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Is local dominant orientation necessary for the classification of rotation invariant texture?

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ABSTRACT

Extracting local rotation invariant features is a popular method for the classification of rotation invariant texture. To address the issue of local rotation invariance, many algorithms based on anisotropic features were proposed. Usually a dominant orientation is found out first, and then anisotropic feature is extracted by this orientation. To validate whether local dominant orientation is necessary for the classification of rotation invariant texture, in this paper, two isotropic statistical texton based methods are proposed. These two methods are the counterparts of two state-of-the-art anisotropic texton based methods: maximum response 8 (MR8) and gray value image patch. Experimental results on three public databases show that local dominant orientation plays an important role when the training set is less; when training samples are enough, local dominant orientation may not be necessary.

1. Introduction

Texture analysis is a hot research topic in the fields of computer vision and pattern recognition. It includes four fundamental problems: classifying texture images based on content [1–4,34,35]; segmenting an image into regions with homogeneous texture [5]; synthesizing textures for computer graphics [6]; and establishing shape information from texture cue [7]. Among them, texture classification has been widely studied because of its wide range of applications, such as medical image analysis [1], remote sensing [2], surface inspection [3], biometrics [4] and plant image classification [34,35].

In the early stage, extracting statistical features to classify texture images is the main stream. The representative methods include the co-occurrence matrix method [8] and the filtering based methods [9]. Their classification results are good as long as the training and test samples have identical or similar orientations. However, in real situations, the rotations of textures could vary arbitrarily, severely affecting the performance of the statistical methods and raising the classification issue of rotation invariant texture.

To address the issue of rotation invariance, many algorithms were proposed. Kashyap and Khotanzad [10] were among the first researchers to study rotation-invariant texture classification by utilizing a circular autoregressive model. After that, many other models were explored, including the multiresolution autoregressive model [11], hidden Markov model [12], and Gaussian Markov random field [13].

In general, there are three kinds of methods for the classification of rotation invariant texture: computing global rotation invariant features [14,15], extracting local rotation invariant features [16–19], and global matching scheme with local rotation variant features [20,21]. The local rotation invariant feature is intuitive and simple, as it processes the image directly and does not require complicated operations, such as thresholding [36] and moment computation [37]. And it could get good results [16–19], especially for small size images [14]. In Ojala et al. [16] proposed to use the local binary pattern (LBP) histogram for the classification of rotation invariant texture. LBP is a simple but efficient operator to describe local image patterns. Using a group of filter banks, Varma and Zisserman [17] proposed a statistical learning based algorithm, namely maximum response 8 (VZ_MR8), with which a rotation invariant texton library is first built from a training set and then an unknown texture image is classified according to its texton distribution. Later, Varma and Zisserman [18,19] extended their work by proposing a new texton, VZ_Joint, using image patch to represent features directly. Similar to VZ_MR8, an image is classified by its texton distribution. LBP, VZ_MR8 and VZ_Joint are three typical local rotation invariant features, while their underlying local invariance is different: LBP extracts an isotropic feature, as it does not consider any local dominant orientation; VZ_MR8 and VZ_Joint select anisotropic features, as VZ_MR8 defines a dominant orientation from six

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orientations and keeps the response at that orientation only, while VZ_Joint finds a dominant orientation and aligns the local patch by that orientation. To investigate whether local dominant orientation is important for the classification of rotation invariant texture, two operators, complex response 8 (CR8) and Joint_Sort are proposed. These two operators could be regarded as the counterparts of VZ_MR8 and VZ_Joint, as they own the same framework of image classification and the only difference is how to represent the local rotation invariant feature. In CR8, instead of getting the maximal response among six orientations, average and standard deviation of responses are computed and an 8-dimensional complex feature is extracted. In Joint_Sort, without finding a dominant orientation, intensity values of each radius in a local patch are sorted in descending order, then these values are concatenated together one radius by one radius to represent the local patch. Since the same filters and feature extraction scheme are used, it is relatively fair to evaluate the role of local dominant orientation in texture classification. Based on three public texture databases: Outex [22], CUReT [23] and UIUC [24], it is empirically found that local dominant orientation may not be necessary for the classification of rotation invariant texture when the training set is enough.

The rest of the paper is organized as follows: Section 2 reviews VZ_MR8 and VZ_Joint. Section 3 introduces the proposed CR8 and Joint_Sort, and the dissimilarity metric. Section 4 reports the experimental results on three representative texture databases. Section 5 gives the conclusion and future work.

2. Review of VZ_MR8 and VZ_Joint

2.1. Review of VZ_MR8

The VZ_MR8 filter bank consists of 38 filters, which are shown in Fig. 1. To achieve rotation invariance, the filters are implemented at multiple orientations and multiple scales. At each scale, only the maximal response among the different orientations is kept. The final response at each position is an 8-dimension feature vector. After getting all 8-dimension feature vectors from a training set, a texton library is learned by clustering. For a given image, each position is assigned a texton by searching the closest one from the trained library, and finally a statistical histogram is built according to its texton distribution [17].

