Blocking Contourlet Transform: An Improvement of Contourlet Transformand Its Application to Image Retrieval

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***Abstract*—Contourlet transform is an effective solution to solve two or more dimensional singularity and has good direction and anisotropy. Against the shortage of ability of describing the spatial distribution characteristic of object's edge information, this paper proposed a new image retrieval algorithm based on Contourlet transform, which blocks the indexed image and decomposes each sub-block images using Contourlet transform. At first, carry out weighted processing for sub-band data of each sub-block image, extract features with high classification ability from high and low frequency sub-band data, and give greater weight for those features with high classification ability. Then, according to the energy of each sub-block image, give greater weight for those sub-block image with strong texture characteristic. At last, retrieve the images using weighted Euclidean distance between two image feature vectors as image similarity. The experiment results show that our algorithm has good retrieval performance.**

***Index Terms*—edge-spatial distribution; Contourlet transform; image blocking; image retrieval**

I. INTRODUCTION

At present, most image retrieval algorithms use the underlying characteristics of the images to describe them, such as color, texture, appearance, etc. The main purpose of shoes image retrieval is to retrieve and return the shoes whose styles people are interested in. As shoes' edge information is abundant, the texture features of shoes should be considered more. Texture features are usually obtained by statistical methods, structural methods, model method and frequency-domain method, Including co-occurrence matrix, Markov random field model, wavelet transform, etc[1]. In 2002, based on the wavelet multi-scale analysis, Do and Vetterli put forward Contourlet Transform[2], which is a new non-adaptive, directional and multi-scale analysis and can achieve decomposition in any direction and on any scale. It is good enough to describe the contours and direction of the image texture information in pictures, which makes up for the lack of the wavelet transform. Contourlet transform is a multi-resolution, local, and directional method of image representation. It has unique advantages when it is used to express a small, directional segment and contour[3].

Contourlet transform is currently used in image segmentation[4,5], image denoising[6,7], image fusion[8,9] and others[10], but less used in image retrieval application. Literature[11] studied the use of Contourlet transform in image retrieval applications, which proposed that the extraction of characteristic quantities have a high ability of classification from the high and low frequency sub-band data has a great improvement when compared to traditional Contourlet transform. Without considering the spatial distribution of directional texture information in the image, however, the effect of its application in this study of image retrieval is not good. In this paper, by decomposing each sub-block after blocking the searched image, we give greater weight to the sub-blocks have a higher texture feature based on the energy of each sub-block. While the local characteristics of the image, we also take considering the overall characteristics of the image into account. Experimental results show that the algorithm has a good retrieval performance.

II. CONTOURLET TRANSFORM

Contourlet transform is also called Pyramid Directional Filter Bank(PDFB). To achieve Contourlet decomposition transform, two steps need be completed: Laplacian Pyramid(LP) decomposition and Directional Filter Bank(DFB). Synthetic transformation process is the anti-process of the decomposition process[12]. Contourlet transform firstly uses LP filter to do the multi-scale image decomposition, in order to capture the singular points in images. One LP Decomposition divides the original image signal into its low-frequency components and the difference between original signal and low-frequency sampling signal, that is the high-frequency components. And then we continue the decomposition to the low-frequency components. At last, we get the entire multi-resolution image. We should use DFB filter to do the multi-directional decomposition to each high-frequency signal we get by LP decomposition. Contourlet transformation process is shown in Figure 1.

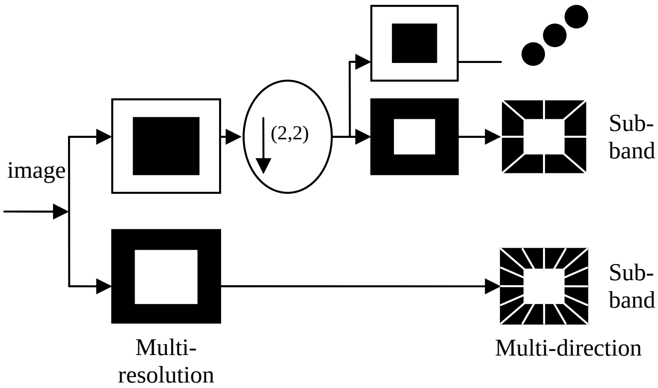


Figure 1. Contourlet transform structure schematic.

