2D 지역푸리에변환 기반 텍스쳐 특징 서술자에 관한 연구

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Texture Feature Extractor Based on 2D Local Fourier Transform

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Abstract

Recently, image matching becomes important in Computer Aided Diagnosis (CAD) due to the huge amount of medical images. Specially, texture feature is useful in medical image matching. However, texture features such as co-occurrence matrices can't describe well the spatial distribution of gray levels of the neighborhood pixels. In this paper we propose a frequency domain-based texture feature extractor that describes the local spatial distribution for medical image retrieval. This method is based on 2D Local Discrete Fourier transform of local images. The features are extracted from local Fourier histograms that generated by four Fourier images. Experimental results using 40 classes Brodatz textures and 1 class of Emphysema CT images show that the average accuracy of retrieval is about 93%.

1. INTRODUCTION

Texture, which represent the coarseness and statistical character of local variation of brightness between neighboring pixels play an important role in image analysis and pattern recognition. This variation of brightness can be expressed with a 2D Fourier spectrum which will be used in this paper as the core concept for the feature extraction.

In the newly emerged multimedia application CBIR, texture is exploited as one of the several primary low level image features for image retrieval. A lot of shape-based representations and retrieval methods exist but shape-based feature extraction doesn't work well for images that have textures such as medical images because it generates a lot of keypoints or signatures. Because of that, it will be better to extract texture feature from these kinds of images.

There are various local frequency domain-based texture descriptor[1][2][3]. A method using global 2D Fourier transform is proposed in [6] and the result shows that Fourier transform-based texture feature extractor performs well in extracting texture feature. In [1] the local Fourier transform is introduced by H. Yu and in [2] and [3] this method is extended to make it more robust to rotation. In this paper, instead of using global 2D Fourier transform, we present a method using a 2D local-based Fourier transform to extract the statistical character of local variation of brightness in a window size of 3x3 pixels.

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In particular this variation of brightness of local neighborhood reflects the local activities of a texture, so it will catch the important characteristic of the texture In [5], Haralick etc. developed a typical method named co-occurrence matrices, it uses some second order moment to describe the gray-tone spatial dependencies. But this method considers only the co-occurrence of the pair of gray levels with special distance at special orientation. It could hardly describe the spatial distribution of gray levels of neighborhood pixels [1]. In our previous method of feature extraction, we use Spatial Gray Level Dependent Matrix (SGLDM) based on co-occurrence matrices to extract the texture feature from CT images [7]. Because of the problem with the co-occurrence matrices, a better texture feature extractor is developed.

In this paper we present a 2D local Fourier transform based texture descriptor. With 2D Local Fourier transform, the spatial distribution of gray levels of neighborhood pixels can be extracted and therefore it can resolve above problem more easily. First the 2D local Fourier transform is computed on a 3x3 pixels window. This window will be moved around the image. This window will generate nine Fourier coefficients which only four will be taken for next process. These coefficients then will generate four Fourier images. From [1][2][3], these Fourier coefficients images can be represented by histogram of the image. So eight bins of statistical histogram corresponding to the value of the Fourier image pixels is then generated. These histograms will represent the texture features of the original image.

2D local Fourier transform will be introduced in section 2. The texture feature from the histogram will be described in section 3. In section 4 the experiment and result will be

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explained in detail. Finally, the conclusion is written in the section 5 of the paper.

2. 2D LOCAL FOURIER TRANSFORM

A 2 dimensional Fourier transform is defined by:

$$F(m,n) = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)e^{-j\left(\frac{2\pi xm}{M}+\frac{2\pi yn}{N}\right)} \quad (1)$$

And the inverse of the transform is defined by:

$$f(x,y) = \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} F(m,n)e^{j\left(\frac{2\pi xm}{M}+\frac{2\pi yn}{N}\right)} \quad (2)$$

Similarly for a 3x3 images the 2D local discrete Fourier transform is defined by:

$$L(m,n) = \frac{1}{9}\sum_{x=0}^{2}\sum_{y=0}^{2} l(x,y)e^{-j(\pi xm+\pi yn)} \quad (3)$$

Where L(m,n) is the 2D local Fourier transform and l(x,y) is the local 3x3 pixels window as shown in Figure 1 and Figure 2.

Let $\{I(x,y)|x=0,1,...,M-1, y=0,1,...,N-1\}$ denotes the original image. The window of 3x3 pixels is defined as Figure 1. Then l(0,0), l(0,1), l(0,2), l(1,0), l(1,1), l(1,2), l(2,0), l(2,1), l(2,2) can be treated as local images of the original image.

l(0,0)	l(0,1)	l(0,2)
l(1,0)	l(1,1)	l(1,2)
l(2,0)	l(2,1)	l(2,2)

Figure 1. The 3x3 window of an original image.

