Image Texture Feature Extraction Based on Gabor Transform

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Abstract
As a regional feature, texture is a description of the spatial distribution of the image pixels. As texture can fully utilize the image information, it can become an important basis to describe and recognize the image. Compared with other image features, texture can take both the macro image properties and micro structure into consideration; therefore, feature has become a significant feature to be extracted in the target recognition. This paper analyzes the performance of Gabor filter, designs a multi-channel Gabor filter and selects its parameters. By extracting various local feature information (direction, phase, energy and so on) of the image with multi-channel filter, this method can decompose an image into the sub-images based on different frequency directions and channels and it classifies the sub-images with the statistical feature extracted from the sub-image as the texture feature to represent different texture region features of the image. It is quite convenient to realize and it can obtain the optimal comparison effect in the spatial and frequency domains. The experiment result shows that the Gabor filter of this paper have excellent performance in analyzing the frequency and the direction information of the local regions of digital image.

Key words: Image Texture, Feature Extraction, Gabor Transform.

1. INTRODUCTION

Texture analysis has been widely applied in remote-sensing image, x-ray picture, cell image interpretation and processing and texture analysis can be conducted with statistics and structure methods for spatial-domain image and transform-domain image. Generally speaking, the image texture shows periodicity; in other words, it has certain frequency of occurrence in the image space; therefore, texture feature can be extracted by making spectral analysis on the image. As Gabor transform belongs to windowed Fourier transform, Gabor function can extract relevant features in different scales and directions of the frequency domain. Besides, since Gabor function has similar biological effects to human eyes, it is frequently used in texture recognition and it has achieved excellent effects. In essence, Gabor filter is to extract the feature component of the image and it is usually applied in fingerprint recognition, iris recognition and face recognition. It is convenient to realize Gabor filter and it can obtain the optimal comparison effect in the spatial and frequency domain(Zyout and Czajkowska et al, 2015; Heng-Chao and Turgay et al, 2015).

As for texture, there is no uniform mathematical model and it can be used to described the arrangements of any physical components, including the lung texture and vascular texture of medical x-ray pictures as well as the lithological texture of aerospace and topography pictures. The visual texture in the image processing is usually interpreted as the repetitive arrangement of certain basic pattern (color primitive). Texture mapping technology is firstly come up with by Catmull in 1947. Catmull has been the first to find the corresponding relationship (mapping relationship) between the double-variable real-number space (texture space) and the three-dimensional curve represented with parameters(Yadav and Anand et al, 2015). At present, there are many methods to extract texture feature such as the methods based on local statistical feature, random field modeling feature, spatial frequency feature and fractal feature. Among them, the method based on gray level co-occurrence (GLCM) has been used most widely. Scholars have conducted plenty of research on image texture feature extraction with Fourier transform. For instance, perform Fourier transform to extract features in the maximum internal rectangular region of the image. The texture feature obtained with this method can only reflect the local texture of the image. Gabor transform is an important time-frequency analysis method and as a time-frequency signal analysis method, Gabor transform is developed on the basis of Fourier transform. It is firstly proposed by D.Gabor in his paper published in 1946. In order to extract the local information of Fourier transform of the signal, he has introduced a time localization window function and its parameters can be used to translate the window to cover the entire time domain(Jaya and Dheeba et al, 2015; Niehans and Daniela et al, 2015). The main idea of Gabor transform is that different image textures usually have different central frequency and bandwidth and a group of Gabor filters can be designed with these frequencies and bandwidths to filter the texture image. Every Gabor filter only allows the textures corresponding to their frequencies to pass through and
it suppresses the energy of other textures. After that, it analyzes and extracts the texture features from the output results of each filter and use them in the follow-up classification or segmentation (Ascensi, 2015).

This paper firstly analyzes the principles of image texture feature extraction and then compares Fourier transform and Gabor wavelet transform. Because different image textures usually have different central frequencies and bandwidths, according to which a group of Gabor filters can be designed to filter the texture image. This paper designs a multi-channel Gabor filter and selects its parameters. This paper extracts and describes the image texture features with the multi-channel Gabor filter and an eigenvector method respectively. The final part of this paper is the experimental analysis, which proves that the algorithm of this paper is effective.

