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Texture Image Retrieval Using DTCWT-SVD and Local Binary Pattern Features

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Abstract

The combination texture feature extraction approach for texture image retrieval is proposed in this paper. Two kinds of low level texture features were combined in the approach. One of them was extracted from singular value decomposition (SVD) based dual-tree complex wavelet transform (DTCWT) coefficients, and the other one was extracted from multi-scale local binary patterns (LBPs). The fusion features of SVD based multi-directional wavelet features and multi-scale LBP features have short dimensions of feature vector. The comparing experiments are conducted on Brodatz and Vistex datasets. According to the experimental results, the proposed method has a relatively better performance in aspect of retrieval accuracy and time complexity upon the existing methods.

Keywords

Dual-Tree Complex Wavelet Transform, Image Retrieval, Local Binary Pattern, SVD, Texture Feature

1. Introduction

With enormous amount of images being uploaded to the social network, the development of image retrieval faced severe challenges. The image retrieval is usually conducted by comparing the similarities in the image's visual contents such as color space, texture, and shape. Recently, various image retrieval approaches are springing up like mushrooms with the increasing image datasets being uploaded. Although there are many new efficient methods for image retrieval, the image visual content based image retrieval method is still being widely used.

The color and shape content based image retrieval methods have been gradually improved and perfected on a daily basis. The field of texture feature extraction method, however, still has great prospects for development. Therefore, the research on the texture content based image retrieval method still has significance.

There exist two important classical texture feature extraction methods; one of them is based on the wavelet and the other one is based on local binary pattern (LBP). The main characteristic of the wavelet based methods is multi-resolution. The wavelet transform can divide a signal into several separate frequency domains. The two-dimensional Gabor filters with different frequencies and with multi-

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directional orientations are widely applied for image processing. Because the frequency and orientation of wavelet filters are similar to the human visual system, the wavelet filters are particularly appropriate for the image's texture features representation. The mean and standard deviation values of frequencies from Gabor transform were used for texture features representation [1]. Uddin et al. [2] used a multi-class support vector machine (MCSVM) to classify the acoustic emission fault signals features extracted from gray level co-occurrence matrix (GLCM), Gabor filter, and global neighborhood structure (GNS). The discrete wavelet transform (DWT) based method uses generalized Gaussian density to model the marginal distribution of wavelet coefficients and uses the Kullback–Leibler distance to measure the similarity of features [3]. Kokare et al. [4] proposed an approach that combined the rotated complex wavelet filters (RCWF) and dual-tree complex wavelet filters (DT-CWF) to extract texture features. The retrieval performance shows that the combined filter bank is better than each single filter bank. Dong et al. [5] presented a method using linear regression to model the shearlet subband dependences, but the method required training process.

As a visual descriptor, LBP has further been developed and used for texture classification since it was proposed in 1994 by T. Ojala. Afterwards, Ojala et al. [6] proposed rotational invariant LBP. Tan and Triggs [7] presented local ternary patterns (LTP). This extended LBP has more discriminant validity and has less sensitive in the condition of noise in uniform regions. Guo et al. [8] proposed a texture classification scheme which combined globally spatial information with locally variant LBP. Local derivative pattern (LDP), which is a high order directional pattern features based on encoding local derivative variations [9]. Local tetra pattern (LTrP) encodes the local pattern based on the directions instead of gray values of neighbors and it obtains first-order derivatives in vertical and horizontal directions [10]. Local oppugnant color texture pattern (LOCTP), an enhancement of LTrP, which was derived from spatial inter-chromatic texture patterns of different spectral channels within a region [11].

Local maximum edge binary patterns (LMEBP) extracts the information based on distribution of edges [12]. Color directional local quinary pattern (CDLQP) is computed from R, G, and B color channels respectively, and then it calculates the directional edge on each color space and local quinary value for each pixel [13]. Local quantized extrema patterns (LQEP) [14] integrates the contents of directional local extrema patterns (DLEP), local quantized patterns (LQP), and RGB color histogram. Hassan et al. [15] proposed method combines standard support vector machines to keep the discriminative contents of the features intact by handling the feature invariance at the classifier layer.

