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Space and Contourlet Domains Texture Image Retrieval Algorithm

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Abstract. Contourlet transform has been widely used in many image processing applications including digital image denoising, texture image retrieval, etc. When contourlet transform is used for texture image retrieval problems, features like standard deviation, skewness, kurtosis, L1-energy, L2-energy and others of contourlet subbands was used to characterize the nature of textures in digital images. Many other methods like local binary patterns are often used to construct texture image retrieval systems. In this work, we combine features from traditional approaches with local oriented statistics information booster (LOSIB) to improve the texture image retrieval rates. Experiments on Brodatz texture image database was carried out, and the results show that the combination of the features from contourlet and space domains can improve the results efficiently.

Introduction

Information is always important to every one of us ever since the beginning of human history. Every day, we hope to get different categories information to boost the quality of our lives. Maybe, one of the most important forms of the information is digital images. And for these images, the most important things what we care about, maybe, is the content of the images. It is well know that almost all the images nowadays are digital images, and the content of images should be the shape, texture and colors. Obviously, among them, the texture information is most outstanding, because this part has many detailed information hence can affect us determination [1]. So the very import topic which is how we can characterize the features of textures in images and how we can recognize them.

Ever since the FFT was implemented by computers about fifty years ago, the FFT method was widely used in digital image texture classification problems. And then, about thirty years ago, the development of wavelet transform make wavelet based texture image classification and retrieval problem much more depended on the new super strong tool [2-4]. And due to the weakness of direction resolution, many stronger tools suitable for two and three dimensional signals were developed rapidly. They are contourlet, bandelet, wedgelet, shearlet, beamlet, etc. It should be noted that contourlet[5] is promising and has been extended into several advanced versions, including non-subsampled contourlet transform [6], contourlet-2.3, contourlet-1.3, dual tree complex contourlet transform, etc, the motivation is shift invariant level and localized character. And all the transforms have been studied on how to characterize the features of textures in digital images. The basic process of the transform based methods including the same steps like: (1) Feature extraction in transform domain. (2) Compare the feature of the query image with the features in the database and get the most similar objects [7].

With the development of transformed based methods, space domain based method was developed very rapidly at the same time. Maybe, the most outstanding one is local binary pattern (LBP) which was demonstrated in 2002 by Ojala [8]. Space domain local descriptors become more and more import during the past fifteen years due to the simplicity and capability to extract texture features. Several modified versions of LBP were proposed in the last few years, including LBP variance (LBPV), complete LBP (CLBP) and adaptive LBP (ALBP). Inspired by the idea of LBP and its variances, Oscar, Enrique, et al proposed a booster (LOSIB) for texture classification, and they combine the

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booster with Haralick, Hu, Zernike moments, LBP, LBPV, ALBP, CLBP, and get significant improvements [9]. In this paper, we will use the feature called LOSIB to improve the contourlet based texture image retrieval rates by combining LOSIB and the statistics parameters including mean, standard deviation, L1-energy, L2-energy, skewness, and kurtosis. And in the system, we use Canberra distance to measure the difference of different images.

Feature vectors

In this work, we use two kinds of features. The first kind feature comes from all the subbands coefficients in contourlet domain. That is, we first transform an image into contourlet domain, then, for each subband, we calculate one statistical parameter for the coefficients, and cascade them to form feature vector for the image. As we all know, there are lots of statistical parameters and they can be used to characterize the texture distributions. Here, we will use the following parameters: mean, standard deviation, L1-energy, L2-energy, skewness, and kurtosis. For clarity, we list the index of each feature in table one for reference later. And from Eq.1~Eq.6 defined all the contourlet domain features.

Table 1: Index of features and some combinations

F1	*F2*	*F3*	*F4*	*F5*	*F6*
mean	standard deviation	L1-energy	L2-energy	skewness	kurtosis

$$F1(s,k)=\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}|W_{s,k}(m,n)| \tag{1}$$

$$F2(s,k)=\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\left|W_{s,k}(m,n)-m(s,k)\right| \tag{2}$$

$$F3(s,k)=\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}|W_{s,k}(m,n)| \tag{3}$$

$$F4(s,k)=\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}|W_{s,k}(m,n)|^{2} \tag{4}$$

$$F5(s,k)=\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\frac{\left(W_{s,k}(m,n)-m(s,k)\right)^{3}}{s\,(s,k)^{3}} \tag{5}$$

$$F6(s,k)=\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\frac{\left(W_{s,k}(m,n)-m(s,k)\right)^{4}}{s\,(s,k)^{4}} \tag{6}$$

Where s and k denote the index of scale and direction, M,N stand for the row and column number of the sub-band coefficients, W is the coefficient of row M and column N in sub-band indexed by s and k, µ and represent mean and standard deviation, respectively. So the number of contourlet domain is the number of subbands plus 1, here 1 arises from the low frequency subband.

The second kind feature comes from local oriented statistics information booster. As the authors mentioned, the parameters for the booster including radius and the number of neighbors should be determined by some special criteria [9]. For different kind of images, maybe the parameters should be different. The texture descriptor can be expressed as Eq.7.

$$LOSIB(R,P)=\bigcup_{p=0}^{P-1}\frac{\sum_{x_c=1}^{M}\sum_{y_c=1}^{N}\left|g_c-g_p\right|}{M\cdot N} \tag{7}$$

R and P denote the radius and the number of neighbors, respectively. g_c and g_p are the gray levels of the center and neighbor pixels. x_c and y_c are the coordinates of the center pixel. M and N are the columns and rows of the image. So the number of LOSIB features for an image equals to P.