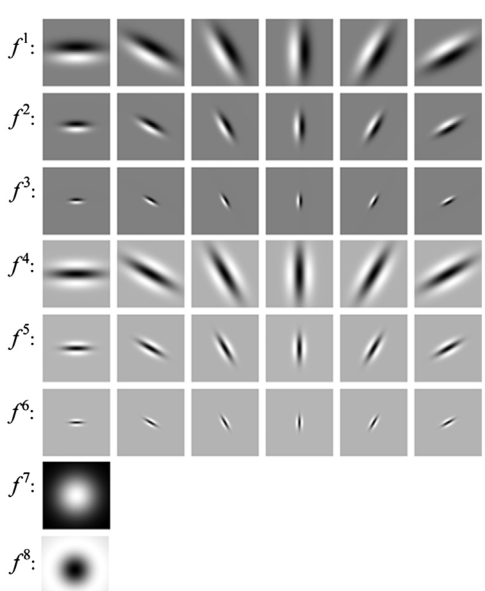

Fig. 1. The VZ_MR8 filter bank consists of a series of anisotropic filters (an edge and a bar filter at 6 orientations and 3 scales), and 2 rotationally symmetric ones (a Gaussian and a Laplacian of Gaussian) [17].

2.2. Review of VZ_Joint

Instead of using a filter bank to generate filter responses at a point, VZ_Joint takes pixels by row and records raw pixel intensities of an $N \times N$ square neighborhood around that point to form a vector in an N^2dimensional feature space. Similar to VZ_MR8, a texton library is first built from a training set and then an unknown texture image is classified according to its texton distribution [18,19]. Fig. 2 shows the main difference between VZ_MR8 and VZ_Joint.

To address rotation invariant issue, VZ_Joint finds a dominant orientation of the patch and measure the neighborhood relative to this orientation. And instead of using $N \times N$ square patch, the neighborhood is redefined to be circular with a given radius [19].

3. Proposed CR8 and Joint_Sort

VZ_MR8 and VZ_Joint have shown good performance on texture classification [17–19]. However, finding an accurate dominant orientation is not a trivial issue for VZ_Joint. Furthermore, it takes time to compute the orientation especially when the size of local patch is big. As a typical isotropic feature, LBP has achieved success in texture classification [16], thus, it is intuitive to develop isotropic features based on the framework of VZ_MR8 and VZ_Joint.

3.1. Feature extraction of CR8

As shown in Fig. 3, some local regions may have multiple dominant orientations or no dominant orientations. One dominant orientation may not be able to fully represent local characteristics. And, there may contain different dominant orientations in different patches of the same image. For example, as illustrated in Fig. 4, there are two distinctive orientations in each of the two patches; the angle difference between the two orientations in (b) is different with the angle difference between the two orientations in (c). Average and standard deviation of filter responses for the same scale could convey more information and they are rotation invariant. They were also proven to contain discriminant and robust features for classification [25]. Thus, a complex response is defined:

$$CR8^k(x,y) = \begin{cases} u^k(x,y) + i \times \sigma^k(x,y), & k = 1,2,\ldots 6 \\ i \times F^k(x,y), & k = 7,8 \end{cases} \tag{1}$$

$$u^k(x,y) = \frac{\sum_{j=0}^{5} F_{\theta_j}^k(x,y)}{6}, \quad \sigma^k(x,y) = \sqrt{\frac{\sum_{j=0}^{5} (F_{\theta_j}^k(x,y) - u^k(x,y))^2}{5}} \tag{2}$$

$$F_{\theta_j}^k(x,y) = f_{\theta_j}^k * I(x,y), \quad k = 1,2,\ldots,6,\ \theta_j = \tfrac{j\pi}{6}\,(j = 0,1,\ldots,5)$$
$$F^k(x,y) = f^k * I(x,y), \quad k = 7,8 \tag{3}$$

where i is the imaginary unit, $*$ is the convolution operation, $\times$ is the multiply operation, and I is the input image. Fig. 5 shows an example to illustrate VZ_MR8 and CR8. It is empirically found that representing $F^7(x,y)$ and $F^8(x,y)$ as the imaginary parts could get better results.

Similar to VZ_MR8, after getting an 8-dimensional complex feature for each pixel, a texton dictionary is learnt from a training set by clustering [17]. Before clustering, different weights could be assigned for the real and imaginary parts of CR8, as it is found that average and standard deviation of filter response could

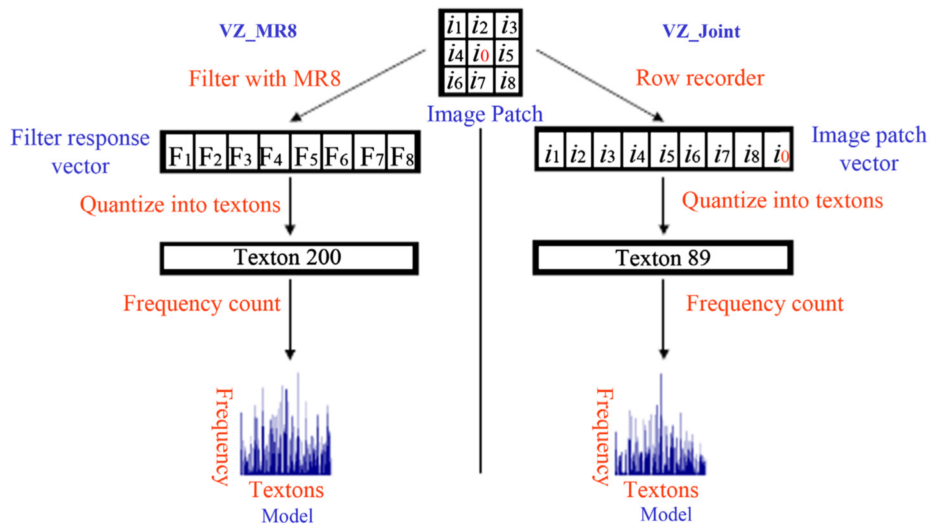

Fig. 2. The main difference between VZ_MR8 and VZ_Joint. (The figure is copied from Ref. [19]).

