Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.12785/amis/090347

Image Retrieval using the Improved Double Density Contourlet Transform

Xie Qingsong[1], *Guo Jie*[2], *Li Mengjun*[2] *and An Zhiyong*[3,*]

[1] Key Laboratory of Intelligent Information Processing in Universities of Shandong (ShandongInstitute of Business and Technology), Yantai, 264005, China
[2] School of Information Science and Engineering, Shandong Normal University, Jinan, 250014, China
[3] School of Computer Science and Technology, Shandong Institute of Business and Technology, Yantai, 264005, China

Received: 17 Aug. 2014, Revised: 18 Nov. 2014, Accepted: 19 Nov. 2014
Published online: 1 May 2015

Abstract: A new image retrieval algorithm based on the improved double density contourlet transform(DDCT) is proposed in this paper. The improved double density contourlet transform have the property of shift invariance and non-Gaussian for the high frequency sub-bands. In order to obtain the high frequency texture feature, we design the quantization histograms using the high frequency direction sub-bands. The 0/1 quantization is used to deal with the energy matrix of high frequency sub-bands. A texture point is defined as an 8-D vector by integrating different channel values from high frequency sub-bands and the quantization histograms are computed. In order to get the texture-spatial features, the local binary pattern is used to describe the texture feature of low frequency sub-band. Then the quantization histograms and the local binary pattern (LBP) can be used to denote the texture features of the image. Experiments show that the proposed algorithm using the improved double density contourlet transform outperforms the SD algorithm based on the contourlet transform in the natural image retrieval.

Keywords: Contourlet transform,Wavelet transform , Image retrieval

1 Introduction

With the rapid growth of digital image and video, content-based image retrieval (CBIR) has become an important issue to help people to search and retrieval useful information. The wavelet transform has the advantage of time-frequency analysis and has been used widely in CBIR. Han[1] proposed the Gabor texture algorithm that yields a fairly poor performance in retrieving the rotated and scaled texture image. Manesh[2] have proposed the texture image retrieval algorithm using new rotated complex wavelet filters that significantly improves retrieval performance over the traditional approach and retains comparable levels of computational complexity. Wang[3] presents an image retrieval algorithm that efficiently integrates color features and Gabor texture features.

However, in high-dimensional case, the wavelet transform doesn't make full use of the geometric characteristics, and can not describe high-dimensional signal effectively. Therefore, contourlet transform have been proposed for image processing that can efficiently represent images containing contours and textures[4,5,6]. Rao[7] proposed the SD algorithm based on the contourlet transform that outperforms the Gabor-Zernike algorithm in the face image database. Qu[8] proposed the GGD algorithm of the contourlet transform using the improved maximum likelihood (ML) parameter estimation method.Recently, Li[9] presented the nonsampled double density contourlet transform that be used in the field of eliminating the image noise effectively. Although these algorithms based on the contourlet transform have the good performance in the texture images, the retrieval performance is still poor in the nature images.

In order to reduce the time-frequency invariant sensitivity and improve retrieval rate, a new image retrieval algorithm based on the improved double density contourlet transform(DDCT) is proposed. The rest of this paper is organized as follows. In Section 2, we introduce the improved DDCT and analysis the property of the improved DDCT. In Section 3, the image retrieval algorithm using the improved DDCT is presented. In

* Corresponding author e-mail: azytyut@163.com

section 4, the procedure to retrieve texture images and the experimental results are presented. Finally, we discuss the results and conclusion in section 5.

2 The improved Double Density Contourlet Transform

In order to reduce the time-frequency invariant sensitivity of the wavelet, Selesnick [10]proposed the double density wavelet transform(DDWT). There are three-channel filter bank in the frame of DDWT. The scaling $\phi(t)$ and wavelet functions $\psi_i(t)(i=1,2)$ are defined implicitly through the dilation and wavelet equations

$$\phi(t)=\sqrt{2}h_0(n)\phi(2t-n) \quad (1)$$

$$\psi_i(t)=\sqrt{2}h_i(n)\phi(2t-n), i=1,2 \quad (2)$$

where $h_0(n)$ is low frequency filters and $h_i(n)(i=1,2)$ are high frequency filters.For the single level decomposed of DDWT, there are nine channels that consist of $\{H_0H_0, H_0H_1, H_0H_2, H_1H_0, H_1H_1, H_1H_2, H_2H_0, H_2H_1, H_2H_2\}$,where H_0H_0 is the low frequency filter and others are the high frequency filters.