2. IMAGE TEXTURE FEATURE

Texture is the repetitive pattern formed by the arrangement of elements or primitives according to certain rules. Texture analysis refers to the extraction and analysis of the spatial distribution pattern of image gray-level (dark and light). Therefore, the description of a texture includes the confirmation of the color primitives forming the texture and the confirmation of the correlation among the primitives. Texture is closely related to the high-frequency components of the image spectrum and a smooth image is generally not seen as a texture image. Besides, texture is also closely related to the scale. Texture can be observed with the characteristic of regional property only in a certain scale and it is treated as a measurement of the relationship among the pixels in the local region. Texture is a regional feature and it is related to the size and shape of the regions. The boundary between two texture patterns can be determined by observing whether there is any significant change in the texture measurement. As a reflection of physical structure, texture analysis can obtain the important information of the image objects and it is also a significant means for image segmentation, feature extraction as well as classification and recognition, as indicated in Fig.1.

![Image](image.jpg)

**Figure 1.** Texture difference feature curves of various land uses of image at different phases

Structural texture analysis investigates the primitives which form the texture and their arrangement rules. Primitive can be the gray-level of a pixel or the set of the connected pixels with specific properties. Texture analysis seeks the numerical features to carve the texture so as to classify the image regions (instead of a single pixel) with these features or combining other non-texture features (Wenqi and Maria et al, 2015).

3. TEXTURE FEATURE EXTRACTION WITH FOURIER TRANSFORM

Digital image processing methods mainly include spatial-domain analysis method and frequency-domain analysis method. The former method processes the image matrix while the latter transforms the image from spatial domain to frequency domain through image transformation and then analyzes and processes the image features from another perspective. Fourier transform is a common method to transform the image from spatial domain to frequency domain. Fourier power spectrum reflects the intensity of different frequency components. From the angle of physical effects, Fourier transform converts the image from spatial domain to frequency domain while Fourier inversion converts from frequency domain to spatial domain. In other words, Fourier transform physically converts the gray-level distribution function of the image to the frequency distribution function and Fourier inversion is to convert the frequency distribution function to gray-level distribution function (Tiryaki and Adia-Nimuwa et al, 2015).

If a signal \( f(t) \) meets the following conditions in \( (-\infty, +\infty) \),

1. \( f(t) \) meets the Dirichlet condition in any finite interval.
(2) $f(t)$ is absolutely integrable in $(-\infty, +\infty)$, namely $\int_{-\infty}^{\infty} |f(t)|dt < \infty$.

Then, process the time-domain signal $f(t)$ after converting it to the frequency domain with Fourier transform $F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-j\omega t}dt = F[f(t)]$.

After that, convert the frequency-domain signal to the time domain with Fourier inversion. $F(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega)e^{j\omega t}d\omega = F^{-1}[f(t)]$.

Fourier transform has been widely applied in the study of image processing and one of its advantages is to underline the main frequency domain and the main direction included in the image and another advantage is that frequency-domain feature has better anti-noise capability than spatial-domain feature. Perform Fourier transform on the image and define texture feature according to the energy spectrum and phase spectrum, as shown in Fig.2.

![Figure 2. Texture image and its fourier transform](image)