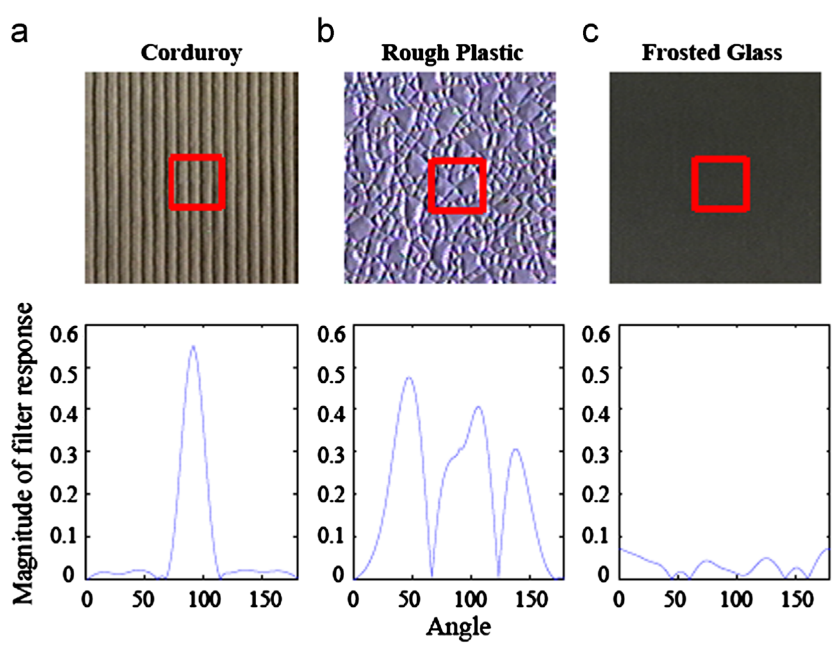

Fig. 3. The top row shows 3 texture images. The central image patch (highlighted by red rectangle) is matched with an edge filter at all orientations. The magnitude of the filter response versus the orientation is plotted in the bottom row. (The figure is copied from Ref. [17]). (a) Concrete (b)and (c).

represent different properties of image and these values have different discriminant abilities on different databases.

$$\overline{CR8}(x,y) = w_r \times \text{real}(CR8(x,y)) + w_i \times i \times \text{imagery}(CR8(x,y)) \quad (4)$$

where w_r and w_i are two weights for the real and imaginary parts. These two weights are set empirically.

Following [17] and motivated by Weber's law [26], a preprocessing step is used to lead to better classification results. $\overline{CR8}(x,y)$ at each pixel is normalized as:

$$F(\overline{CR8}(x,y)) \leftarrow F(\overline{CR8}(x,y))[\log(1+L(\overline{CR8}(x,y))/0.03)]/L(\overline{CR8}(x,y)) \quad (5)$$

where $L(\overline{CR8}(x,y)) = \|F(\overline{CR8}(x,y))\|_2$ is the magnitude of the filter response vector at that pixel.

Then, k-means clustering [27] is used to learn the CR8 dictionary. For a given image, the 8-dimensinal feature of each pixel is labeled by the closest texton in the dictionary; finally a histogram representing the frequency of each texton is built as the feature for classification.

3.2. Feature extraction of Joint_Sort

It is not a trivial issue to find an accurate orientation for VZ_Joint. More importantly, it is time consuming to get the orientation when the size of local patch is big. Recently, Khellah [28] found that intensity value alone plays more important roles in describing a local structure. Based on this finding, an isotropic local patch method, Joint_Sort, is proposed.

For a given local patch, the center of the local patch is defined as the origin of a coordinate. The intensity values are sampled on circles of various radiuses based on the origin. If a point is not in the image grid, its value can be estimated by interpolation. For a patch of size 7×7, 4 circles ($R=0$–3, R is the radius of circles) are used to cover the whole region. Then, the intensity values of each circle are sorted separately in descending order. Finally, a feature