Contourlet transform domain can be extended from discrete space to continuous function in the square integrable space $L^2(R^2)$. Just like the wavelet decomposition, Contourlet transform in the continuous domains to decompose the whole space $L^2(R^2)$ into multi-scale, multi-dimensional sub-space sequence by the use of the iterative filter group. That is,

$$L^2(R^2) = V_0 \oplus (\bigoplus_{j \le 0} (\bigoplus_{k=0}^{2^{l_j}} W_{j,k}^{l_j})) \tag{1}$$

In (1), $\oplus$ is an orthogonal summation, subspace V_0 is an approaching component of the lowest scale, which is consisted of orthogonal base of scaling functions after its zoom and pan. $W_{j,k}^{l_j}$ is the balance unchanged directional subspace. If j, k, n are used respectively as the scale, orientation and location parameter, and then Contourlet function can be expressed as,

$$\{\rho_{j,k,n}^{l_j}(t)\} = \sum_{m \in z^2} g_k^{l_j}(m - S_k^{l_j} n)\mu_{j,m}(t) \tag{2}$$

In (2), $g_k^{l_j}$ is the low-pass analysis filter. $\mu_{j,m}(t)$ is a frame defined in R^2 , Over-sampling matrix $S_k^{l_j}$ is defined as,

$$S_k^{l_j} = \begin{cases} diag(2^{l-1},2), 0 < k < 2^{l_j - 1} \\ diag(2,2^{l-1}), 2^{l_j - 1} \le k < 2^{l_j} \end{cases} \tag{3}$$

In (3), parameter k determines the direction of the DFB Analysis.

Meixue and others have studied the effect Contourlet transform decomposition scale to the separation degree of different types of target. It was found that the separation degree between classes of third level sub-band is max[13]. This paper uses three-level LP decomposition and the numbers of each direction sub-band are respectively 4,8,8.

Figure 2 is a three-level, eight-direction Contourlet transform rendering of the athletic shoes.

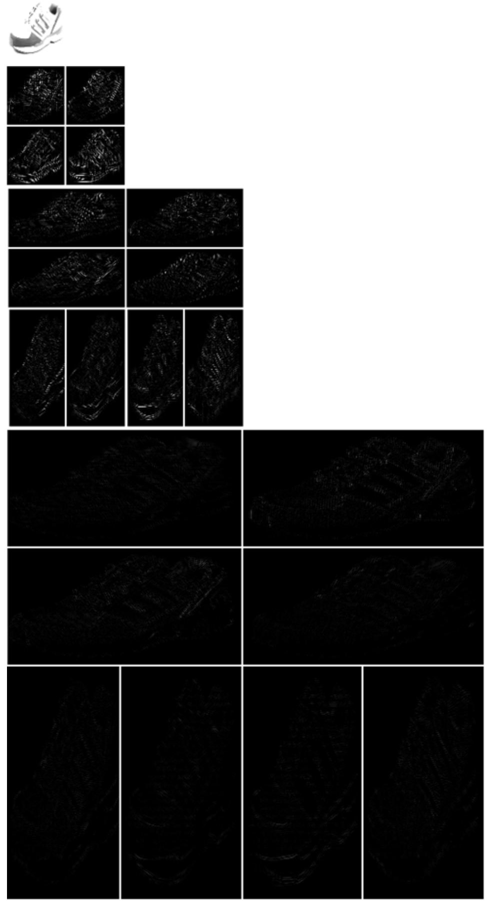


Figure 2. All sub-bands after Contourlet transform

III. Feature Extraction Algorithm

A. *Thinking of Image Blocking*

Contourlet transform mainly takes the signal's global characteristics into account. In order to consider image local features as well as global features, in this paper blocking Contourlet transform algorithm is used to extract the sub-band coefficients of each sub-block of the image. Feature extraction algorithm is shown in Figure 3.

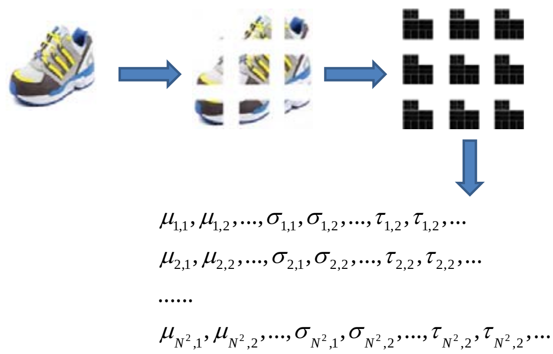


Figure 3. Feature extraction algorithm schematic based on blocking Contourlet transform

The procedure is as follows:

(1) Read the image.