The dimension of the features for an image is the sum of contourlet feature and LOSIB feature.

Experimental results

According to the opinion of the parameters of LOSIB features as we talked above, we could not determine the radius and the number of neighbors of the central pixels, we did some numeric experiments on Brodatz Album [10] to test how to choose the two parameters.

First, we choose radius value as 1, and the number of neighbors from 3 to 14, and only use the LOSIB features; we can get the retrieval rates as shown in table 2.

Table 2 LOSIB features contribution to retrieval rates when radius is 1 and neighbors from3-14

d\p	16	20	30	40	50	60	70	80	90	100
3	0.3873	0.4286	0.4985	0.5396	0.5763	0.6061	0.6336	0.6566	0.6760	0.6943
4	0.3614	0.3966	0.4660	0.5189	0.5613	0.5945	0.6227	0.6508	0.6759	0.7001
5	0.4083	0.4447	0.5038	0.5471	0.5811	0.6074	0.6327	0.6567	0.6784	0.6958
6	0.3858	0.4293	0.4976	0.5383	0.5752	0.6047	0.6323	0.6557	0.6748	0.6937
7	0.4073	0.4426	0.5029	0.5477	0.5810	0.6068	0.6331	0.6570	0.6776	0.6953
8	0.4178	0.4500	0.5133	0.5566	0.5874	0.6124	0.6385	0.6628	0.6826	0.6987
9	0.4077	0.4427	0.5048	0.5482	0.5816	0.6069	0.6328	0.6564	0.6778	0.6958
10	0.4068	0.4438	0.5038	0.5467	0.5810	0.6076	0.6323	0.6567	0.6778	0.6963
11	0.4071	0.4427	0.5038	0.5473	0.5814	0.6066	0.6324	0.6564	0.6770	0.6955
12	0.4142	0.4484	0.5085	0.5520	0.5845	0.6093	0.6355	0.6607	0.6802	0.6980
13	0.4071	0.4424	0.5039	0.5470	0.5813	0.6066	0.6330	0.6561	0.6776	0.6956
14	0.4078	0.4433	0.5038	0.5471	0.5811	0.6066	0.6326	0.6563	0.6773	0.6950

It should be noted that the retrieval rates is defined as Eq.8.

$$R(p)=\frac{1}{q}\sum_{i=1}^{q}R(p,i)=\frac{1}{q}\sum_{i=1}^{q}\frac{S(p,i)}{16} \tag{8}$$

In Eq.8, q=1744, R(p) denotes the average retrieval rate for each p∈ {16, 20, 30, 40, 50, 60, 70, 80, 90,100}, hence 10 retrieval results can be acquired. S(p, i) is the number of images belong to the correct group when the i-th image used as query image.

From table 2 we can see that if radius equals to 1, the number of neighbors can be chosen as 8.

Next, we combine LOSIB feature with the six statistical parameters one by one, and get the retrieval rates shown in table 3. From table 3, we can see that LOSIB can improve every statistical parameter results from contourlet domain by different degrees. It should be noted that in table 3, F1-F6 means the contourlet subband statistical parameters, and Fx_L means the combination features of LOSIB and the corresponding contourlet parameters with the index x. The decomposition structure parameters of contourlet transform here from coarsest to finest scale, the number of direction subbands are 4, 4, 8. In the contourlet transform, the directional and pyramid filter type are “pkva”.

Conclusions

Texture image retrieval problem is an ongoing hot topic for information retrieval system. In this paper, a new approach was proposed to construct texture feature vectors. The vector is a combination of

LOSIB and contourlet domain subband statistical parameters. Experiment results show that LOSIB feature can improve contourlet texture image retrieval rates when combining it with the classical texture descriptors.

Table 3 . Retrieval rates of combining LOSIB and contourlet domain statistical parameters

N	16	20	30	40	50	60	70	80	90	100
F1	0.231	0.245	0.270	0.290	0.310	0.328	0.346	0.364	0.379	0.394
F1_L	0.388	0.422	0.486	0.537	0.575	0.604	0.630	0.655	0.676	0.694
F2	0.662	0.713	0.771	0.803	0.823	0.838	0.849	0.860	0.870	0.879
F2_L	0.676	0.722	0.774	0.803	0.821	0.835	0.846	0.857	0.867	0.875
F3	0.676	0.726	0.783	0.814	0.837	0.854	0.868	0.880	0.890	0.899
F3_L	0.677	0.722	0.771	0.802	0.823	0.838	0.850	0.862	0.872	0.880
F4	0.668	0.719	0.778	0.807	0.825	0.840	0.852	0.863	0.874	0.884
F4_L	0.690	0.735	0.784	0.813	0.829	0.843	0.855	0.866	0.876	0.886
F5	0.197	0.208	0.232	0.255	0.275	0.292	0.308	0.323	0.337	0.351
F5_L	0.265	0.284	0.329	0.365	0.399	0.426	0.451	0.473	0.493	0.511
F6	0.492	0.527	0.588	0.629	0.663	0.687	0.708	0.726	0.741	0.755
F6_L	0.580	0.626	0.693	0.729	0.757	0.780	0.798	0.813	0.826	0.837

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