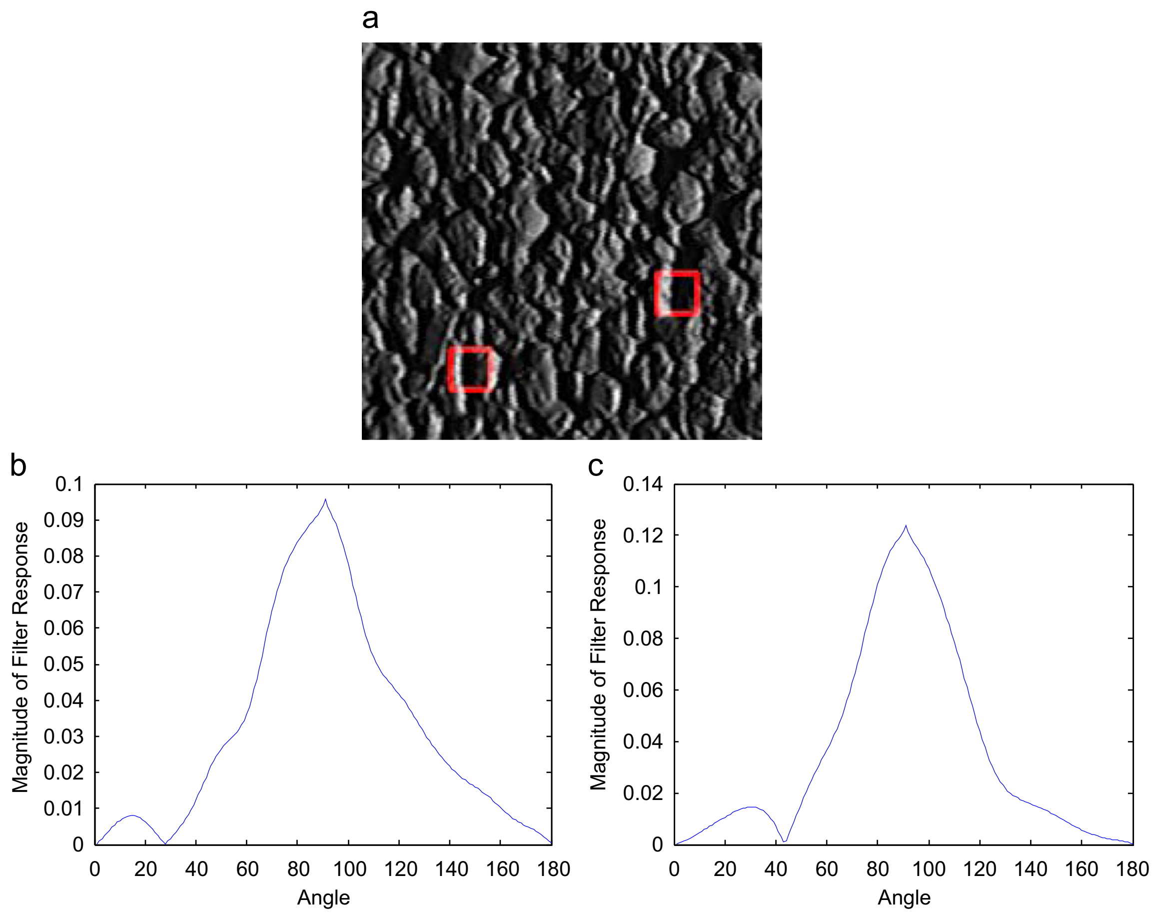

Fig. 4. The top row shows 1 texture image. Two image patches (highlighted by red rectangles) are matched with a bar filter at all orientations. The magnitude of the filter response versus the orientation is plotted in the bottom row.

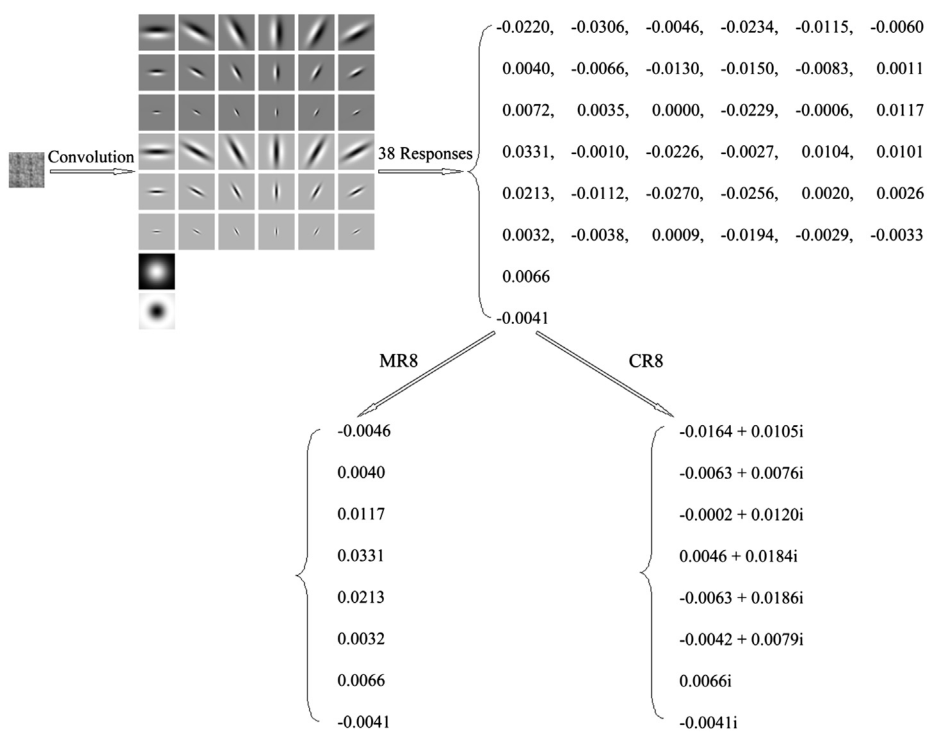

Fig. 5. An illustration of VZ_MR8 and CR8.