(a) Texture image (b) Texture image based on fourier transform

Classical Fourier transform can only reflect the global properties (time domain and frequency domain) of the signal on the condition that the signal meets the stationary condition. To study the spectral characteristics of time-domain signal with Fourier transform requires the acquisition of all information in the time domain. If there are some changes in the signal in a small field at a certain moment, the entire frequency spectrum of the signal will be affected, however, fundamentally, the change of the frequency spectrum can’t calibrate the time position on which the change occurs and how dramatic the change is. It is easy to prove that if the texture of an image is rough, namely that the image gray-level changes rarely or slowly, $|F(x, y)|^2$ will have a bigger value at the value of the smaller $\sqrt{x^2 + y^2}$ while if the texture is quite fine and smooth, namely that the image gray-levels changes frequently or quickly, $|F(x, y)|^2$ will have a bigger value at the value of the bigger $\sqrt{x^2 + y^2}$. Therefore, a useful measurement to detect when the texture is rough or not is the change of $|F(x, y)|^2$ with $\sqrt{x^2 + y^2}$. Represent $|F(x, y)|^2$ as $|F(\rho, \theta)|^2$ with polar coordinate and $\sqrt{x^2 + y^2}$ becomes $\rho$. $|F(\rho, \theta)|^2$ is related to both $\rho$ and $\theta$. One method to confirm the feature with Fourier spectrum is to partition Fourier space into blocks and calculate the energy in the blocks (Xiaoran and Feng et al, 2015). There are two common block forms: included angle and radiation, as indicated in Fig.3.

![Figure 3. Fourier Spatial Block Partitioning](image)

(a) Included angle reflect texture size (b) Radiation reflect texture direction

In Fig.3, the total energy of each ring and wedge regions form the texture eigenvector. Fourier transform can’t provide the spectrum information description in the internal spectrum of each local time range of the signal;
however, in practical applications such as image edge detection and contour extraction, the position information is very important. Detect the roughness of the texture with the following comprehensive measurement.

\[ t(\rho) = \int_{0}^{\infty} |F(\rho, \theta)|^2 d\theta \quad (1) \]

In the above formula, the peak position of \( t(\rho) \) reflects the size of the texture element or texture primitive. Assuming that \( \rho_{0} \) is the peak point of \( t(\rho) \), the smaller \( \rho_{0} \) is, the bigger the texture primitive is and the texture is rougher; the bigger \( \rho_{0} \) is, the smaller the texture primitive is and the texture is finer. If \( t(\rho) \) doesn’t have significant peak or has many peaks, the image texture is disorganized and there is texture or space correlation in multiple scales(Yifang, 2016).

4. IMAGE TEXTURE FEATURE EXTRACTION WITH MULTICHANNEL GABOR FILTER

4.1. Gabor Transform

Different from the entire time-domain analysis method of Fourier transform, Gabor transform has the ability to study the local properties of the signal in different positions. It is the function to reach the lower bound where time domain can’t have a correct detection and it can present excellent locality in both the spatial domain and frequency domain. Therefore, it has been widely applied in such fields as image analysis and image recognition. As Gabor transform belongs to windowed Fourier transform, Gabor function can extract relevant features in different scales and directions of the frequency domain. Generally, two-dimensional Gabor function \( g(x, y) \) and its Fourier transform can be written as

\[ g(x, y) = \frac{k^2}{\sigma^2} \exp \left( -\frac{k^2(x^2 + y^2)}{2\sigma^2} \right) \exp \left( i \left( \frac{x}{\sigma_x} - \frac{y}{\sigma_y} \right) \right) \quad (2) \]

\[ G(u, v) = \exp \left[ -\frac{1}{2} \left( \frac{(u - \omega)^2}{\sigma^2_x} + \frac{v^2}{\sigma^2_y} \right) \right] \quad (3) \]

Among them, \( \sigma_x = \frac{1}{2\pi \sigma_x^2} \), \( \sigma_y = \frac{1}{2\pi \sigma_y^2} \). Gabor function forms a complete non-orthogonal basis function and the description of local frequency domain can be provided with the signal extended from the basis. A self-similar function is called as Gabor wavelet. Take \( g(x, y) \) as mother wavelet and Gabor wavelet transform can be obtained with the expansion and rotation of the mother wavelet.

\[ g_{mn}(x, y) = a^{-m}G(x', y') \quad a > 1, n, m \in Z \quad (4) \]

\[ x' = a^{-m}(x \cos \theta + y \sin \theta), y' = a^{-m}(-x \sin \theta + y \cos \theta) \quad (5) \]

Here, \( \theta = \frac{n \pi}{k}, k \) is the number of directions and \( a^{-m} \) is the scale factor. Gabor function is frequently used in texture recognition and it has made excellent achievements(Jiang-Yong and Shyh-Jier et al, 2015; Chen, and Liang, 2015).