Both wavelet based methods and LBPs based methods are not the mask key for all texture images. The wavelet based methods are limited in directional selectivity. The LBPs based methods have long vector histogram features and those are sensitive to noise. In order to reduce these impacts of drawbacks, wavelet based methods and LBPs based methods are combined. On the one hand, the SVD was applied to DTCWT. The DTCWT has multi-directions and multi-scale and the SVD has characteristics of dimensionality reduction and noise reduction. On the other hand, the traditional LBP is a 256-dimension vector. To reduce the computational complexity, the uniform circle LBPs (ULBPs) and rotated uniform circle LBPs (RULBPs) are used. The combined LBPs ensure the dimension length of the feature vector and enlarge the scale of the neighborhood operator.

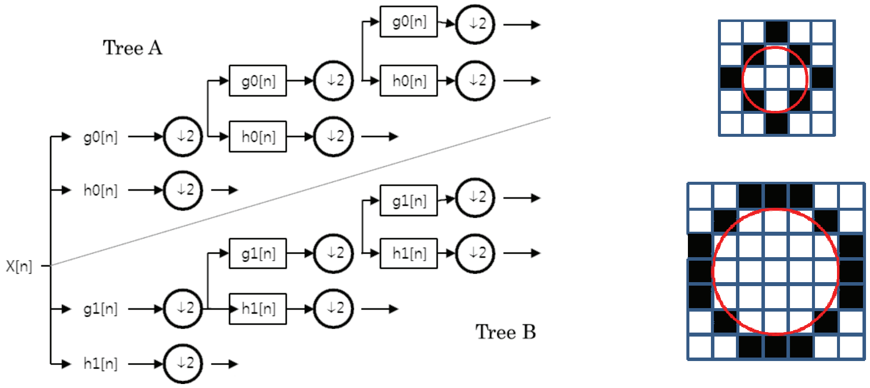
The method combined DTCWT-SVD and multi-scale LBPs for texture feature extraction is elaborated in the paper. The Brodatz DB and Vistex DB are used for verifying the efficiency of method. Finally, the existing global texture feature extraction methods are compared and analyzed.

The paper is organized as follows. In the next section, the proposed method and the procedure to retrieve texture images are discussed. The experimental results are presented in Section 3. Conclusions are derived in Section 4.

2. Proposed Method

In this section, the proposed combination method is presented and discussed. One of the proposed texture feature extraction methods is based on DTCWT-SVD. DTCWT is a well-known and efficient method has been used for texture image retrieval. The DTCWT can extract not only the multi-scale and multi-orientation wavelet frequencies but also has stability features under noise. It also has better performance for image retrieval than other transforms such as DWT and Gabor. Therefore, DTCWT was based on to generate more reliable texture features. In consideration of the huge length of the dispersive wavelet frequency coefficients, reducing the dimension of features is especially important. The SVD was employed to simplify and refine the high-dimension features. Fig. 1(a) shows a block diagram for a three-level DTCWT. Here x[n] represents a texture image. Tree A and Tree B are two different discrete wavelet filters with half a sample period differ. The designed filters produce the real coefficients and the imaginary coefficients for complex wavelet decomposition.

Another proposed texture feature extraction method is based on multi-scale LBPs. The traditional LBP uses square neighborhood operator for calculating local descriptor. The most striking limitation of the square neighborhood operator, however, is its small spatial support area. Only the 3×3 square neighborhood operator can be used for a small image structure. The circle LBP enables larger radius and number of pixels in the neighbor to encode the gray values. So circle LBP has an advantage to model larger scale structure. Fig. 1(b) shows two different circle block LBPs with different sample neighbor points and radius.



(a) Three-level DTCWT (b) Circle LBPs

Fig. 1. Block diagram for a three-level DTCWT (a) and examples of circle LBPs (b).