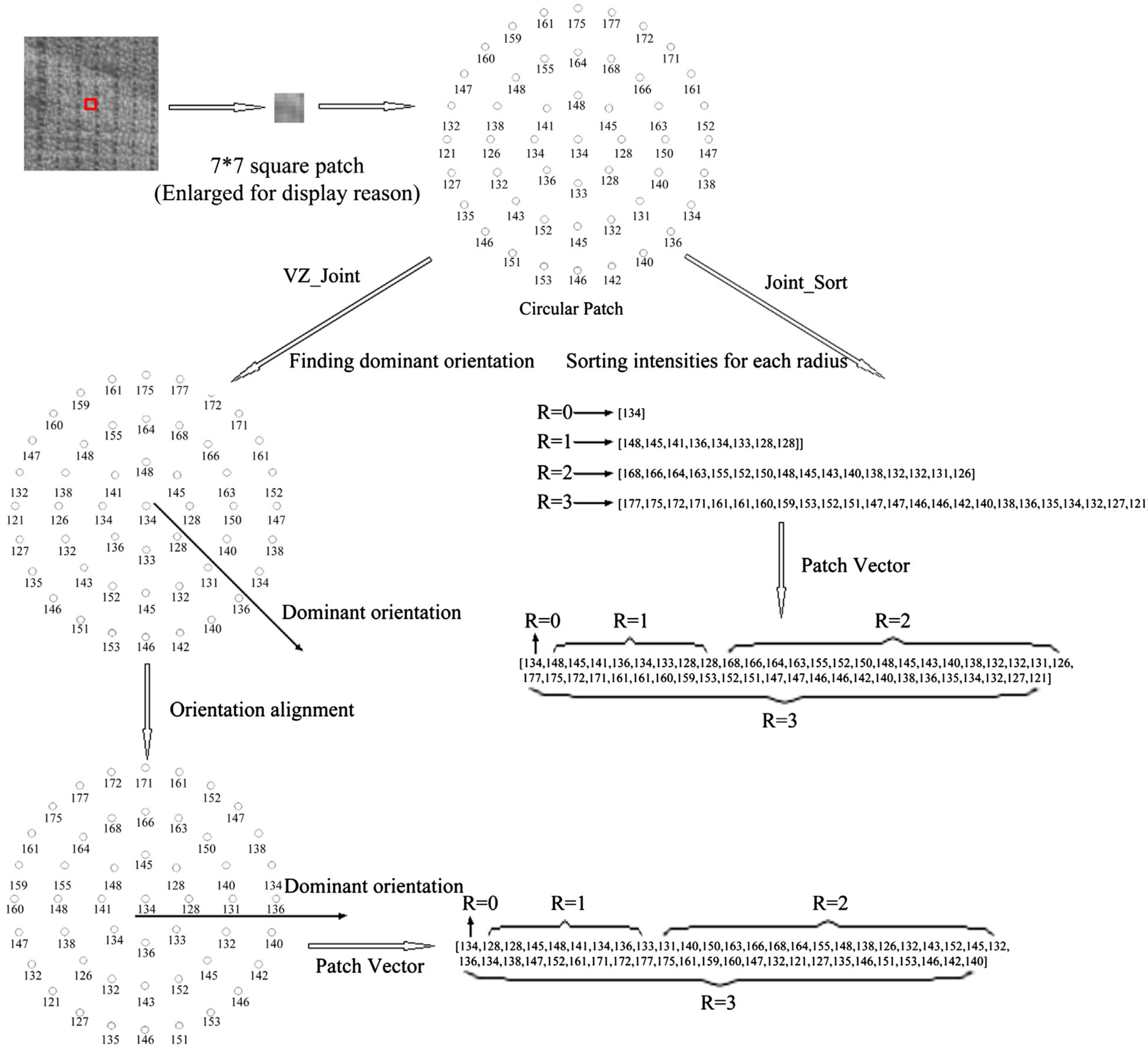

Fig. 6. An illustration of VZ_Joint and Joint_Sort. Here, structure tensor is used to find the dominant orientation [31].

vector is constructed by concatenating sorted values of each circle from the innermost circle and moving up to the outermost circle. Fig. 6 shows an illustration of Joint_Sort and VZ_Joint.

Similar to CR, a preprocessing step defined as Eq. (5) is applied for vector normalization and k-means clustering algorithm is used to build the texton library.

3.3. Dissimilarity metric

The dissimilarity of sample and model histograms is a test of goodness-of-fit, which can be measured with a nonparametric statistic test. There are many metrics for evaluating the fit between two histograms, such as histogram intersection, log-likelihood ratio, and chi-square statistic [16]. In this study, a test sample S was assigned to the class of model M that minimizes the chi-square distance:

$$D(S,M) = \sum_{l=1}^{L} \frac{(S_l - M_l)^2}{S_l + M_l} \tag{6}$$

where L is the number of bins. S_l and M_l are the values of the sample and model images at the lth bin, respectively. Here, we use the nearest neighborhood classifier with chi-square distance as it is equivalent to the optimal Bayesian classification [29] and shows good performance for texture classification [30].

4. Experimental results

To evaluate the effectiveness of the proposed methods, we carried out a series of experiments on three large and comprehensive texture databases: the Outex database [22], which includes 24 classes of textures collected under three illuminations and at nine angles, the Columbia–Utrecht Reflection and Texture (CUReT) database, which contains 61 classes of real-world textures, each imaged under different combinations of illumination and viewing angle [23], and University of Illinois at Urbana-Champaign (UIUC) database [24], which includes 25 classes, and there are 40 images collected under significant viewpoint variations for each class.

The typical isotropic feature, LBP, is compared with VZ_MR8, VZ_Joint and the proposed methods. In the following experiments, for LBP, each texture sample was normalized to have an average intensity of 128 and a standard deviation of 20 [16]. For VZ_MR8, VZ_Joint, CR8 and Joint_Sort methods, the image sample was normalized to have an average intensity of 0 and a standard deviation of 1

[17–19]. This is to remove global intensity and contrast [16–19]. To get better results, multiscale scheme is used for the LBP method [16]. For VZ_Joint, the largest eigenvector of structure tensor is defined as the dominant orientation [31]. 7×7 local patch (49 dimensions) is used for VZ_Joint and Joint_Sort. Although large size patch could get better recognition accuracy, it is more time consuming [19] and the main focus of this work is to investigate the effect of local dominant orientation. The Chi-square dissimilarity defined in Section 3.3 and the nearest neighborhood classifier were used for all methods here.