Traditional Contourlet transform has the advantage of excellent multi-directional resolution capability, but its translational sensitivity limits its application in image processing to some extent. In recent years, Li[9] proposed the double density contourlet transform(DDCT) that is a cascade of a DDWT decomposition followed by directional filterbanks applied on each bandpass subband. However, the DDCT has a larger complexity than the traditional contourlet transform.

In order to reduce the complexity and time-frequency invariant sensitivity, we designed the improved DDCT based on the integrated DDWT and the nonsubsampled directional filter bands(NSDFB). According to the two high frequency filters H_1 and H_2, we integrated the H_1H_0, H_1H_1, H_1H_2 and H_0H_1 as a high frequency filters $H_1(Z_1,Z_2)$. And the H_2H_0, H_0H_1, H_2H_2 and H_0H_2 are integrated as a high frequency filters $H_2(Z_1,Z_2)$. Then the improved DDCT has a fast implementation based on the two high frequency filters $H_1(Z_1,Z_2)$ and $H_2(Z_1,Z_2)$ followed by NSDFB. Figure 1 shows the improved DDCT structure.

Since the double density wavelet transform and NSDFB has the property of shift invariance, the improved DDCT have shift invariance. For the improved DDCT, there are only two high frequency sub-bands that be used. Thus, the improved DDCT have the lower complexity with the shift invariance over the DDCT.

The contourlet transform can be described by the Generalized Gaussian Density (GGD) model. It is necessary to study the GGD model of texture image in the improved DDCT domain since it is different from the contourlet transform. The generalized Gaussian density is defined as

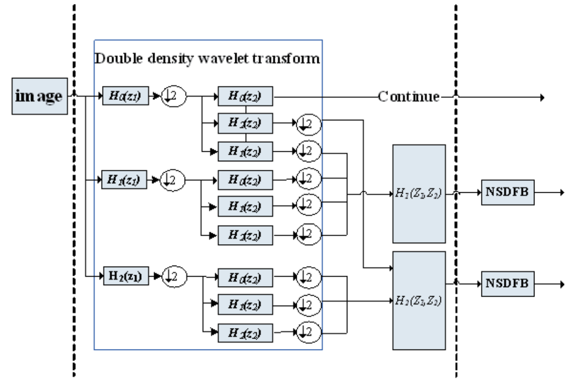

Fig. 1: The structure of the improved double density contourlet transform

$$f(x;\alpha,\beta)=\frac{\beta}{2\alpha\Gamma(1/\beta)}e^{-(|x|/\alpha)^{\beta}} \quad (3)$$

where α is the GGD model parameters indicating the width of probability density function and β indicating the peakness of probability density function[11]. Here $\Gamma(x)$ is the Gamma function and can be defined as $\Gamma(x)=\int_0^{\infty}e^{-t}t^{x-1}dt(x>0)$. The parameters α and β can be calculated by the moment estimator or by the maximum-likelihood estimator for every level wavelet sub-band.

In the paper, we will use the maximum-likelihood estimator for GGD. Suppose that the sample $x=\{x_1,x_2,\cdots,x_L\}$, is independent component and the likelihood function can be defined as:

$$L(x;\alpha,\beta)=\log\prod_{i=1}^{L}p(x_i;\alpha,\beta) \quad (4)$$

where α and β are parameters to be estimated by the estimator. The maximum likelihood estimator in the following likelihood equations will have a unique root in probability.

$$\frac{\partial L(x;\alpha,\beta)}{\partial\alpha}=-\frac{L}{\alpha}+\sum_{i=1}^{L}\frac{\beta|x_i|\alpha^{-\beta}}{\alpha}=0 \quad (5)$$

$$\frac{\partial L(x;\alpha,\beta)}{\partial\beta}=\frac{L}{\beta}+\frac{L\Psi(1/\beta)}{\beta^2}-\sum_{i=1}^{L}(\frac{|x_i|}{\alpha})^{\beta}\log((\frac{|x_i|}{\alpha}))=0 \quad (6)$$

where Ψ is the digamma function, i.e.,$\Psi(z)=\Gamma'(z)/\Gamma(z)$. Fix $\beta>0$, then (5) has a unique, real, and positive solution as:

$$\hat{\alpha}=(\frac{\beta}{L}\sum_{i=1}^{L}|x_i|^{\beta})^{1/\beta} \quad (7)$$