(2) Divide the image into $N \times N$ blocks and we get N^2 sub-blocks.

$$
\begin{aligned}
&image\_strel\{(i-1)*n+j\} = \\
&imcrop(image,[(j-1)*width+1, \\
&(i-1)*width+1, width-1, width-1]) \qquad (4)
\end{aligned}
$$

In formular (4), $width$ is the side length of each block and $imcrop$ is used to cut the image.

(3) Calculate each sub-block's Contourlet feature $Character\{i\}$.

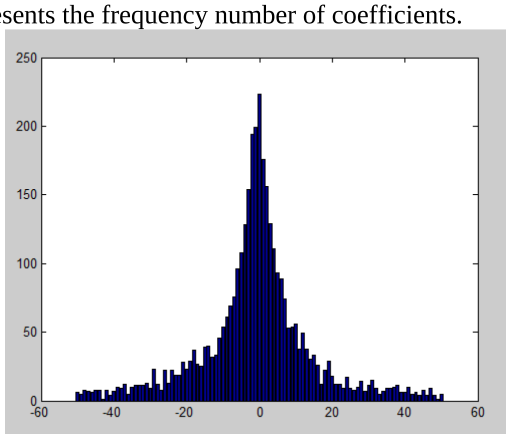
After blocking the image, implement Contourlet transform to each sub-block, and then extract mathematical characteristics of directional sub-band's coefficient distribution from every level in each sub-block of the image as the characteristics vector.

(4) Give each sub-block weight.

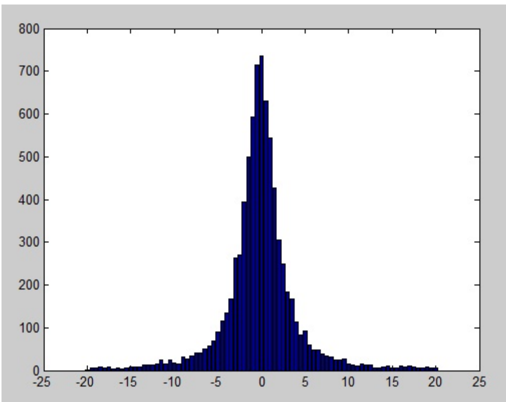
After blocking, not every sub-block can well reflect the image texture information and their contributions to the description of image's texture features are different. Effective sub-blocks' weights can help us effectively improve the retrieval precision.

B. High-frequency Sub-band Features

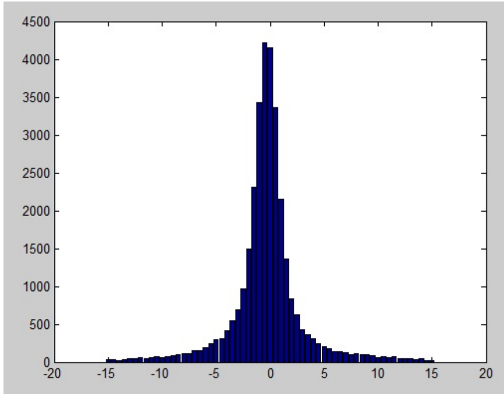
After blocking Figure 2, we can implement the Contourlet decomposition to it. Figure 4 shows the edge statistical information of any three sub-bands' coefficients from 1,2,3 level of the upper left corner of the image sub-block. Abscissa represents the transform coefficients after transformation while Ordinate represents the frequency number of coefficients.



(a) Sub-band 1, layer 1



(b) Sub-band 4, layer 2



(c) Sub-band 7, layer 3

Figure 4. Statistical histogram of sub-bands' coefficients of every Layer

As can be seen from the figure that Contourlet coefficient's probability distribution has a very sharp peak in the zero, both sides are long tails and the value is closer and closer to zero and the peak is more and more prominent with the number of layers growing.The rest scale and direction of the image are also like this. The distribution of sub-band coefficients of Image's Contourlet transform is in line with the generalized Gaussian distribution. From the view of sparse, Contourlet transform can be used to express the original images more sparse.