4.1. Experimental results on Outex database

This section reports the experimental results on two test suites of Outex: Outex_TC_00010 (TC10) and Outex_TC_00012 (TC12). These two test suites contain the same 24 classes of textures as shown in Fig. 7. Each texture class was collected under three different illuminants ("horizon", "inca" and "*t*184") and nine different angles of rotation (0°, 5°, 10°, 15°, 30°, 45°, 60°, 75° and 90°). There are 20 non-overlapping 128×128 texture samples for each class under each setting. The experimental setups are as follows:

1. For TC10, the classifier was trained using samples of illuminant "inca" and 0° angle in each texture class and the classifier was tested using the other eight angles of rotation, under the same illuminant. There are a total of 480 (24×20) models and 3840 ($24 \times 8 \times 20$) validation samples.
2. For TC12, the classifier was trained with the same training samples as TC10 and tested with all samples captured under illuminant "*t*184" or "horizon". There are a total of 480 (24×20) models and 4320 ($24 \times 20 \times 9$) validation samples for each illuminant.

In this database, 40 textons are clustered from each of the texture classes using the training samples, and then a histogram is computed based on the 960 (40×24) textons for each model and sample image.

Table 1 lists the experimental results by different schemes. Under TC12, "*t*" represents the test setup of illuminant "*t*184" and "*h*" represents "horizon". Here, w_r and w_i are set to 0 and 1 empirically.

Three findings could be found from Table 1. First, CR8 could get comparable results with VZ_MR8. CR8 and VZ_MR8 could get same accuracy for TC10 data set, while when the illumination changes, CR8 is a little inferior to VZ_MR8 as shown in TC12 test.

Second, Joint_Sort is more illumination sensitive than VZ_Joint. Joint_Sort is better than VZ_Joint in TC10 test, while it is worse than VZ_Joint in TC12 test. It shows that when the illumination is fixed, intensity value itself plays more important roles. Thus, Joint_Sort is more suitable for applications with fixed illumination, such as fabric defect detection [32]. Although VZ_Joint could get better results than Joint_Sort, it is time consuming in feature extraction, as estimating local dominant orientation by structure tensor [31] takes time. The algorithms are implemented using Matlab R2010a on a Windows XP, E2160 CPU (1.8 GHz) and 2 G RAM PC. For a 128×128 image, VZ_Joint takes about 280 s, while Joint_Sort spends 5 s only on feature extraction.

Third, CR8 and VZ_MR8 get better results than LBP for TC12 test set, but they are worse than LBP in TC10. It is probably because of the fact that LBP has finer orientation resolution (15° when $P=24$) than CR8 and VZ_MR8 (30°), so it could get better performance when there is only rotation variance. However, when the illumination changes like TC12, LBP is too short to contain enough discriminant information.

4.2. Experimental results on CUReT database

The CURet database contains 61 textures, as shown in Fig. 8, and there are 205 images of each texture acquired at different viewpoints and illumination orientations. There are 118 images which have been shot from a viewing angle of less than 60°. Of these 118 images, we selected 92 images, from which a sufficiently large region could be cropped (200×200) across all texture classes [17]. To get statistically significant experimental results [19], L training

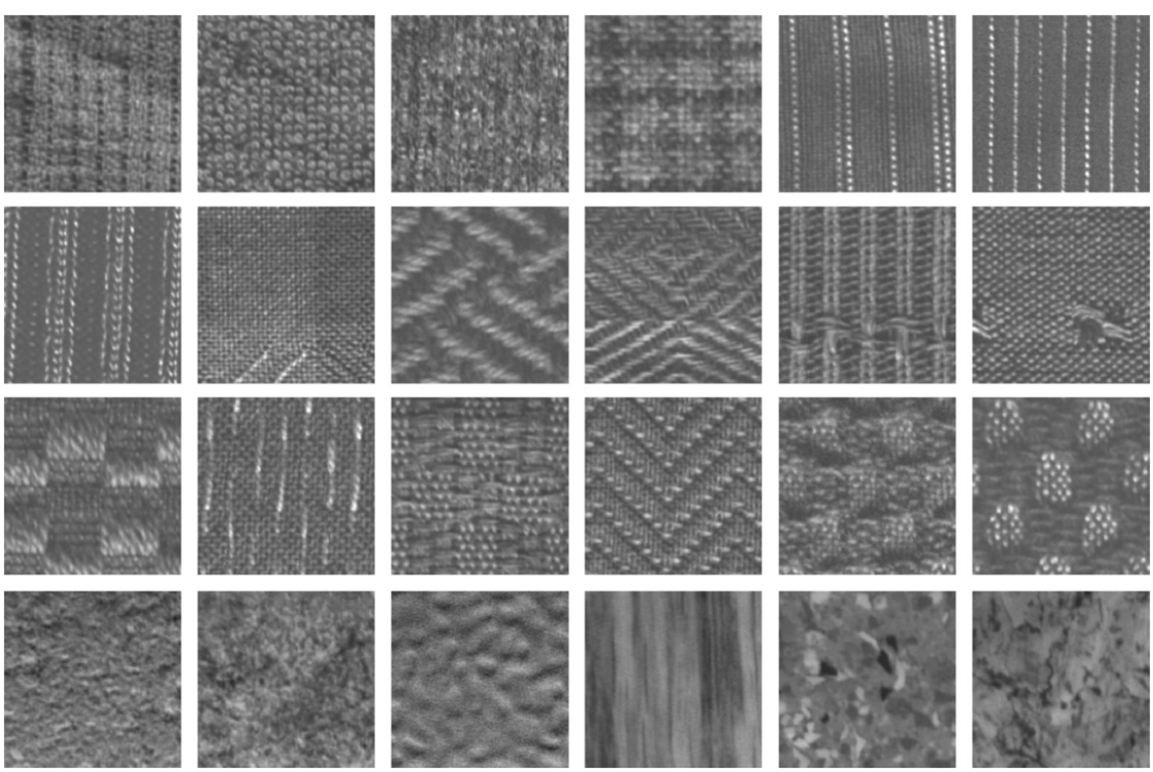

Fig. 7. Samples of the 24 textures in TC10 and TC12.

images are randomly chosen from each class while the remaining 92-L images are used as the test set. The first 23 images of each class are used to learn the library and 40 textons are clustered from each of the texture classes. The average accuracy and standard deviation over 1000 randomly splits are listed in Table 2. Here, w_r and w_i are set to 1 and 1 empirically for CR8.