Substitute (7) into (6), the shape parameter is the solution of the following transcendental equation which can be solved numerically.

$$1+\frac{\Psi(1/\hat{\beta})}{\hat{\beta}}-\frac{\sum_{i=1}^{L}|x_i|^{\hat{\beta}}\log|x_i|}{\sum|x_i|^{\hat{\beta}}}+\frac{\log(\frac{\hat{\beta}}{L}\sum_{i=1}^{L}|x_i|^{\hat{\beta}})}{\hat{\beta}}=0 \quad (8)$$

In order to analyze the improved DDCT sub-band whether fitting the GGD model or not, we use the fitness to describe the differences between the GGD model and the wavelet coefficients histograms. The fitness is defined as:

$$fitness=\frac{1}{N}\sum_{i=1}^{N}(h(x_i)-h^*(x_i)) \quad (9)$$

where $h(x_i)$ denotes the actual coefficient histograms and $h^*(x_i)$ denotes the actual coefficient histograms. In the experiments, a subset of the Brodatz image database is used. This subset contains 50 different textures of size 512×512. Table 1 is the mean of the fitness of improved DDCT for the 50 different textures.

Table 1: The fitness of the improved double density Contourlet transform

The high frequency sub-band	The improved DDCT	CT
0	0.0032	0.0022
1	0.0038	0.0025
2	0.0025	0.0027
3	0.0047	0.0019
4	0.0029	0.0021
5	0.0033	0.0017
6	0.0041	0.0020
7	0.0024	0.0019

From table 1, we can find that the fitness of the improved DDCT is very small for the texture images. Then the GGD model can be used to describe the high frequency subband coefficients histograms.

3 Image Retrieval Using The Contourlet Transform

3.1 The Quantization Histogram Signatures

In order to reduce the complexity of algorithms, we use the single level decomposition of improved DDCT and 3-level binary tree DFB. Therefore, for each high frequency sub-bands, there will be 8 high frequency sub-bands at each stage: H_0, H_1, H_2, H_3, H_4, H_5, H_6 and H_7. Here, we will extract the quantization histogram signatures of DDCT. Fig.2 shows the structure of quantization histogram signatures. Firstly, the energy

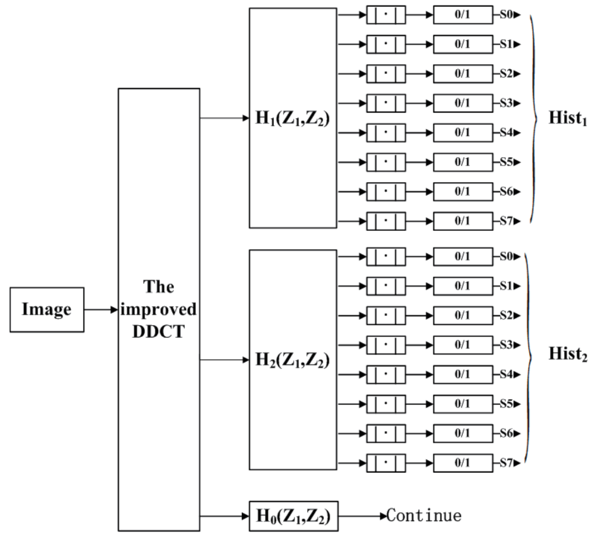

Fig. 2: Texture point generation of DDCT

matrix of each sub-band is computed using the magnitudes of sub-bands coefficients.

