably.

Second, histograms concatenated over different scales increase the performance of the methods .So, the best classification rats is obtained by concatenated features histograms extracted from the three scales. We can observe that LBP exceeds slightly the proposed method for TC10 and TC12 "t". But our method exceeds LBP for TC12"h" in different cases . Knowing that the fuzzed LBP feature size 54(10+ 18+26) is about two times the feature size of the fuzzed RRC_S 24(3×8).

Third,RRC_S performance decrease when S increase because the information patterns acquired is more global but less accurate.

Table2.Classification rate (%) on TC10 and TC12 using different Schemes

Methods	Classification Accuracy (%)		
	TC10	TC12 "t"	TC12 "h"
$LBP_{1,8}^{riu2}$	84.81	65.46	63.68
$LBP_{2,16}^{riu2}$	89.40	82.26	75.20
$LBP_{3,24}^{riu2}$	95.07	85.04	80.78
$LBP_{8,1}^{riu2}/LBP_{2,16}^{riu2}$	93.20	84.32	79.35
$LBP_{8,1}^{riu2}/LBP_{3,24}^{riu2}$	**97.65**	**90.76**	**85.25**
$LBP_{2,16}^{riu2}/LBP_{3,24}^{riu2}$	96.40	87.82	82.89
$LBP_{8,1}^{riu2}/LBP_{2,16}^{riu2}$ $/LBP_{3,24}^{riu2}$	97.21	89.21	84.32
RRC_3	92.79	84.42	84.14
RRC_5	86.38	76.97	76.55
RRC_7	79.95	71.06	70.28
RRC_3/ RRC_5	93.91	87.94	87.52
RRC_5/ RRC_7	90.81	81.78	83.43
RRC_3/ RRC_7	94.14	88.77	88.94
RRC_3/ RRC_5 / RRC_7	**94.77**	**88.96**	**89.17**

5. Conclusion

This paper introduced new rotation invariant texture descriptors based on regional rank coding. The features are extracted by combining the regional rank order and the pixel gray level information. Eight rotation invariant features are then extracted. Different neighborhood search space dimension are exploited. Also, the features histogram has the same size in different scales. So, features extracted from each scale are concatenated in a single feature histogram with n*8 feature dimension where n is number of scales.

As demonstrated in the experimental results performed on the Outex database . RRC_3 outperforms $LBP_{1,8}^{riu2}$for TC10 and TC12. RRC_S features produces the best classification rate for TC12 "h" in different cases .

The concactenated histogram features extracted over different scales performs results. The best rate is obtained by using the tree scales exceeding 94% for TC10 and reaching respectively 88.96% and 89.17% for TC 12"t" and TC 12"h".

We think that RRC_3 features has a large area of perspectives to be exploited. Especially to make features more discriminates and eventually robust to noise.

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