After implementing Contourlet transform to the image, sub-band coefficients in different directions and different scales can be obtained. Amplitude values of these coefficients characterize the energy of the image in different directions and scales. The formula of calculating the mean μ_{kl} and standard deviation σ_{kl} of Contourlet decomposition coefficients of sub-bands in every direction are as follows:

$$\mu_{kl} = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} | w_{kl}(i, j) | \qquad (5)$$

$$\sigma_{kl} = \sqrt{\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (w_{kl}(i, j) - \mu_{kl})^2} \qquad (6)$$

In (5) and (6), $M \times N$ is the size of Contourlet decomposition's sub-band, μ_{kl} is the mean of the sub-band l in layer k and σ_{kl} is the standard deviation of the sub-band l in layer k.

C. Low-frequency Sub-band Features

As the direction filter only consider the high frequency components, the low frequency components are missing. In order to apply all the features, the GLCM is used to extract low-frequency characteristics. Assuming the original image is $f(x, y)$, $x = 1, 2, \ldots M$, $y = 1, 2, \ldots N$, the size of image is $M \times N$ and grayscale is 256. In order to reduce the amount of computation, it is necessary to compress the image's grayscale and quantify the graylevel to 16. 4 independent directions (0^0, 45^0, 9^0, 135^0) are selected to calculate the secondary statistical features of the image. In 1979, Hralick raised 14 representative texture features from GLCM, which include four texture features as follows:

a) Energy

$$Q_1 = \sum_{j=0}^{n-1} \sum_{j=0}^{n-1} p(i, j)^2 \quad (7)$$

b) Entropy

$$Q_2 = \sum_{j=0}^{n-1} \sum_{j=0}^{n-1} p(i, j) \ln p(i, j) \quad (8)$$

c) Moment of inertia

$$Q_3 = \sum_{k=0}^{n-1} n^2 \{\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} p(i, j)\} \quad (9)$$

d) Relation

$$Q_4 = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} ijp(i, j) - \mu_x \mu_y}{\sigma_x^2 \sigma_y^2} \quad (10)$$

In the formulas above,

$$\mu_x = \sum_{i=0}^{n-1} i \sum_{j=0}^{n-1} p(i, j)$$

$$\mu_y = \sum_{i=0}^{n-1} j \sum_{j=0}^{n-1} p(i, j)$$

$$\sigma_x^2 = \sum_{i=0}^{n-1} (i - \mu_x)^2 \sum_{j=0}^{n-1} p(i, j)$$

$$\sigma_y^2 = \sum_{i=0}^{n-1} (j - \mu_y)^2 \sum_{j=0}^{n-1} p(i, j)$$

After calculating the characteristics of GLCM, their mean and standard deviation are calculated as the final feature vector.

D. Sub-block Weighting

Since the amplitude value of Contourlet coefficients response the change in direction at different scales of the image. The energy reflects image texture features in a particular direction and scale. The sub-band's energy is , smaller, texture features are weaker. So the energy of each sub-block can be used to reflect their contribution to the search.

The energy of Contourlet transformcan be approximated as:

$$E_k = \sum_{m=1}^{C_m} \frac{1}{n_{km}} \sum_{n_1 * n_2} [y_{km}(i, j)]^2 \quad (11)$$

$E_k (1 \le k \le N^2)$ represents the sum of energy of the k sub-block. C_m represents the number of the sub-band in the k th sub-block, n_{km} represents the number of the m th sub-band's coefficient in the k th sub-block, $y_{km}(i, j)$ represents Contourlet coefficient on the Sub-band position (i, j). As the sub-block energy reflects the texture features, if the energy sub-block is greater, the texture is stronger, so greater weight should be given to it. On the contrary, it should be given smaller weight. Suppose the kth sub-block has a weight of α_k,

$$\alpha_k = \frac{E_k}{\sum_{k=1}^{N^2} E_k} \quad (12)$$

IV. Algorithm Implementation

In this paper, a three-layer Contourlet transform is implemented, and the sub-band's number of every layer is 4,8,8. Finally, it will produce a 48-dimensional feature vector, which is used in image retrieval, the vector is expressed as:

$$character = [\mu_1, \mu_2, ..., \mu_{20}, \sigma_1, \sigma_2, ..., \sigma_{20}, \tau_1, \tau_2, ..., \tau_8] \quad (13)$$