Secondly, the 0/1 quantization is used to deal with the energy matrix of DDCT decomposition. In order to make the threshold self-adoptive, we will make use of the mean of sub-band as threshold. Suppose that w[i, j] is a coefficient of sub-band and Tmean is threshold such that:

$$F(i,j)=\begin{cases}1|w(i,j)|\geq T_{mean}\\0\end{cases} \quad (10)$$

Each coefficient of sub-bands is quantified as 0 or 1. Then a texture point is defined as an 8-D vector by considering texture channel values from the same location of all eight bands. Figure 3 shows the quantization data set of the improved DDCT. These binary data can be

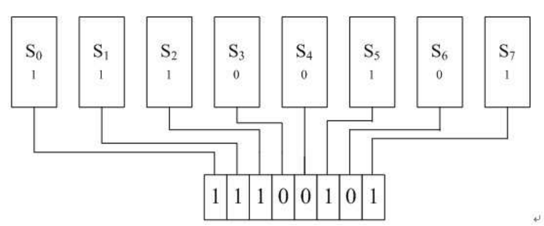

Fig. 3: The quantization data set of the improved DDCT

transformed as the decimal data. Thus the quantization histograms can be obtained and there are 256 bins (because 8-bands). The quantization histograms describe the array information of high frequency sub-bands and can be used as the texture features of image.The histograms $Hist_1$ and $Hist_2$ are integrated as the new quantization histograms.

Let H_{qh1} denotes the quantization histograms of queering image and H_{qh2} denotes the quantization histograms of an image. The texture similarity between H_{qh1} and H_{qh2} can be calculated by the (11).

$$d_{qh}(H_{qh1}, H_{qh2}) = 1 - \frac{\sum_{i=1}^{n} \min(h_1^i, h_2^i)}{\min(\sum_{i=1}^{n} h_1^i, \sum_{i=1}^{n} h_2^i)} \tag{11}$$

where n is the number of bins.

3.2 Local binary patterns Signatures

The quantization histograms is not making full use of the low frequency sub-bands. Therefore we will use the Local Binary Pattern (LBP)[12] to describe the texture features of low frequency sub-band. The LBP operator can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. The LBP feature is created in the following manner. Firstly, we compare the every pixel with its 8 neighbors. If the center pixel's value is greater than the neighbor, the center pixel's value can be set as 1". Otherwise, the center pixel's value can be set as "0".The quantization can be defined as:

$$s(g_0, g_i) = \begin{cases} 1, g_i \geq g_0 \\ 0, g_i < g_0 \end{cases} (1 \leq i \leq 8) \tag{12}$$

where g_0 denote the gray values of the center pixel and g_i denote the gray value of the center pixel of the local neighborhood.

Secondly, follow the pixels along a circle, i.e. clockwise or counter-clockwise can give an 8-digit binary number. Finally, the histograms of each "number" can be texture feature vector of image. Therefore, the $LBP_{P,R}$ histograms can be used to describe the texture feature of low frequency sub-band.

Let I_1 denotes low frequency sub-band of queering image and I_2 denotes low frequency sub-band of an image. Then, the texture similarity between I_1 and I_2 can be calculated by the (13).

$$d_{LBP}(H_{LBP1}, H_{LBP2}) = 1 - \frac{\sum_{i=1}^{n} \min(h_{LBP1}^i, h_{LBP2}^i)}{\min(\sum_{i=1}^{n} h_{LBP1}^i, \sum_{i=1}^{n} h_{LBP2}^i)} \tag{13}$$

where n is the number of bins.

3.3 The algorithm description

The quantization histograms denote the texture feature of the high frequency sub-band and the LBP signature denotes the texture feature of the low frequency sub-band of the improved DDCT. Then the similarity between two images can be defined as the distance:

$$D(P,Q) = \omega_1 d_{qh} + \omega_2 d_{LBP} (\omega_1, \omega_2 > 0, \omega_1 + \omega_2 = 1) \tag{14}$$

where ω_1 is the weight of quantization histograms and ω_2 is the weight of the LBP. The image retrieval algorithm based on the improved DDCT can be described as follows.

Step1: The retrieval image is decomposed by the improved DDCT.
Step2: The quantization histograms are used to describe the texture features of the high frequency sub-bands and the similarity can be computed by the histograms intersection method.
Step3: The LBP can be used to describe the texture features of the low frequency sub-band and the similarity can be computed by the histograms intersection method.
Step4: The Gaussian normalization is used to normalize the d_{qh} and d_{LBP}.
Step5: The texture similarity of the querying image and other images is computed by the weighted distance.