By using formula (3) the 2D local Fourier transform is calculated for every window of the original image. l(0,0) point of the window will move pixel by pixel from x=0 to x=M and from y=0 to y=N to calculate the whole local Fourier transform of the original image. As we can see, a single window will produce nine local Fourier coefficients as shown in Figure 2.

L(0,0)	L(0,1)	L(0,2)
L(1,0)	L(1,1)	L(1,2)
L(2,0)	L(2,1)	L(2,2)

Figure 2. The 3x3 window of Fourier transformed image.

Because the image only consists of real part and has no imaginary part, only a quarter of the coefficients are distinct. Furthermore in a 2D Fourier transform for real value, every corner of the image is almost identical because of their symmetries property. So we only consider L(0,0), L(0,1), L(1,0) and L(1,1) as the coefficients that we will use to generate the histogram later in the section 3. These are the local Fourier coefficients maps of the image which represent the variation of local brightness, the co-occurrence of gray levels and their spatial distribution as well.

3. TEXTURE FEATURE

The similar local parts of the texture have similar series of l(x,y). The Fourier transform coefficients L(m,n) are similar correspondingly. So the selected local Fourier coefficients are utilized to extract the feature of local gray-tone spatial dependencies.

Every window will generate another four selected value coefficients which are L(0,0), L(0,1),L(1,0) and L(1,1). These values will be saved in four images separately. After moving the window around the original image pixel by pixel based on point l(0,0), four images are generated. These images are called Fourier images as shown in Figure 3. Figure 3 (a), (b), (d) and (e) are the selected L(0,1), L(1,1), L(0,0) and L(1,0) Fourier images. Figure 3 (c) is the 2D Fourier transformed images of 3x3 window extracted from the original image (f).

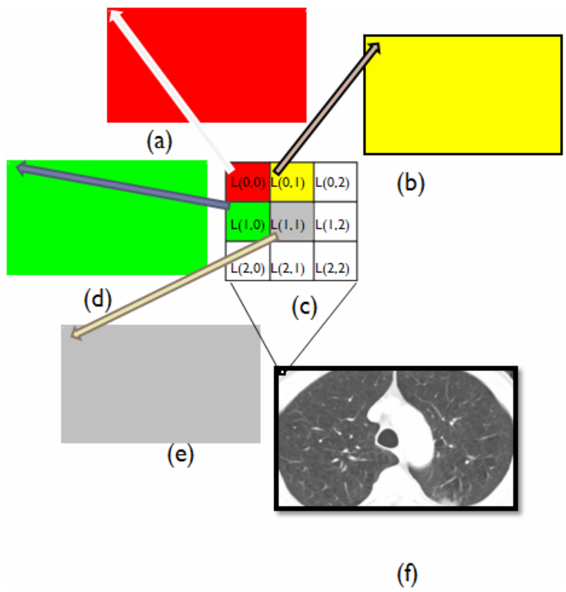

Figure 3. Generation of four Fourier images.

Using these four Fourier images, four histogram will be generated. Because the value is in complex number, we find the magnitude and phase from it. The phase contains the direction information so we excluded it to make the feature to be translation invariant. So only the magnitude value will be used as the features with the formula as below:

$$\text{Mag}(x) = \sqrt{\text{Re}(x)^2 + \text{Im}(x)^2} \quad (4)$$

Then the magnitude value of the Fourier images is normalized to the value between 0 and 255. Next, image histogram is generated for every Fourier image and because some of the histogram class widths are small, the histograms are streched before being transformed into eight bins histograms. These eight values for every histogram are the texture features of the image. So, 32 features are generated from the four histograms.

From the histogram, it is easily to know some properties of this feature:

1) It is tolerant to the gray displacement and linear transform
2) It is translation invariant because the phase is excluded from the feature.

4. EXPERIMENT RESULTS

Texture based image retrieval experiment is conducted for testing the 2D local Fourier transform method. In this experiment, the Euclidian distance is measured between the bins of every histogram. The similar texture will generate the nearest Euclidian distance to the original image.

The texture database used in this experiment consisted of 40 different texture classes from Brodatz texture which are D3, D6, D9, D11, D15, D16, D21, D22, D28, D29, D32, D34, D49, D52, D53, D54, D55, D57, D65, D66, D69, D76, D77, D78, D80, D82, D84, D85, D87, D92, D93, D100, D101, D102, D103, D104, D109, D110, D111, D112 [4]and a set of Emphysema subregion images from Inha University Hospital. Because this method will be used to extract features from the Emphysema texture later, only the detail and specific texture is selected from the Brodatz textures and big pattern of texture is excluded from this experiment. From each texture, 16 sample images of size 50x50 are extracted. So the total images on the database are 656 images. The sample of the images from the database can be viewed in Figure 4.

