Filtering Methods for Texture Discrimination

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Abstract

Filtering methods have recently raised increasing interests in texture analysis due to their simulation of human vision. The goal of this paper is to evaluate the performance of four filtering methods including Fourier transform, spatial filter, Gabor filter, and wavelet transform for texture discrimination. Experimental results on both natural textures and synthesized Markov random field (MRF) textures indicate that the wavelet features achieve almost the same recognition rate with the Gabor features, which is higher than the other two methods, whereas the computation time shows the wavelet features are preferred.

Keywords: Fourier transform, spatial filter, Gabor filter, wavelet transform, Markov random field (MRF), texture discrimination.

1. Introduction

The purpose of texture discrimination is to find a best matched category for a given texture among existing textures. Many previous works are proposed to solve this problem (Haralick et al., 1973; Tamura et al., 1978; Chellappa et al., 1985). A comparison of textural features from Fourier power spectrum, second-order gray level statistics, and first-order statistics of gray level differences were shown in previous work (Weszka et al., 1976). Other textural features including co-occurrence features, Gabor features, MRF based features, and fractal features were compared in another work (Ohanian and Dubes, 1992).

Filtering methods for texture discrimination attempts to decompose image signals into different projected spaces which correspond to human visual receptive fields. In this paper, we make a comparison of four commonly used filtering methods including Fourier transform, spatial filter, Gabor filter, and wavelet transform to demonstrate their performance on discriminating natural textures (Brodatz, 1966) and synthesized MRF textures (Dubes and Jain, 1989).

The Fourier transform for texture discrimination was tested in a comparison work (Weszka et al., 1976), where the Fourier transform performs an energy concentration of the input image and a significant textural feature is obtained from the variance of area selection on the Fourier power spectrum. Based on the early visual research (Ginsburg, 1977), Coggins and Jain (1985) proposed the spatial filter for texture discrimination. The Gabor filter is famous of its simulation with human vision (Marcelja, 1980) and it was applied to texture discrimination (Jain and Farrokhnia, 1991). The wavelet transform is a good scale analysis tool (Daubechies, 1988; Mallat, 1989), where Laine and Fan (1993) applied the wavelet transform to texture discrimination. The variance of each filtered image of the spatial filter, the Gabor filter, and the wavelet transform is used as a textural feature.

The remaining of this paper is organized as follows. Section 2 reviews the Fourier transform for texture discrimination. Section 3 recalls the spatial filter for texture discrimination. The Gabor filter for texture discrimination is described in Section 4. Section 5 describes the wavelet transform for texture discrimination. Experimental results on discriminating natural textures and synthesized MRF textures are reported in Section 6. Section 7 gives the conclusion.

2. Fourier Transform for Texture Discrimination

The discrete Fourier transform of an image $\{f(x,y)\}$ is defined by

$$F(u,v)=\frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)e^{-2\pi\sqrt{-1}(ux+vy)} \tag{1}$$

where M and N are the ranges in two axes and the Fourier power spectrum is $|F|^2=FF^*$ (where * denotes the complex conjugate).

There are two kinds of textural features based on the Fourier transform. One is the ring-shaped selection that fetches the ring-shaped region centered at the origin with certain radii. Function (2) defines the set of ring-shaped region as follows.

$$R_{r_1,r_2}=\left\{(u,v)\middle| r_1^2\le u^2+v^2<r_2^2, 0\le u,v\le N-1\right\} \tag{2}$$

for all values between the inner ring radius r_1 and outer ring radius r_2. Weszka et al. (1976) used the four ring sets: [2,4), [4,8), [8,16), [16,32) to extract textural features. The other is the wedge-shaped selection that fetches the wedge-shaped region of the form

$$W_{\theta_1,\theta_2}=\left\{(u,v)\middle| \theta_1\le \tan^{-1}(v/u)<\theta_2, 0\le u,v\le N-1\right\} \tag{3}$$

The adopted wedges are 45^o wide from 0^o to 360^o. Consequently, 8 textural feature sets are acquired from wedge-shaped selection. The feature selection method on the Fourier transform contains 4 ring-shaped and 8 wedge-shaped selected regions. The variance of Fourier power spectrum defined on $R_{r1,r2}$ or W_{θ_1,θ_2} is used as a textural feature. Thus, there are up to twelve textural features obtained for texture discrimination.