Block Contourlet algorithm is used for feature extraction of every sub-block. Then we get $N^2 \times 48$ features as follows.

$$\mu_{1,1}, \mu_{1,2}, ..., \sigma_{1,1}, \sigma_{1,2}, ..., \tau_{1,2}, \tau_{1,2}, ...$$

$$\mu_{2,1}, \mu_{2,2}, ..., \sigma_{2,1}, \sigma_{2,2}, ..., \tau_{2,2}, \tau_{2,2}, ...$$

......

$$\mu_{N^2,1}, \mu_{N^2,2}, ..., \sigma_{N^2,1}, \sigma_{N^2,2}, ..., \tau_{N^2,2}, \tau_{N^2,2}, ...$$

As the statistic of various features is different dimension, in order to express the similarity better, we use the weighted Euclidean distance to measure three types of feature extracted in the previoussection, the formula is as follows:

$$D(k) = \omega_1 \sqrt{\sum_{i=1}^{20} (\mu_{xi} - \mu_{mi})^2} + \omega_2 \sqrt{\sum_{i=21}^{40} (\mu_{xi} - \mu_{mi})^2} + \omega_3 \sqrt{\sum_{i=41}^{48} (\mu_{xi} - \mu_{mi})^2} \quad (14)$$

In the formula, ω_1, ω_2, ω_3 represent distinguishing weight correspondingly, and $\omega_1 + \omega_2 + \omega_3 = 1$, μ_{xi} represents the feature vector of the retrieved image, μ_{mi} represents the feature vector of the m th image. D_k is the distance among the k th sub-image, then the similarity between two images can be expressed as:

$$Dist = \sum_{k=1}^{N^2} \alpha_k D_k \quad (15)$$

V. Experimental Results and Analysis

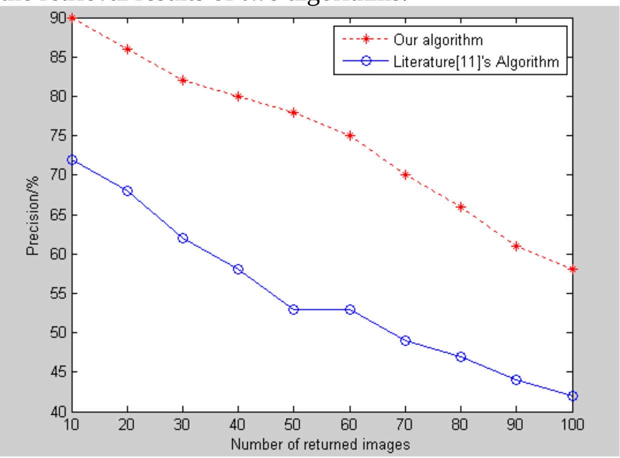
In order to test the performance of the algorithm proposed in this paper, we get various kinds of shoes from several B2C websites, such as Letao.com, OkeyBuy.com and TaoXie.com According to the shoes style, we divide shoes into six classes, they respectively are: high-heeled shoes, boots, sport shoes, flats, slippers and sandals. One hundred images from each class are extracted respectively and the 600 test images make up the test image library.

One of the important steps in the algorithm is to divide the image into several blocks. The property of image retrieval using theContourlet algorithm which is on basis of the "block" is better than which is not. But the different method for dividing the image will lead to different results. With the increasing of the block's number, it is difficult to fine the statistical properties of sub-block and it will also influence the final retrieval results. Three block-dividing methods are proposed in the experiment, they are 2×2, 3×3 and 4×4. 10 images are randomly selected from each class and there are 60 queries. Table 1 shows that search results of six kind's shoes when the block numbers are 2×2, 3×3 and 4×4 andthe searching number is 50.