Similar findings could be found in Table 2. First, CR8 could get comparable results with VZ_MR8. Second, Joint_Sort could get comparable results with VZ_Joint when the number of training sample is large. As L decreases, Joint_Sort is worse than VZ_Joint. However, Joint_Sort is much faster on feature extraction. By the same hardware as mentioned in Section 4.1, Joint_Sort takes 27 s, while VZ_Joint spends about 717 s to build a texton histogram for one image in CUReT database.

4.3. Experimental results on UIUC database

The UIUC texture database [24] includes 25 classes and 40 images in each class. The resolution of each image is 640×480. The database contains materials imaged under significant viewpoint variations as shown in Fig. 9. To assess classification performance, L training images are randomly chosen from each class while the remaining 40-L images are used as the test set. The first 10 images of each class are used to learn the library and 100 textons are clustered from each of the texture classes. The average accuracy and standard deviation over 1000 randomly splits are listed in Table 3. Here, w_r and w_i are set to 1 and 1 empirically for CR8.

Three findings could be found in Table 3. First, CR8 is a little worse than VZ_MR8 in this database. Second, Joint_Sort could get comparable results with VZ_Joint, but the former is much faster than the latter. Joint_Sort spends 220 s while VZ_Joint takes 6235 s on feature extraction for one image. Third, because this database contains big affine and scale variation, rotation and gray level invariant based LBP method could not get good results.

Table 1
Classification rate (%) for Outex database.

Method	Feature size	TC10	TC12"t"	TC12"h"
$LBP_{8,1}^{riu2}+LBP_{16,2}^{riu2}+LBP_{24,3}^{riu2}$	54	97.21	89.21	84.32
VZ_MR8	960	94.06	92.61	93.31
CR8	960	94.06	92.31	92.80
VZ_Joint	960	98.51	97.45	98.35
Joint_Sort	960	99.19	94.88	96.82

5. Conclusion

To achieve rotation invariance, extracting local isotropic and anisotropic features are two popular methods. Few studies have compared different ways to see which way is more suitable for texture classification. As the counterparts of VZ_MR8 and VZ_Joint, two local isotropic operators, CR8 and Joint_Sort are proposed. By three large public databases, it is empirically shown that local dominant orientation provides useful information for rotation invariance. However, when the training set is big enough, local dominant