Fig. 2 illustrates the block diagram of the proposed image retrieval system. The processing of the image retrieval method is presented in detail as follows:

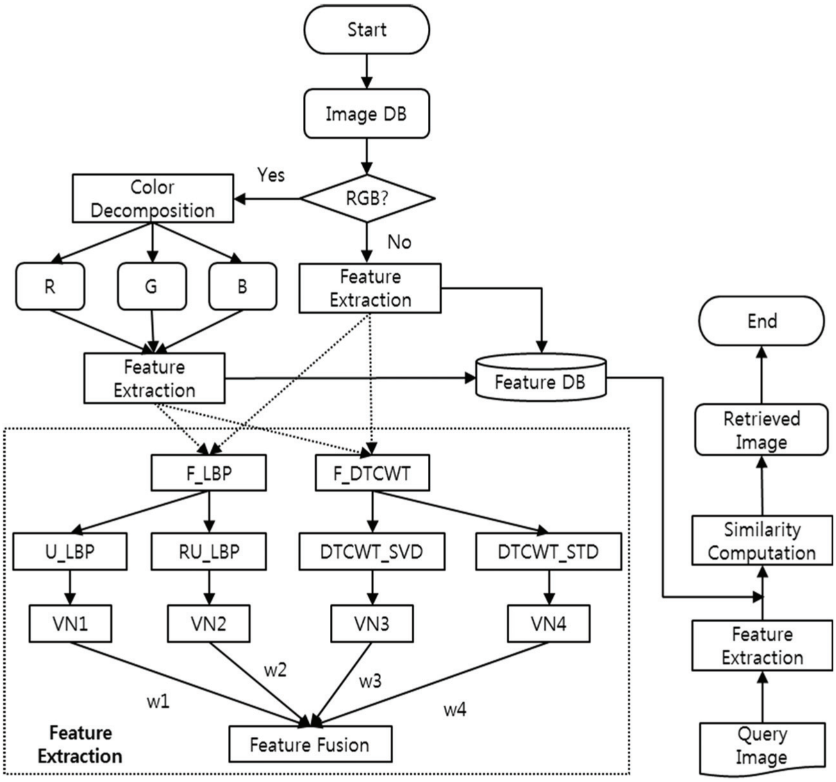


Fig. 2. Schematic diagram of proposed texture image retrieval frame structure.

Step 1: Image preprocessing. Firstly, the color mode of the image dataset is determined. Secondly, the texture image is decomposed into red, green and blue color channel separately if the statement of RGB mode is true. Finally, texture features are extracted from each color channel by using the method mentioned as bellow. Here, in order to reduce the impact of color features for texture image retrieval, the texture features of color mode image are extracted from each color channel.

Step 2: Generate SVD based wavelet features DTCWT_SVD. The SVD is applied to reduce the dimensionality of three-level DTCWT frequency coefficients. The lowest real coefficients and complex coefficients of three different scales are all selected to generate feature vectors. Here, the maximum singular value of coefficients in each scale was chosen. To compare with the traditional DTCWT, the STD variances of coefficients DTCWT_STD are also computed.

Step 3: Generate LBP features U_LBP and RU_LBP. Two kinds of circle block LBPs with different radius and sample neighbor points are used to extract more complete features from large texture images. Uniform LBP features are computed for circle LBP with a radius of 1 pixel and 8 neighbor sample pixels (as shown at the top of Fig. 1(b)). Since the length of uniform LBP feature vector is too big with using 16 neighbor sample pixels. Rotation invariant uniform LBP features are calculated for circle LBP with a radius of 2 pixels (as shown at the bottom of Fig. 1(b)).

Step 4: Fuse texture features. First, the texture features are normalized through dividing each feature by its sums. Here, the normalized feature of VN1, VN2, VN3, and VN4 represents the feature of

U_LBP, RU_LBP, DTCWT_SVD and DTCWT_STD, respectively. Then, iterator method is used to find the adaptive weights of each feature. Then all features are fused to form the final texture feature vector. Finally, the feature database of original image database is generated.

Step 5: Image retrieval. The same feature extraction method and the same parameters of weights are used for extracting the fusing features of query image. Then the L1 distance function is chosen to compute the similarity of query image and feature database. Finally the top-N most similar image is retrieved.

3. Experimental Results and Discussions

In this section, the performance of the proposed method is experimented. Two texture datasets were used to evaluate the performance of texture extraction methods. The dataset DB1 has 116 different gray scale texture images. One hundred and nine images are collected from the Brodatz DB [16] and 7 images are collected from USC DB [17]. The dataset DB2 consists of 40 different color texture categories from the Vistex DB [18]. The size of all images in two datasets is 512×512.