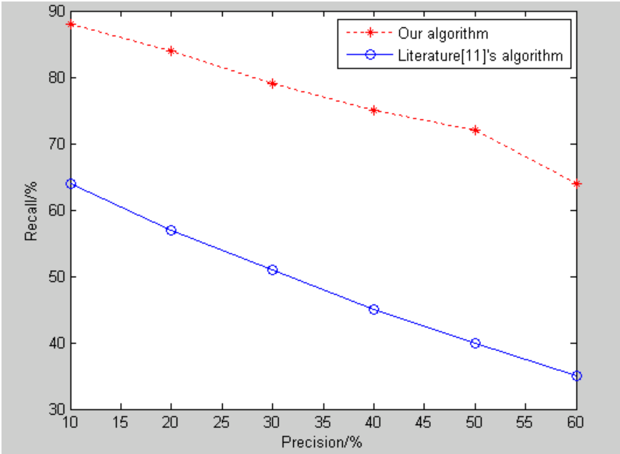
TABLE I.
RETURNED RESULTS ON DIFFERENT DIVIDING METHOD

No.	type of shoes	2×2	3×3	4×4
1	high-heeled shoes	58%	76%	70%
2	boots	99%	90%	85%
3	sport shoes	58%	74%	88%
4	flats	53%	73%	44%
5	slippers	89%	90%	85%
6	sandals	56%	58%	36%

Table 1 figures out that there is difference among the adaptability of different method. For comprehensive, the 3×3 method is chosen in the experiment. In this paper,precision rate and recall rate are used as the evaluation rules of similarity retrieval. In the same retrieval conditions,the higher precision rate and recall rate are, the better the corresponding algorithm is. The algorithm in this paper compares with the algorithm from literature 11. Without loss of generality, 20 images are randomly selected from each class as examples of each experiment and we then get 120 queries. Figure 5 shows the retrieval results of two algorithms.



(a)The comparison of precision rate when changing the number of images



(b)The comparison of the relationship between precision rate and recall rate

Figure 5. The performance of two algorithms

From figure 5, we can see that the average precision rate of two algorithms decreases while the number of the returned images increasing. And the algorithm proposed in this paperis much better than the algorithm proposed by literature [11]. Literature [11] partly solve the problem that traditional Contourlet transform did not make full use of the coefficient of high-frequency and low frequency sub-band, but it has the drawback that the image's space distribution about directional texture information is poor presented, and it is lack of the ability to describe the distribution character of the edge information space of target.

In order to visually analyze the retrieve results of two algorithms, sport shoes and slippers are selected for testing.Figure 6 is a test for sports shoes and Figure 7 is a test for slippers. Figure 6 and 7 show the retrieval result of the same query instance when the two algorithms return 29 images. In figure 6 and 7, the image on the top left corner is a query instance, the rest 29 ones are the results. The similarity decreases between the query instance and the results from left to right, and top to bottom in the figures.

Figure 6 and 7 also show that the results of the algorithm from literature [11] is not ideal. Because the right images returned after retrieval are just 20 and 22 respectively and the precision rate are 69% and 76% respectively. On the opposite, the numbers of the algorithm proposed in this paper are both 28 and the precision rate reach 97% , which is more higher than the literature [11]. And the retrieval results are more consistent with the human visual. Thus, this algorithm has a higher performance.

(a) With the algorithm from literature [11]

(b) With the algorithm proposed in the paper

Figure 6. The retrieval results for the same query instance (sport shoes)

(a) With the algorithm from literature [11]

(b) With the algorithm proposed in this paper

Figure 7. The retrieval results for the same query instance (slippers)

To illustrate the retrieval results of different class using two algorithms, we randomly select 30 images from each class as the query image and retrieve 180 times in the library. The average precision rate for each class is used to evaluate the effect of retrieval results. Figure 8 shows the average precision rate of six classes using two algorithms when the number of returned querying images is 50.

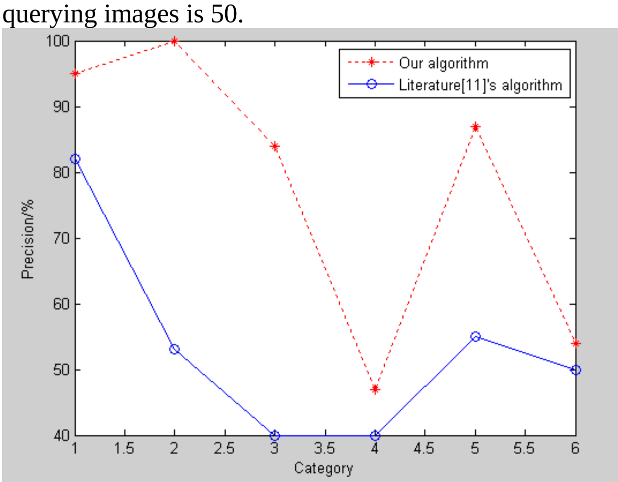


Figure 8. The comparison of the precision rate of different class with two algorithms

From Figure 8, we know that two algorithms have distinctly difference about the precision rate of different class images. The algorithm in this paper is better the algorithm proposed in literature [11]. Especially for four classes of No.1, No.2, No.3 and No.5, the algorithm in this paper is obviously better than the one literature [11] proposed.

