Spatial and Frequency Domain–Based Feature Fusion Method for Texture Retrieval

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Abstract. This work presents a novel feature fusion method for texture retrieval. Considering the advantages of both the spatial and frequency domain, we first carry on the experiments in spatial domain and frequency domain respectively. On one hand, sober and histogram feature are used to calculate the similarity. On the other hand, Fourier is applied to obtain the frequency feature. Then a feature fusion scheme is used to join the two features came from spatial and frequency domain. Experimental results on MIT texture database show that the proposed method is effective.

Keywords: texture retrieval, spatial domain, frequency domain, fusion.

1 Introduction

Texture has played an important role in computer vision. It is almost everywhere around our daily life. This vital property provides us abundant information for feature extraction. The texture consists of varieties of types. For example, a smooth texture appears in the furniture demonstrating its good looking for appreciation, the hardness texture in the wildness depicting the nature of the life. In addition, some of the texture have fix pattern and some have dynamic pattern such as the wave and the swaying trees. However, due to the strong intrinsic of the texture between local area and the difference between different textures, we benefit a lot from these advantages. People also make good use of the texture information to recognize all of the things around us.

The statistic-based method has been developed for many years. Many researches validate that this type of method is one of the effective one, among which the grey level co-occurrence matrix (GLCM) is good texture analysis tool that has been a mainstream method. Haralick et al. [1] first proposed the GLCM method when he was doing the research on land use. The GLCM method describes the appearance probability that belongs to a couple of grey level. Although GLCM method owns good discrimination ability, it still suffers from high computation complexity, especially for the texture classification on pixel level. The researchers have tried many methods to improve the original version of GLCM. Soh and Tsatsoulis [2] reduced the computation burden of GLCM through different scale and direction. Ulaby et al. [3] discovered that four features that in terms of contrast, inverse gap, correlation and energy is irrelevant, which is convenient for computation and gives high classification accuracy. Baraldi [4] had made a detail research on the six high

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texture features and recognized that the contrast and the entropy are the two most important features. B. Hua [5] had carried on the optimization of computation of GLCM and had obtained three irrelevant features with best discrimination ability, namely the contrast, entropy and correlation. Although the above mentioned methods can reduce the computation burden but it cannot solve the existing problem of GLCM. Aiming at tackling with the above problems, Clausi et al. [6] made a deep inside of GLCM and finally obtained a good improvement of the original version. In addition, Walker et al. [7] proposed an adaptive multiple scale GLCM method and an improved version of GLCM based on genetic algorithms. Experimental results show that the classification error rates of both proposed method are obviously lower than traditional GLCM method and reduce the computation burden of feature selection. Kandaswamy [8] analyzed the computation complexity of GLCM. Enlightened by the statistic model, they proposed an efficient texture analysis method. Their conclusion shows that the analogy texture feature is able to improve the efficiency of texture analysis, but they do not arouse the decreasing of the classification error rate.

The parameter-based method first built a model of the image texture, and then regarded the texture feature extraction as the process of parameter evaluation. It is an essential work to evaluate the optimal parameters. The random field model tries to use the probability model to depict the random process. The essence of the random field model is to depict the statistical dependence relation, among which Markov random field (MRF) model is the most popular one. The basic idea of MRF texture modeling is to describe the statistical feature of the texture according to the conditional probability distribution of a pixel in terms of its neighbor pixel. According to the Hammersley-Clifford theory [9], there is an equivalent property between the random field of MRF and Gibbs. Hence, it is convenient to depict the space constrains of the images through conditional probability function or the union distribution. Besides the MRF model, McCormick et al. [10] proposed to use the autoregressive model for texture analysis. This method evaluates the pixel level form the corresponding pixel level of its neighborhood, where the evaluation of the parameters are carried on by using the criterion of minimum mean square error or maximum likelihood parameter estimation. There is a notable change to the parameters of the model for the smooth texture, but no changes for the rough texture.

In this paper, we present a novel feature fusion method for texture retrieval. Considering the advantages of both the spatial and frequency domain, we first carry on the experiments in spatial domain and frequency domain respectively. On one hand, sobel and histogram feature are used to calculate the similarity. On the other hand, Fourier is applied to obtain the frequency feature. Then a feature fusion scheme is used to join the two features came from spatial and frequency domain. Experimental results on MIT texture database show that the proposed method is effective.

The paper is organized as follows. In the next section we introduce related work. Section 3 describes our method. In section 4, we give a number of experiment results. Section 5 offers our conclusions.