According to the existing methods, each 512×512 image is further divided into sixteen 128×128 non-overlapping sub-images. This means that the generated image retrieval datasets DB1 contains 1856 (116×16) images and DB2 has 640 (40×16) images. In the experiments, each image is considered as the query image. The retrieved images in the same category only can be flagged for correct usage. Figs. 3 and 4 show 20 sample texture images in each dataset, respectively.

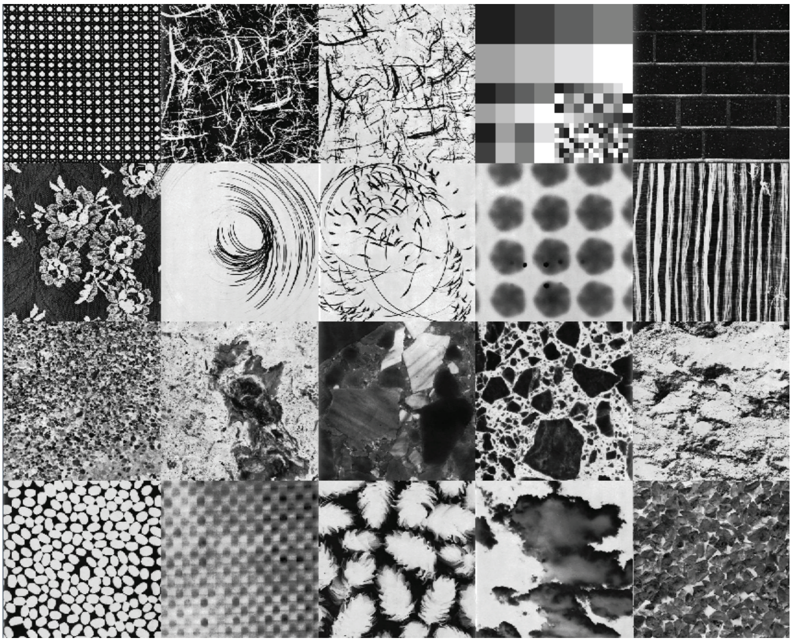


Fig. 3. Twenty texture samples in dataset DB1.

Fig. 4. Twenty texture samples in dataset DB2.

Average retrieval rate (ARR) is used for measuring the performance of different image retrieval methods. Here, the sign |DB| denotes the total number of images in each dataset, the sign n_i and sign N_i respectively denote the number of relevant images of query image i and the number of all relevant images of a query image I, here, all the values of sign N_i are set as 16.

$$ARR = \frac{1}{|DB|}\sum\nolimits_{i=1}^{|DB|}\frac{n_i}{N_i}|_{n\geq 16} \tag{1}$$

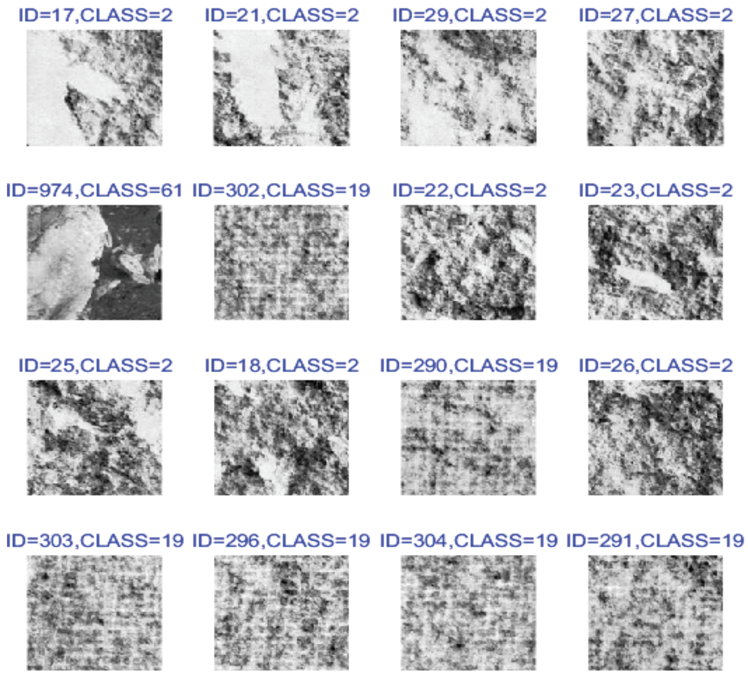
The retrieval results are discussed in the following subsections. The ARR is calculated in each category. The average ARR of a category is defined by formula 2, where sign $ARR(q, n)$ represents the average retrieval rate of nth image in q category.