4 Retrieval Performance Analysis

In the retrieval experiments, a subset of COREL image database is used. This subset contains 2000 different images, including flowers,horses,dinosaurs,bus,etc. The retrieval accuracy was measured by the recall and precision. Through the use of human subjects, the image set can be divided into two sets: the set of images relevant for the query q, R(q) and its complement, the set of irrelevant images $\overline{R}(q)$. Suppose that the query q is given to a data set and that it returns a set of images A(q) as the answer. Precision is the fraction of retrieved image that are relevant to the search[13]:

$$precision = \frac{|A(q) \cap R(q)|}{|A(q)|} \tag{15}$$

Recall is the fraction of relevant images that is returned by the query:

$$recall = \frac{|A(q) \cap R(q)|}{|R(q)|} \tag{16}$$

We compare the proposed algorithm with the SD algorithm in the paper. The parameter settings are: $\omega_1 = \omega_2 = 0.5$ in this paper. We random select 20 images as the query,where each query is set as an entire image because we need to automatically perform the experiment on the large query set: 400 query images. Figure 4 shows the experimental data for the different algorithms, where the vertical and horizontal coordinates denote the precision and the recall.

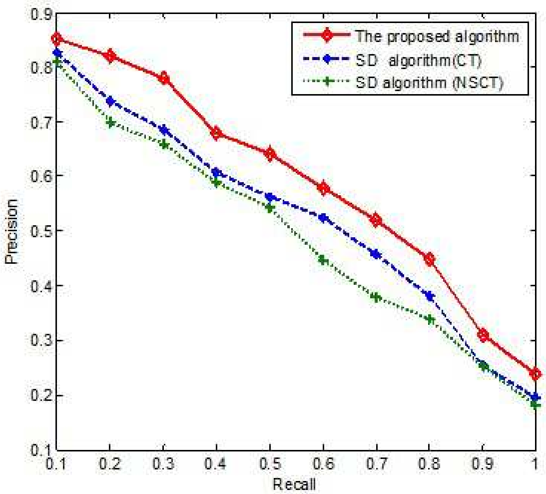

Fig. 4: Performances of different algorithms

From Figure 4, it is observed that the proposed algorithm yields better retrieval accuracy than the SD algorithm based on the improved DDCT. Because the improved DDCT has the advantages of both good directionality and shift-invariant, the proposed algorithm possesses more the direction texture information than the SD algorithm. At the same time, the quantization histograms and the LBP histograms in the proposed algorithm denote the high frequency and low frequency texture feature roundly. Therefore the proposed method provides a superior performance in the natural image retrieval than the SD algorithm.

5 Conclusion

An improved double density contourlet transform is proposed in this paper. Compared with double density contourlet transform, the improved DDCT have the lower complexity with the shift invariance. Experiments show the high frequency subbands of improved DDCT fit the non-Gaussian and the GGD model can be used to describe the coefficient distribution. The quantization histograms denote the texture feature of the high frequency sub-bands and the LBP signature denotes the texture feature of the low frequency sub-band. The proposed method provides a superior performance than the SD algorithm in the natural image retrieval. Further research can be carried out on extracting the shape feature to retrieval by the improved DDCT.

Acknowledgement

This work is supported by National Natural Science Foundation of China (NSFC) under Grant(61173173, 61272430);Shandong Natural Science Foundation (ZR2013FL017,ZR2013FL018).
The authors are grateful to the anonymous referee for a careful checking of the details and for helpful comments that improved this paper.

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Xie Qingsong received the MS degree in computer science from Shandong University of Technology in 1996. He is currently a professor in Shandong Institute of Business and Technology. His research interests are in the areas of patter recognition and information processing.

Guo Jie born in 1990. In 2012, she graduated from shandong normal university, abtained a bachelor's degree. In the same year, she was admitted to institute of information science and engineering in shandong normal university .Now she is studying for her MS degree in computer science at Shandong Normal University.Her research interests is image processing.

Li Mengjun born in 1985. In 2009, he graduated from shandong normal university. In the 2012 year, he was admitted to institute of information science and engineering in Shandong normal university. Now he is studying for his MS degree in computer science at Shandong Normal University.His research interests is image processing.

An Zhiyong received the MS degree in computer science from XiDian University in 2004, and the PhD degree in computer science from XiDian University in 2008. He is currently an associate professor in Shandong Institute of Business and Technology. His research interests are in the areas of image retrieval and information.