4.2. Texture Feature Extraction with Gabor Filter Bank

Partition the input image into \( 3 \times 3 \) (9 blocks) and \( 4 \times 4 \) (16 blocks) image blocks. Build Gabor filter bank. Select 4 scales and 6 directions and form 24 Gabor filters. The imaginary parts of Gabor filter can provide the information of gray-level change at different directions of the pixel and its neighborhood. 2D Gabor filter formula (Formula (6)) is the product of elliptic Gaussian function and circular harmonic function and its imaginary part is shown as Formula (7).

\[ g(x, y; f, \theta, \gamma, \eta; \phi) = \frac{f^2}{\pi \gamma \eta} \exp \left( -\frac{f^2}{\gamma^2} x^2 + \frac{f^2}{\eta^2} y^2 \right) \exp(i \cdot 2\pi fx + \phi) \quad (6) \]

\[ h(x, y; f, \theta, \gamma, \eta; \phi) = \frac{f^2}{\pi \gamma \eta} \exp \left( -\frac{f^2}{\gamma^2} x^2 + \frac{f^2}{\eta^2} y^2 \right) \sin(2\pi fx + \phi) \quad (7) \]

Here, \( f \) represents the frequency of the filter center, \( \gamma \) and \( \eta \) represent the variances of the semi-major axis and semi-minor axis respectively, \( \theta \) is the filter direction and \( \phi \) is the phase offset with a value of 0 or \( \pi \).
The relationship between $\tilde{x}$ and $\tilde{y}$ and the original coordinates is shown in Formula (8). Fig.(9) is the two-dimensional image of the imaginary part of Gabor filter with 8 directions, as shown in Fig.4.

$$\begin{cases} \tilde{x} = x \cos \theta + y \sin \theta \\ \tilde{y} = -x \sin \theta + y \cos \theta \end{cases} \tag{8}$$

**Figure 4.** Images of imaginary parts of Gabor filter of 8 directions

In specific applications, parameters $f$, $\gamma$ and $\eta$ are constants and for the convenience of the subsequent description, mark $g(x, y; f, \theta, \gamma, \eta, \phi)$ and $h(x, y; f, \theta, \gamma, \eta, \phi)$ simply as $g(x, y; \theta, \phi)$ and $h(x, y; \theta, \phi)$ respectively. Gabor energy filter response is as follows.

$$E(x, y; \theta) = \sqrt{\left((f \ast h)(x, y; \theta, 0)\right)^2 + \left((f \ast h)(x, y; \theta, \pi)\right)^2} \tag{9}$$

The imaginary part of Gabor energy filter can reflect the gray-level changes in different directions, which is similar to first-order derivative. As for the edge, Gabor energy filter only has bigger response in two directions. Gabor filter bank convolutes with each image block in the spatial domain and every image block will have 24 filter outputs, which are the images with the same size of the image block. If they are directly taken as the eigenvector, there will be many dimensions in the feature space, therefore, they should be reduced (Riabchenko and Kamarainen, 2015; Kumar and Sumathi et al., 2015).

**5 EXPERIMENT SIMULATION AND ANALYSIS**

**5.1 Objective Evaluation Index of Image Texture Feature Extraction**

In order to describe the image textures more visually, some scalar indexes are usually used in their representation.

(1) Mean value

It reflects the regularity degree of the texture. The mean value is small if the texture is disorderly and difficult to describe and it is big if it is regular and easy to describe. Its formula is as follows.

$$Mean = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} ijp(i, j) \tag{10}$$

(2) Contrast

It reflects the clarity of the image and groove of the texture. The deeper the groove is, the bigger the contrast will be and the clearer the image is, otherwise, the smaller the contrast is, the shallower the groove will be and the more blur the image will be. The more pixels with bigger gray-level difference, namely contrast, the bigger it will be. The bigger the value of the element far away from the diagonal line in GLCM is, the bigger contrast will be.