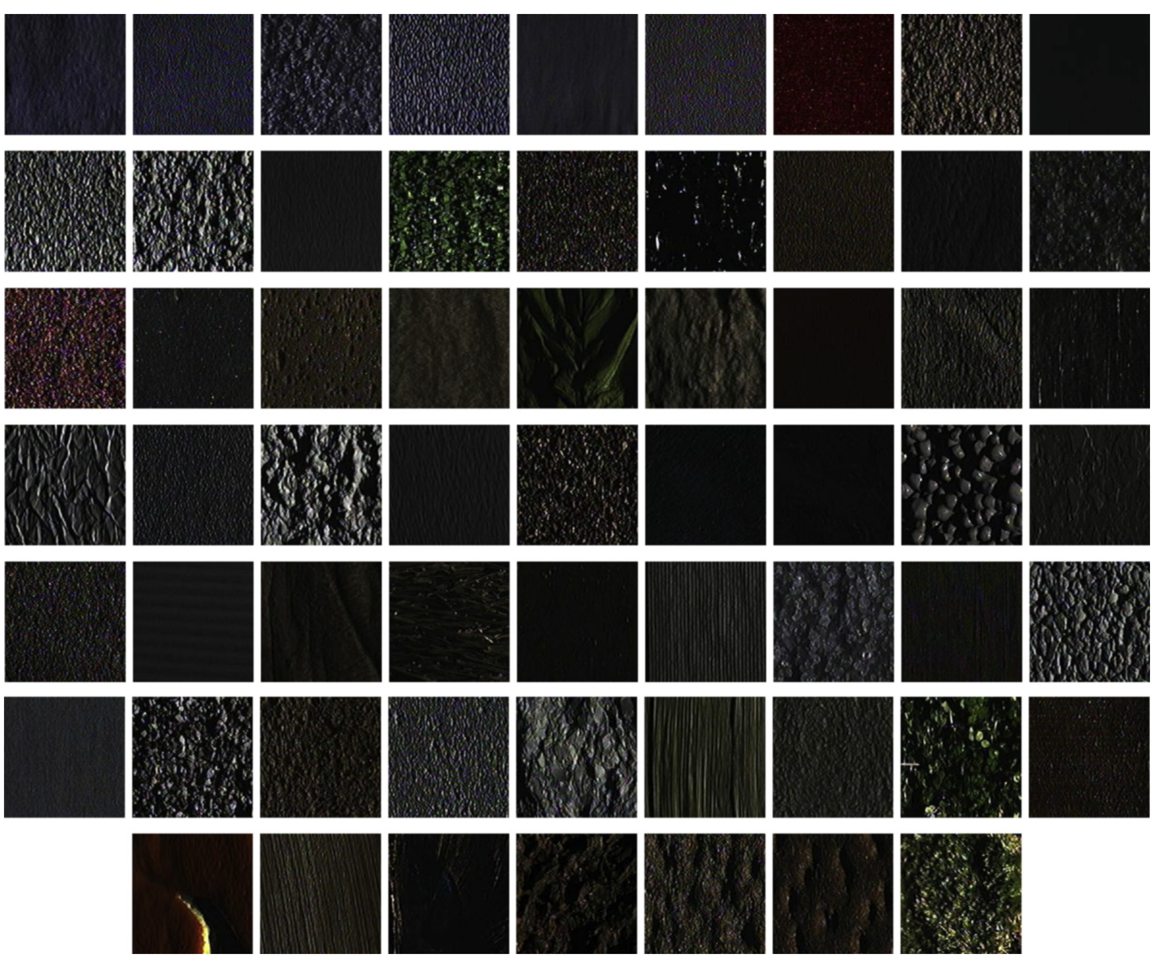

Fig. 8. Textures from the Columbia–Utrecht database. In this work, all images are converted to monochrome so colour is not used to discriminate between different textures.

Table 2
Classification rate (%) for CUReT database.

Method	Feature size	L			
		46	23	12	6
$LBP^{riu2}_{8,1}+LBP^{riu2}_{16,3}+LBP^{riu2}_{24,5}$	54	95.84 ± 0.82	91.96 ± 1.39	86.41 ± 2.05	78.09 ± 3.33
VZ_MR8	2440	98.68 ± 0.52	96.41 ± 1.08	92.28 ± 2.07	85.01 ± 3.51
CR8	2440	98.62 ± 0.59	96.35 ± 1.25	92.08 ± 2.26	84.89 ± 3.56
VZ_Joint	2440	97.51 ± 0.75	94.27 ± 1.63	89.00 ± 2.66	80.22 ± 3.93
Joint_Sort	2440	96.93 ± 0.95	93.00 ± 1.92	86.28 ± 3.11	76.24 ± 4.16

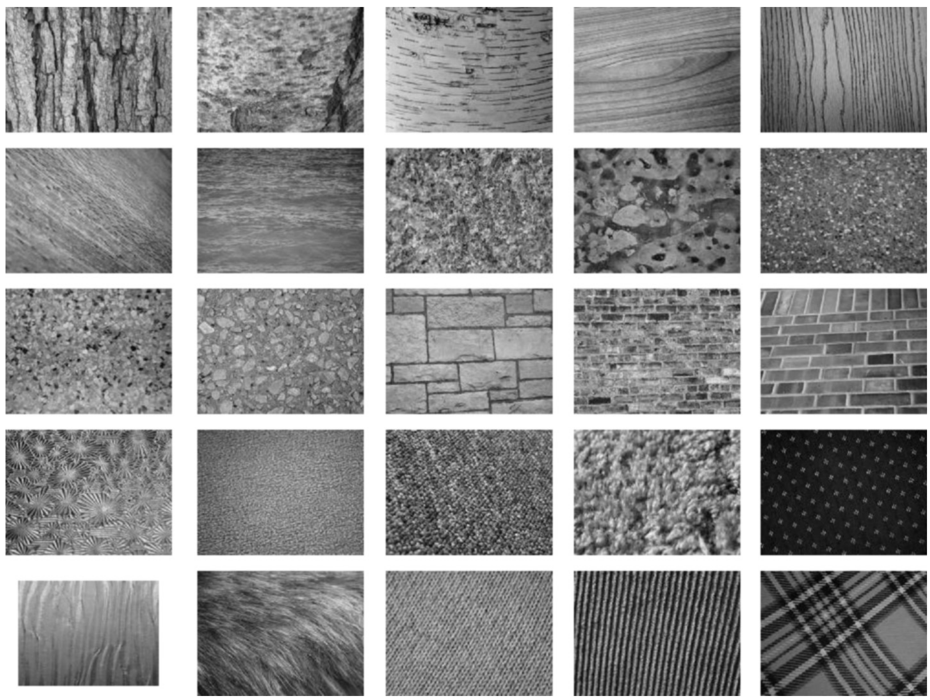

Fig. 9. Samples of the 25 textures in UIUC Database.

Table 3
Classification rate (%) for UIUC database.

Method	Feature size	L			
		20	15	10	5
$LBP^{riu2}_{8,1}+LBP^{riu2}_{16,3}+LBP^{riu2}_{24,5}$	54	76.88 ± 1.87	72.91 ± 1.92	66.66 ± 1.98	55.25 ± 2.07
VZ_MR8	2500	94.68 ± 1.00	93.28 ± 1.01	90.54 ± 1.22	83.71 ± 1.74
CR8	2500	93.59 ± 1.07	91.67 ± 1.07	88.35 ± 1.27	80.71 ± 1.73
VZ_Joint	2500	93.47 ± 1.04	92.00 ± 1.06	89.35 ± 1.19	82.87 ± 1.77
Joint_Sort	2500	92.73 ± 0.99	91.03 ± 1.07	88.27 ± 1.28	81.79 ± 1.87

orientation may not be necessary. It is mainly because value and local dominant orientation contain complementary information, when there are enough and comprehensive training sets, value alone could provide enough discrimination for classification. Especially, for fixed environment or real time applications, isotropic feature is more suitable.

As a counterpart of VZ_Joint, the idea of the proposed Joint_Sort could be extended to other local patch based methods, such as VZ_MRF and VZ_Neighborhood [18,19]. In the future we will investigate the correlation between CR8 and VZ_MR8, Joint_Sort and VZ_Joint to further improve recognition accuracy through their fusion. Another direction is to investigate histogram variation for classification [33].

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