2 Related Work

The definition of texture can be stated as follow: The pixel arrangement of the surface of an image, which describes the main property of the image and enables us to tell apart, two different types of things. With the good merits of the texture, there has been a wide scope of applications in a variety of fields. Texture analysis has made great contribution in remote image, X-ray photo, cell image processing. It also can be recognized as a tool that can be used for depicting any arrangement of the substance such as the lung and vascular texture in medical X-ray photo, the texture of the rocks in aerospace terrain. In addition, texture analysis has also been concerned in various biometrics recognition systems, such as the iris recognition system, vein recognition system, palm print recognition system, face recognition and so on. Even though such tool has been used for many fields for a long time, it still suffers from some difficulties which can be stated as follows: (1) It is generally very hard to find a proper mathematical model to describe every detail of the texture; (2) There is still some randomness, namely irregular patterns, in the texture which is hard to be well copped with. (3) It is normally not a realistic work to exploit only the local or the global feature for texture classification. That is to say, a single texture detection method cannot obtain a much better result. (4) It is a challenge work to look for the robust and efficient feature for texture analysis. This hardness on one hand restricts the effectiveness of the current applications in terms of texture analyze, on the other hand facilitate the researchers to make an improvement of the related work.

The frequency-based method assumes that the distribution of the energy in frequency domain can be used to identify the texture. It transforms the texture from one space to another space through a certain linear transform, filters or filter banks, and then applied a certain energy-based criterion to extract the texture feature. The discrete cosine transform [11] and the fourier transform [12] are commonly used methods for feature extraction in frequency domain. Gabor filter is also a good tool for feature extraction. Its main idea is that: Different texture usually owns different central frequency and bandwidth. Hence, the Gabor filter banks can be designed for feature extraction according to such frequency and bandwidth. For each Gabor filter, only the texture that has the same frequency as the Gabor filter can go through the filter, while the texture with other frequency cannot pass. Therefore, the prior task for Gabor filter design is to consider the design of the parameters of each filter and the layout of the Gabor filter banks. Dunn and Higgins [13] had made a fundamental work to demonstrate the detail design criterion of single Gabor filter. The Gabor filter banks should cover the whole space. With this reason, the parameters of frequency, scale and position should be properly set so as to prevent the overlap of frequency banks on the same radius. The frequency bank in radial direction with different radius should not be overlapped too.

The representation-based method holds that the texture consists of basis patches or lied in a lower subspace. Hence, the basis patches can be used for constructing the texture. The syntactic texture description method [14] assumes that the description of the texture of a class can form a language that is expressed by the corresponding grammar. The mathematical morphology method [15] used structural element to look for the repetition property in the space. When the binary texture image is eroded by the structural element, the texture property will appear on the appearance of the eroded image. In addition, another group of representation methods represent the texture in a lower subspace. These methods include PCA, SRC and so on.

3 The Proposed Method

In this section, we propose a fusion method to achieve better texture retrieval result. First, we carry on the experiments in both spatial and frequency domain. Then, the proposed fusion method is used to retrieve the images.

A. The spatial filter

- **Sobel operator**

For the function $f(x, y)$ of an image, the corresponding gradient is defined by using the expression (1).

$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \tag{1}$$

The module of ∇f is given by Equation (2)

$$\nabla f = mag(\nabla f) = \left[G_x^2 + G_y^2\right]^{\frac{1}{2}} = \left[\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2\right]^{\frac{1}{2}} \tag{2}$$

However, it costs lots of computation as soon as Equation (2) is used for calculation, since it contains the square operations and a root operation. In real application, we use the absolute value operation to replace the square and root operations. Therefore, Equation (3) is used to calculate the gradient of function $f(x, y)$. In addition, we use the difference operation over the image to approximate the calculation of Equation (3). With this reason, two masks along X direction and Y direction are used for the gradient calculation. We regard the two masks as sobel operators, which is shown in Figure 1.

$$\nabla f \approx \left|G_x\right| + \left|G_y\right| \tag{3}$$

$$\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \qquad\qquad \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

(a) (b)

Fig. 1. Sobel operator. (a) is the operator along X direction while (b) is the operator along Y direction

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[1] Identify applicable sponsor/s here. (sponsors).

- **Histogram feature**

The object can be described by histogram feature $P = (p_1, p_2, \cdots, p_m)$, among which

$$p_u = C\sum_{i=1}^{n} \delta[c(x_i) - u], (u = 1,2,\cdots,m) \tag{4}$$

$$C = \frac{1}{\sum_{u=1}^{m}\sum_{i=1}^{n} \delta[c(x_i) - u]} \tag{5}$$

$$\delta(x) = \begin{cases} 1, if & x = 0 \\ 0, if & x \neq 0 \end{cases} \tag{6}$$

$$c(x_i) = \left[H(x_i) \Big/ \frac{360}{m} \right] + 1 \tag{7}$$

Where x_i is the pixel value, $H(x_i)$ is the ith pixel value in gray channel, n is the pixel number and m is the bin number.