The feature selection sequence on each filtering method is based on two important texture primitives: coarseness and directionality. The feature sequence is selected from coarsest images to finest images and the directional features are obtained according to the filtering method property.

Thus the first four Fourier features are the coefficients obtained from the ring-shaped selection with the order [2,4), [4,8), [8,16), [16,32), which decides the coarseness of an image. The next eight Fourier features decide the directional characteristics that are obtained from the wedge-shaped selection of 0^o to 360^o with 45^o wide.

3. Spatial Filter for Texture Discrimination

Based on the early visual research (Ginsburg, 1977), Coggins and Jain (1985) proposed the spatial filter for textural feature extraction. They designed two kinds of spatial filters for simulating visual system which are described as follows.

The spatial frequency filter $F_k(u,v)$, $-N+1 \leq u,v \leq N$, of a $2N \times 2N$ image is defined as follows:

$$\text{Image}[F_k(u,v)]=0 \qquad \text{for all } u,\ v,\ k,$$

$$\text{Real}[F_k(0,0)]=1 \qquad \text{for all } k,$$

$$\text{Real}[F_k(u,v)]= e^{-\frac{(\ln(\sqrt{u^2+v^2})-\ln(\mu_k))^2}{2\sigma^2}} \qquad \text{for } (u,v)\neq(0,0).$$

where $\sigma=0.275$ and $\mu_k=2^{k-1}$. For a $2N \times 2N$ image, the spatial frequency filters are selected for $k=1,\ldots,(1+\log_2 N)$.

The orientation channel filter $G_k(u,v)$, $-N+1 \le u,v \le N$, of a $2N \times 2N$ image is defined as follows:

$$\text{Image}[G_k(u,v)]=0 \quad \text{for all } u, v, k,$$

$$\text{Real}[G_k(0,0)]=\frac{1}{2} \quad \text{for all } k,$$

$$\text{Real}[G_k(u,v)]= e^{-\frac{A_k^2}{2\sigma^2}} \quad \text{for } (u,v)\neq(0,0).$$

where A_k = min [$|\mu_k - \tan^{-1}(v/u)|$,$|(\mu_k-180) - \tan^{-1}(v/u)|$], σ=17.8533, and four pairs of (k,μ_k): (0, 0), (1, 45), (2, 90), (3, 135). Two examples of these filters are given in Figure 1. Each textural freature is the variance of each filtered image. For a 128×128 image, we have 8 spatial frequency filters and four orientation channel filters. Thus, 12 textual features are obtained.

<< **Figure 1. (a)** the spatial frequency filter (k=7), **(b)** the orientation channel filter (k, μ_k) = (0,0).>>

The first eight spatial features are obtained from the spatial frequency filters to measure the coarseness, which are obtained from the coarsest filter (k=0) to the finest filter (k=7). The remaining four features are obtained from the orientation channel filters to measure the directionality, which are acquired from the four directional features with the sequence of (0,0), (1,45), (2,90), and (3,135).

4. Gabor Filter for Texture Discrimination

A 2-d symmetrical Gabor filter can be defined as in (4) whose corresponding Fourier transform is computed and given in (5) (Jain and Farrokhnia, 1991).

$$f(x,y) = e^{\left\{-\frac{1}{2}\left[\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right]\right\}} \cdot \cos\left(2\pi\mu_0\left(x\cos\theta + y\sin\theta\right)\right) \quad (4)$$

$$F(u,v) = A\cdot\left(e^{-\frac{1}{2}\left[\frac{(u-\mu_0\cos\theta)^2}{\sigma_u^2}+\frac{(v-\mu_0\sin\theta)^2}{\sigma_v^2}\right]} + e^{-\frac{1}{2}\left[\frac{(u+\mu_0\cos\theta)^2}{\sigma_u^2}+\frac{(v+\mu_0\sin\theta)^2}{\sigma_v^2}\right]}\right) \quad (5)$$

where $A = \pi\sigma_x\sigma_y$, $\sigma_u = \frac{1}{2\pi\sigma_x}$, $\sigma_v = \frac{1}{2\pi\sigma_y}$.