$$AVE\_ARR(q) = \frac{1}{16}\sum\nolimits_{n=1}^{16} ARR(q,n) \tag{2}$$

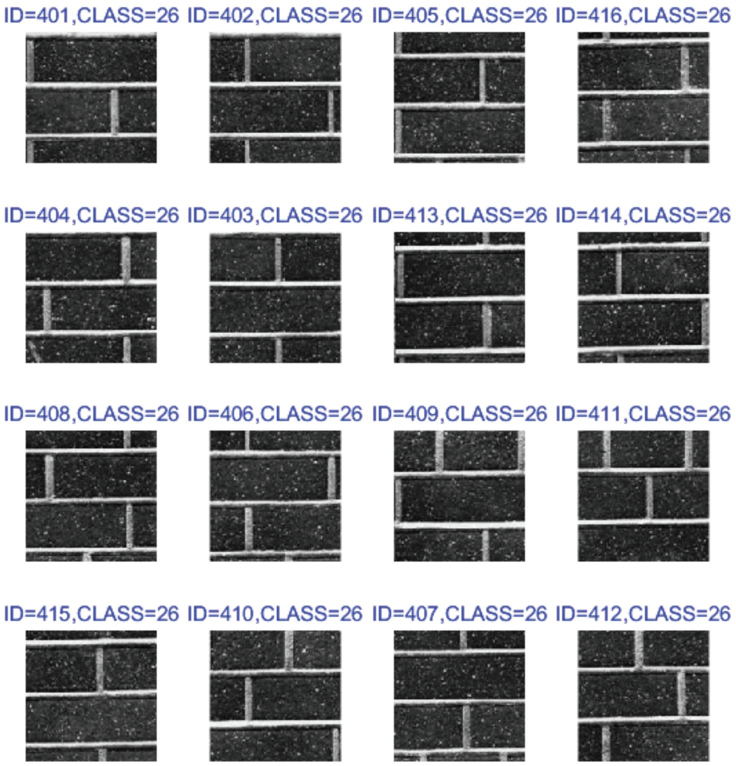
The total average ARR value TOT_{ARR} of the dataset is defined by formula 3, where sign M denotes the number of categories of the dataset.

$$TOT_{ARR} = \frac{1}{M}\sum\nolimits_{q=1}^{M} AVE_{ARR(q)} \tag{3}$$

As shown in Fig. 5(a), the query texture image ID 17 is in category 2. Among the retrieved images, 9 images are in the same category as the query image and 7 images are in the other two different categories. As shown in Fig. 5(b), for query image ID 401, all its relevant images are retrieved.



(a)



(b)

Fig. 5. Retrieved samples of two different query images in DB1. (a) Query Image ID=17, Category=2. (b) Query Image ID=401, Category=26.

As shown in Fig. 6, in all texture categories, the minimum AVE_ARR value is 20.7031%; the maximum AVE_ARR value is 100%; the mean AVE_ARR value is 83.01%; and 43 categories in total are retrieved. As shown in Fig. 7(a), the query image ID 11 is in category 1. Among the retrieved images, 14 images are in the same category and 2 images are in another category. As shown in Fig. 7(b), all of its relevant images are retrieved for query image ID 320.

Fig. 8 shows the AVE_ARR of each category in dataset DB2. The minimum AVE_ARR value is 42.58%; the maximum AVE_ARR value is 100%; and the mean AVE_ARR value is 88.56%. In total, 12 categories are fully retrieved among all 40 texture categories.