As described in section 3, we used the histograms to descript the images. When the query image is put in, first the local Fourier coefficients maps this image are computed, and the four histograms are generated. The same process is conducted to the images in the database. The next step is to compare features of the query image with the features of the database images. Then Euclidian distance is measured and sorted ascending by the distance between them. Every image in the database will be tested as a query image and the best accuracy for each class is recorded. Figure 5 shows some retrieval results. The best retrieval ratios or accuracy of D9 and Emphysema subregion are 94% and 100% respectively. The formula of accuracy used in this experiment is defined as below:

$$Accuracy = \frac{\left|\{\text{relevant information}\} \cap \{\text{retrieved information}\}\right|}{\left|\{\text{relevant information}\}\right|} \quad (5)$$

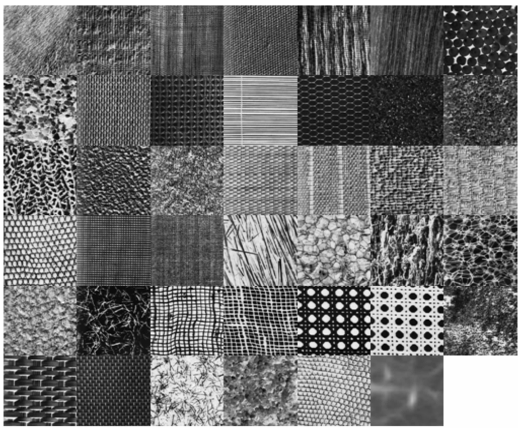

Figure 4. The sample images for each class and Emphysema subregion image (the last image).

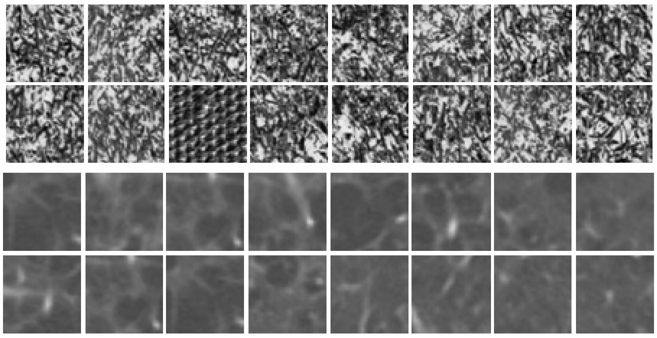

Figure 5. Two examples of texture retrieval. The upper-left image in each block is the query image (The query image in the first block is a subimage of D9, the other query image is from Emphysema).

The total accuracy and average ratio of the best performance for each class is written in the Table 1. From the table we could see that 49% of the classes obtained the accuracy of 100% as their best performance. Luckily the Emphysema image also manages to obtain the 100% of accuracy. The lowest accuracy is 69%. Above all over 98% of the classes manage to obtain accuracy above 70% and this proves that this method is efficient to extract the texture feature from the texture-based image such as medical image.

5. CONCLUSIONS

In this paper we have proposed a method to extract the texture feature based on 2D local Fourier transform. It has been tested on Brodatz and medical image by experimenting the image retrieval performance. From the results, it shows that this method is relevant and efficient for extracting texture information from texture images especially for medical images. For further study, a larger database of images will be experimented. We also planned to test the method in different situation to test the noise invariant, translation invariant, scale invariant and gray scale shift invariant and improve the method to fit those situations. We also would like to compare this method with existing method to see the performance.

Table 1. Best accuracy ratio for each class of 40 Brodatz texture and Emphysema subregion images.

Class	Accuracy	Class	Accuracy
D3	100%	D69	100%
D6	100%	D76	81%
D9	94%	D77	100%
D11	88%	D78	75%
D15	75%	D80	94%
D16	100%	D82	94%
D21	100%	D84	100%
D22	88%	D85	94%
D28	94%	D87	100%
D29	88%	D92	100%
D32	100%	D93	94%
D34	100%	D100	69%
D49	100%	D101	100%
D52	81%	D102	100%
D53	100%	D103	100%
D54	75%	D104	100%
D55	100%	D109	81%
D57	94%	D110	94%
D65	81%	D111	94%
D66	88%	D112	100%
		Emphysema	100%
Average	93%		

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