An example of a 2-d Gabor filter is illustrated in Figure 2. The size of the filter is 64×64 with the center shifted to the position (32,32).

<< **Figure 2.** A 2-d Gabor filter in **(a)** spatial domain, **(b)** frequency domain with the parameters $\sigma_x = \sigma_y = 10.0$, $\mu_0 = 0.05$, and $\theta = 0^0$. >>

A paradigm of using traditional Gabor filter for textural feature extraction is characterized as shown in Figure 3. The bank of the Gabor filters has the form of either (4) or (5) by setting σ_x, σ_y, θ, and μ_0 to certain values. Then, we obtain the textural feature as the variance of each Gabor filtered image. The same σ_x, σ_y, μ_0 with four different θs (0^0, 45^0, 90^0, 135^0) are needed to define a set of Gabor filters. That's because all directions are required for overall cases and these four directions (0^0, 45^0, 90^0, 135^0) are used to cover general cases (Jain and Farrokhnia, 1991). The 12 textural features are acquired from the Gabor filter by using (μ_o, σ) = (0.3536, 1.9099), (0.1768, 3.8197), and (0.0884, 7.6294), where $\sigma_x=\sigma_y=\sigma$ with four directions (0^0, 45^0, 90^0, 135^0) for function (4).

<< **Figure 3.** A paradigm of using traditional Gabor filter for textural feature extraction.>>

The first four Gabor features are acquired from the first set of parameters (μ_o=0.0884, σ=7.6294) with four directions (from 0^0 to 135^0), where they are obtained from the coarsest filtered result. Features acquired from the third set of parameters (μ_o=0.3536, σ=1.9099) are the last four features, which are the finest filtered results. Each feature characterizes the coarseness or fineness along one of the four directions.

5. Wavelet Transform for Texture Discrimination

The wavelet decomposition is to represent a signal f as a linear combination of a family of orthonormal basis $\psi_{m,n}$ that are derived from the dilation and translation of a mother wavelet ψ (Daubechies, 1988; Strang, 1989)

$$f(x) = \sum_{m,n \in Z} C_{m,n} \psi_{m,n}(x) \qquad \forall x \in R \tag{6}$$

with $\psi_{m,n}(x) = 2^{-m/2}\psi(2^{-m}x-n)$. The wavelet coefficients $C_{m,n}$ are computed by the inner product

$$C_{m,n} = \langle f, \psi_{m,n} \rangle = \int f(x)\psi_{m,n}(x)dx \tag{7}$$

A two-scale difference equation ϕ (Strang, 1989) as a scaling function should be defined first before we obtain the mother wavelet ψ.

$$\phi(x) = \sum_n h(n)\phi_{-1,n}(x) \tag{8}$$

where $h(n) = \langle\phi, \phi_{-1,n}\rangle$, $\phi_{m,n}(x) = 2^{-m/2}\phi(2^{-m}x-n)$, and $\sum_n |h(n)|^2 = 1$ for the orthonormal basis $\{\phi_{-1,n}\}$ (Daubechies, 1988). Then, the mother wavelet ψ is obtained from the scaling function ϕ by

$$\psi(x) = \sum_n g(n)\phi_{-1,n}(x) \tag{9}$$

where $g(n)=(-1)^n h(1-n)$ and $h(n)$ is as defined in equation (8).

A 2-D wavelet transform can be treated as two separated 1-D wavelet transform. The coefficients obtained by applying a 2-D wavelet transform on an image are called the subimages of a wavelet transform. After applying a wavelet transform on an image, many subimages are obtained and we put these subimages in one as shown in Figure 4. The selection of wavelet basis is DAUB4 (Daubechies, 1988). The variance of each wavelet subimage is used as a textural feature. Ten subimages are obtained in wavelet decomposition as Figure 4 demonstrates.