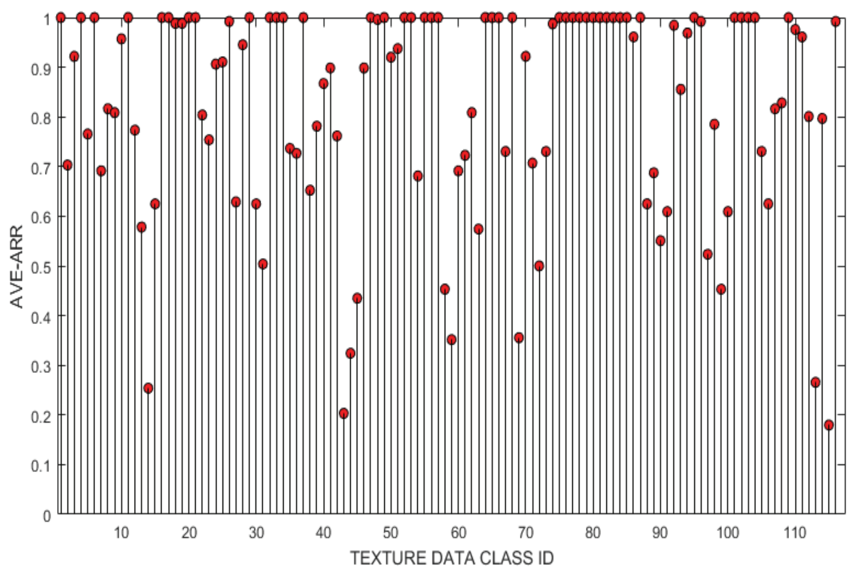
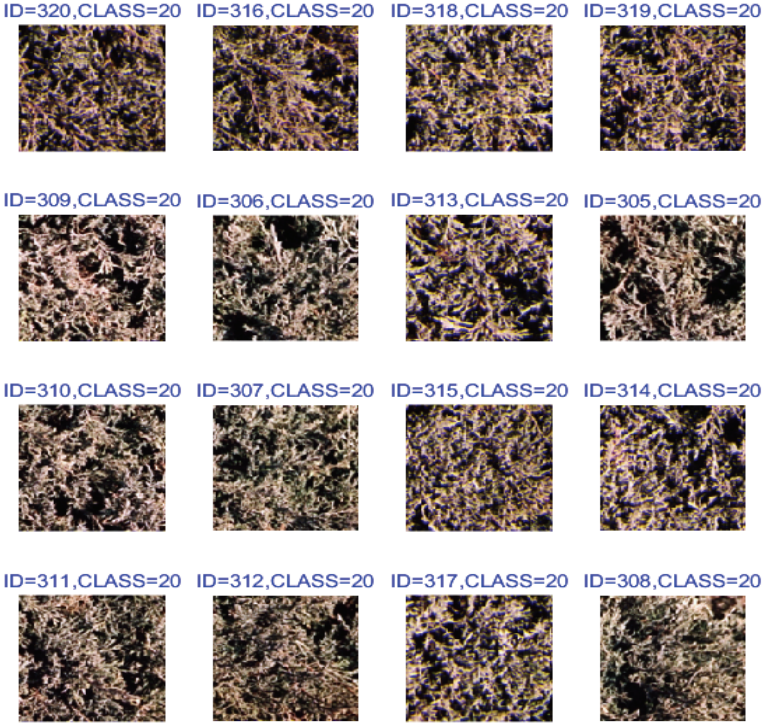


Fig. 6. Average retrieval rate of each category in DB1.

Table 1 represents that the proposed method is relatively outperforming the other existing methods under texture datasets DB1 and DB2. Here, under the DB1, the TOTARR value of the proposed method (83.01%) is slightly larger than GLMEBP and GLTrP. Under the DB2, the TOTARR value (88.56%) is slightly larger than GLMEBP and GLDP. Due to the proposed method combines the wavelet features and LBP features, its performance is over only using wavelet based and simple LBP based methods. As extension LBPs, the methods such as GLBP, GLDP, GLMEBP and GLTrP, and combined Gabor transform and have better performance than LBP, GT, and DTCWT. In particular, GLTrP, GLMEBP has outstanding performance because it doesn't encode the pattern directly using gray values. Compared to GLTrP and GLMEBP, the proposed method also has shorter vector length and better performance.

As shown in Table 2, compared with the traditional wavelet coefficient and LBP method, the proposed methods under DB1 has generally better performance. Although the combination wavelet coefficients based method has low performance than DTCWT and DTRCWT, its average retrieval time is shorter. The combination LBP based method has advantages in accuracy, but it requires slightly longer retrieval time. The combination LBP and wavelet features-based method has better performance of retrieval rate than all of them.