VI. Conclusion

In order to solve the lack of the ability to describe the distribution character of the edge information of images, a new image retrieval algorithm is proposed, which is on the basis of Contourlet transform. The algorithm divides the image into sub-block and decomposes each sub-block with Contourlet transform. Firstly, the sub-band data of each sub-block will be endowed by weight, and we extract the strong classing capacity feature from the high and low sub-band data and assign a bigger weight. Secondly, according to the size of each sub-block's energy, the block with clear texture features is endowed with large weight. Finally, we use the weighted Euclidean distance of feature vector to measure the similarity of the images. Experimental results show that the algorithm has good performance on retrieving. Further research will be carried out from two aspects. On one hand, the Contourlet transform itself is not stable, so the application of Contourlet transform in image retrieval is limited. On the other hand, the characteristics of the index structure can be improved, while the speed of retrieving in large image database can be accelerated.

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REFERENCES

[1] G Rafiee, S S Dlay, W L Woo. A Review of Content-based Image Retrieval[J]. The Seventh International Symposium on Communication Systems, Networks and Digital Signal Processing, Newcastle upon Tyne, United kingdom, July 21-23, 2010, 775-779.

[2] Do M N, Vetterli M. Contourlets: a New Directional Multiresolution Image Representation[C]. The Thirty-Sixth Asilomar Conference on Signals, Systems and Computers, Pacific Grove, CA, USA, Nov. 3-6, 2002, 497-501.

[3] Do M N, Vetterli M. The Contourlet Transform: an Efficient Directional Multiresolution Image Representation [J]. IEEE Transactions on Image Processing, 2005, 14(12):2091-2106.

[4] Zhong Hua, Jiao Li-cheng, Hou Peng. Retinal Vessel Segmentation Using Nonsubsampled Contourlet Transform[J]. Chinese Journal of Computers, 2011, 34(3):574-582.

[5] Gang Liu, Xiao-Geng Liang, Jingguo Zhang. Contourlet Transform and Improved Fuzzy C-means Clustering Based Infrared Image Segmentation[J]. Systems Engineering and Electronics, 2011, 33(2):443-448.

[6] Wu Xiao-yue, Guo Bao-long, Li Lei-da. A New Image Denoising Method Combining the Nonsubsamped Contourlet Transform and Adaptive Total Variation[J]. Journal of Electronics and Information Technology, 2010, 32(2):360-365.

[7] Dai Wei, Yu Sheng-lin, Sun shuan. Image De-noising Algorithm Using Adaptive Threshold Based on Contourlet Transform[J]. Acta Electronica Sinica, 2007, 35(10):1939-1943.

[8] Li Guang-xin, Wang Ke. Color Image Fusion Algorithm Using the Contourlet Transform[J]. Acta Electronica Sinica, 2007, 35(1):112-117.

[9] Yang Xiao-hui, Jia Jian, Jiao Li-cheng. Image Fusion Algorithm in Nonsubsampled Contourlet Domain Based on Activity Measure and Closed Loop Feedback[J]. Journal of Electronics and Information Technology, 2010, 32(2):422-426.

[10] Jian Wu, Zhiming Cui, Pengpeng Zhao, Jian-ming Chen. Research on Vehicle Tracking Algorithm Using Contourlet Transform[C]. The 14th International IEEE Annual Conference on Intelligent Transportation Systems, Washington DC, USA, Oct. 5-7, 2011, 1267-1272.

[11] Huang Chuanbo, Shao Jie, Wan Minghua, Jin Zhong. Image retrieval using Contourlet transform[J]. Computer Engineering and Applications, 2009, 45(3):24-27.

[12] Lin Li-yu, Zhang You-yan, Sun Tao, et al. Contourlet Transform—Image Processing Applications[M]. Beijing: Science Press, 2008:28-42.

[13] Mei Xue and Xia Liang-zheng. Object Invariant Feature Extraction in Contourlet Field[J]. Computer Science, 2010, 37(11):275-277.

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