B. The frequency filter

- **Two-dimensional discrete Fourier transform**

For an image with dimension $M \times N$, the discrete Fourier transform of its function $f(x, y)$ can be expressed as Equation (8)

$$F(u,v) = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x, y)e^{-j2\pi(ux/M + vy/N)} \tag{8}$$

Where $u = 0,1,\cdots,M-1$, $v = 0,1,\cdots,N-1$, , $x = 0,1,\cdots,M-1$, $y = 0,1,\cdots,N-1$. The spectrum and the phase angle are shown in Equation (9) and (10), respectively.

$$|F(u,v)| = \left[R^2(x, y) + I^2(x, y)\right]^{\frac{1}{2}} \tag{9}$$

$$\phi(u,v) = \arctan\left[\frac{I(u,v)}{R(u,v)}\right] \tag{10}$$

Usually, we conduct the discrete Fourier transform on function $f(x, y)(-1)^{x+y}$. According to the property of exponentiation, we have

$$\zeta[f(x,u)(-1)^{x+y}] = F(u - M/2, v - N/2) \tag{11}$$

Where $\zeta[\bullet]$ stands for the Fourier transform. Equation (11) transfer the center of $F(u,v)$ to $(M/2, N/2)$ under frequency coordinate.

C. The fusion scheme

Since the spatial and frequency domain have its own advantages in texture retrieval. In this work, we fuse the results of the methods came from spatial and frequency domain respectively. See in Fig. 1, as soon as we obtain the histogram feature and the frequency feature, we use Equation (12) to obtain the final fused feature.

$$S = \alpha A + (1-\alpha)B \tag{12}$$

Where A is the histogram feature, B is the frequency feature, S is the final fused feature and α is an adjusted factor ranged from 0 to 1.

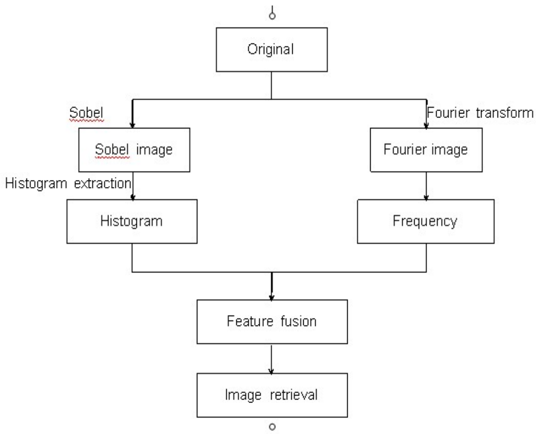

Fig. 2. Fusion scheme of texture retrieval

4 Experimental Results

To validate the effectiveness of the proposed fusion method, we carry on the experiments on MIT texture database. The database has 40 categories. For each category, it contains only one image. We divide the image into four parts. Hence, we obtained 160 images, with 40 categories. For each category, there are only four samples. Figure 3 shows some sample images that we use in the experiments. To test the precision of the proposed method, for a testing image, the retrieval system return four images which are probably the same class as the testing image. The number of the returned images which are the same class as the testing image will be accumulated and finally divide the total number of the returned images so as to obtain the precision of the retrieval system.

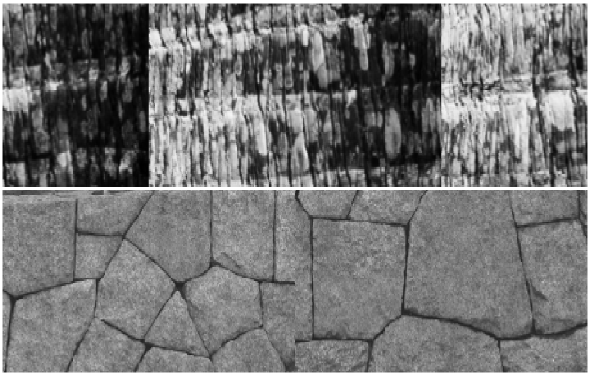

Fig. 3. Sample images from MIT texture database

We run the sobel-histogram method in spatial domain, frequency-based method and the fusion method on the obtained database. Figure 4 shows the experimental results. With the increasing of the alpha factor, the result of the fusion method is becoming much better than its original version.

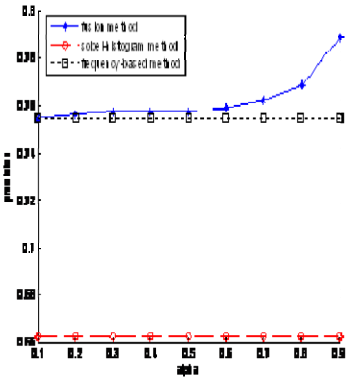

Fig. 4. Precision of the proposed method

We also run our experiments under different scheme whose experimental results are shown in Table 1. The experimental result shows that the proposed fusion scheme shows a competitive result than other methods.

Table 1. Precision under different methods

Method	precision
NN [16]	33.59%
Sobel+NN	28.91%
Sobel+Partitions1+Histogram+NN	65.78%
partitions+Fourier+NN	65.78%
Fourier+Histogram+NN	36.72%
Sobel+Fourier+NN	5%.15%
Sobel+Histogram+NN	66.25%
Fourier+NN	75.47%
fusion method	78.91%

5 Conclusions

In this paper, we have used a fusion method which takes advantage of spatial and frequency domain. In spatial domain, we first extract the sobel image of the testing image, then the histogram feature is obtained. In frequency domain, the Fourier transform is performed to extract the frequency feature. Finally, we combine the obtained two features for texture retrieval. Experimental results on MIT texture database show that, the proposed method is competitive and effective.

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