(a)



(b)

Fig. 7. Retrieved samples of two different query images in DB2. (a) Query image ID=11, Category=1. (b) Query image ID=320, Category=20.

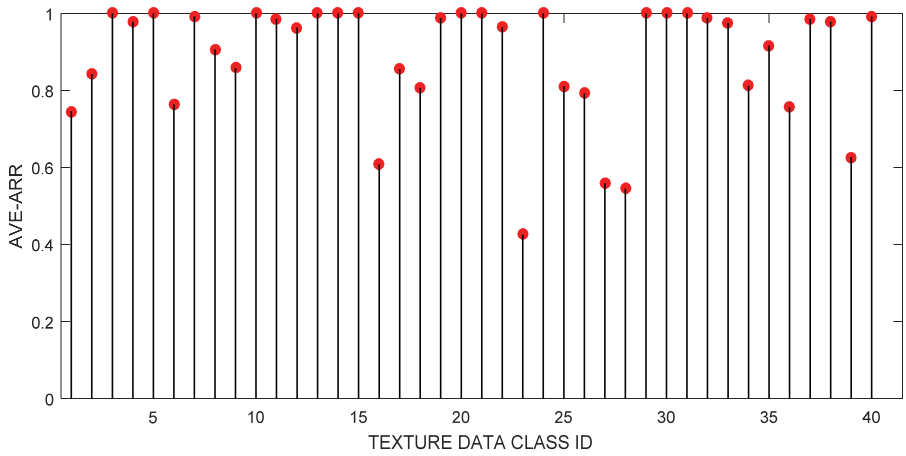


Fig. 8. Average retrieval rate of each category in DB2.

Table 1. Comparisons with former scheme under DB1 and DB2

Method	Feature dimension	TOT_{ARR} (%)	
		DB1	DB2
GT [3]	4×6×2	74.19	76.57
DT-CWT [4]	(3×6+2)×2	73.93	80.78
DT-RCWT [4]	(3×6+2)×2	71.17	75.78
DT-CWT+DT-RCWT [4]	2×(3×6+2)×2	77.75	82.34
LBP [6]	256	73.26	82.27
LTP [7]	2×256	79.96	82.38
GLBP [8]	3×4×256	75.21	84.74
GLDP [9]	4×59	79.24	88.18
GLTrP [10]	13×59	82.04	90.16
GLMEBP [12]	3×4×512	82.01	87.93
LMEBP [12]	8×512	83.28	87.77
Proposed method		83.01	88.56
Gray image	2×(3×6+1)+59+17		
Color mode	(2×(3×6+1)+59+17)×3		

Table 2. Comparisons with traditional wavelet method and local binary pattern under DB1

Method	Feature dimension	AVE_ Retrieval time (s)	TOT_{ARR} (%)
GT [3]	4×6×2	3.54	74.19
DT-CWT [4]	(3×6+2)×2	0.62	73.93
DT-RCWT [4]	(3×6+2)×2	0.80	71.17
DT_CWT+DT_RCWT [4]	2×(3×6+2)×2	1.14	77.75
LBP [6]	256	0.96	73.26
DTCWT_SVD+DTCWT_STD (proposed)	(3×6+1)×2	0.62	74.51
U_LBP+RU_LBP (proposed)	59+17	1.02	78.49
DTCWT_SVD+DTCWT_STD+U_LBP+RU_LBP (proposed)	(3×6+1)×2+59+17	1.42	83.01

4. Conclusions

In this paper, a new texture image retrieval approach based on DTCWT-SVD and multi-scale LBPs is proposed. The DTCWT-SVD employed the SVD to reduce the DTCWT coefficients. The multi-scale LBPs combined ULBPs and RULBPs. The results proved that combination wavelet coefficients based method has better performance than STD and mean value-based DTCWT method. The multi-scale uniform LBPs also promoted the retrieval accuracy. What's more, in comparison to the existing texture image retrieval methods, the proposed method is relatively more efficient with regards to the average accuracy and timeliness. Thus, it can be taken as a potential candidate in the CBIR system and available for artist image dataset retrieval. The proposed method, however, has difficultly in recognizing irregular texture images such as plastic bubbles, gravel, pebble path, and USC texture mosaic images. Therefore, future work will be focusing on object recognition method to solve the said hard texture categories.

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