$$Contrast = \sum_{i=1}^{m} \sum_{j=1}^{n} (i - j)^2 p(i, j) \tag{11}$$

(3) Entropy

It reflects the amount of average information of the image. Texture information is also a kind of image information and it is a random measurement with big entropy. It shows the non-uniform or complexity of the image texture. One-dimensional entropy of the image can represent the clustering feature of image gray-level distribution, but it can’t reflect its spatial feature. The features which can reflect the spatial features of the gray-level distribution can be introduced to form two-dimensional entropy of the image.

$$Entropy = -\sum_{i=1}^{m} \sum_{j=1}^{n} p(i, j) \log_2 p(i, j) \tag{12}$$
5.2. Experiment Test and Results

With 3 test images with real textures, we have used the Gabor filter bank built in Section 4.2 of this paper to extract texture feature in order to obtain image texture information effectively. We will operate by using the parameter ranges of \( \theta = \pi/3 \) and \( \theta = \pi/10 \) respectively. Compared with the texture feature of the original image, the image textures after Gabor filter are smoother. There is a little difference in the mean value of the texture features obtained from the parameters of \( \theta = \pi/3 \) and \( \theta = \pi/10 \). The test results are shown in Fig.5-Fig.7 and Tab.1-Tab.3.

![Figure 5. Results of image 1 after Gabor filter](image)

![Figure 6. Results of image 2 after Gabor filter](image)

![Figure 7. Results of image 3 after Gabor filter](image)

**Table 1. Test results of image 1**

<table>
<thead>
<tr>
<th>Direction of gabor transform</th>
<th>Feature</th>
<th>Mean value</th>
<th>Contrast</th>
<th>Entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta = \pi/3 )</td>
<td></td>
<td>0.0040</td>
<td>1.3664</td>
<td>0.1936</td>
</tr>
<tr>
<td>( \theta = \pi/10 )</td>
<td></td>
<td>0.0043</td>
<td>1.5939</td>
<td>0.4536</td>
</tr>
</tbody>
</table>

**Table 2. Test results of image 2**

<table>
<thead>
<tr>
<th>Direction of gabor transform</th>
<th>Feature</th>
<th>Mean value</th>
<th>Contrast</th>
<th>Entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta = \pi/3 )</td>
<td></td>
<td>0.0048</td>
<td>3.1912</td>
<td>0.8377</td>
</tr>
<tr>
<td>( \theta = \pi/10 )</td>
<td></td>
<td>0.0062</td>
<td>5.3968</td>
<td>1.4830</td>
</tr>
</tbody>
</table>
Table 3. Test results of image 3

<table>
<thead>
<tr>
<th>Direction of gabor transform</th>
<th>Feature</th>
<th>Mean value</th>
<th>Contrast</th>
<th>Entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta=\pi/3$</td>
<td></td>
<td>0.0042</td>
<td>2.3323</td>
<td>0.3846</td>
</tr>
<tr>
<td>$\theta=\pi/10$</td>
<td></td>
<td>0.0051</td>
<td>3.6114</td>
<td>0.9533</td>
</tr>
</tbody>
</table>

It can be seen from the above operation results that compared with the texture features of the original image, the image textures after Gabor transform is smoother. Contrast reflects the image gray-level after the filter and it makes few contributions to texture feature analysis. Entropy reflects the image energy and multiple experiments prove that the more consistent the filter direction is with the image texture direction, the bigger the energy of the output image will be. It further proves that Gabor function can capture a great deal of texture information and it has excellent spatial features.

6. CONCLUSIONS

This paper mainly studies the application of Gabor wavelet transform in the image texture feature extraction. It compares Gabor transform and Fourier transform in the theory and analyzes the performance of two-dimensional Gabor filter. On the basis of the above research, this paper has designed a multi-channel Gabor filter to extract the image texture feature and it has also used an eigenvector method in the description. The experiment result has shown that the Gabor filter of this paper has excellent performance in analyzing the frequency and direction information of the local regions of the digital image.

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REFERENCES