<< **Figure 4.** Illustration of wavelet decomposition up to level 3,
where $C_{i,j}$ means the jth subimage at level i. >>

The variances from the third level: $C_{3,1}$, $C_{3,2}$, $C_{3,3}$, and $C_{3,4}$ are the first four wavelet features, which are obtained from the coarsest filtered results. The variances from the second level: $C_{2,2}$, $C_{2,3}$, and $C_{2,4}$ are the second three features. The last three features are the variances from the first level: $C_{1,2}$, $C_{1,3}$, and $C_{1,4}$, which are acquired from the finest filtered results.

6. Experimental Results

6.1. Performance Evaluation for Natural Textures

Figure 5 shows the six test textures with size 512×512. One hundred 128×128 overlapped subimages are retrieved from each texture. Thus, there are 600 subimages in total as input data. Feature sets of applying four filtering methods on these input data are obtained for measuring the performance of each method. Each textural feature is quantized in a range for avoiding one feature dominating others. Experimental results are given in section 6.2, where the performance is measured by 1-nn classifier with leave-one-out error (Devijver, 1982).

<< **Figure 5.** Six textures from Brodatz book (1966), >>

Table 1 indicates the experimental results of applying four filtering methods for texture discrimination and the CPU time for each method running on a Sun SPARC 20 is shown in Table 2. Table 1 shows that when the first 4 features are used for each method, Fourier transform, spatial filtering, Gabor filtering, and wavelet transform achieve recognition rate, 0.900, 0.9617, 0.9883, and 0.9483, respectively. This result indicates that the coarsest Gabor features have better recognition rate than the third-level wavelet features, four coarse spatial features, and four coarse Fourier features.

When the number of textural features is larger than 7, both the wavelet features and the spatial features achieve recognition rates as good as the Gabor features do, whereas the wavelet features requires the least CPU time. The trade-off between CPU time and recognition rate suggests that the wavelet features be used for discriminating natural textures.

<< **Table 1.** A comparison of features derived from filtering methods for natural textures. >>

<< **Table 2.** CPU time for computing all textural features. >>

6.2. Performance Evaluation for Synthesized MRF Textures

Four categories of each one containing twenty-five 128×128 synthesized MRF textures (Dubes and Jain, 1989) are used for a test. Thus, there are 100 synthesized MRF textures belonging to four categories. Four textures using quite separate MRF parameters

(Dubes and Jain, 1989) corresponding to each category are shown in Figure 6. The purpose is to see if the filtering features perform perfectly on these homogeneous synthesized textures.

<< **Figure 6.** Four synthesized MRF textures. >>

Table 3 indicates that when the first two features used for each method, we have recognition rate 0.82, 0.93, 0.94, 0.99 for Fourier transform, spatial filtering, Gabor filtering, and wavelet transform, respectively. However, when more than 4 features are used, all of the four methods achieve a nearly perfect recognition. Though the textures synthesized from an MRF model with separate sets of parameters are visually similar, these four methods perform perfectly when four or more features are used. The computation time shows that the Fourier features and the wavelet features are more efficient than the other two, for MRF synthesized homogeneous textures.

<< **Table 3.** A comparison of features derived from filtering methods for synthesized MRF textures. >>

7. Conclusion

This work compares four filtering methods: the Fourier transform, the spatial filter, the Gabor filter, and the wavelet transform on discriminating natural textures and synthesized MRF textures. Several conclusions are drawn based on our experimental results by the pre-defined feature sequence, which is based on the filtering property and texture characteristics. First, when few number of features are restricted, for example 4, the Gabor features are preferred. Second, when all 3-level wavelet features are used, and the corresponding 12 features for the other three filtering methods are used, the recognition is nearly perfect, but wavelet transform is computationally more efficient than other methods. So is suggested. Third, for synthesized homogeneous textures, any filtering method performs well even with a few number of predefined sequence of features.

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