An Efficient Texture Classification Algorithm using Gabor Wavelet

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Abstract—**In this paper we have investigated the application of nonseparable Gabor wavelet transform for texture classification. We have compared the effect of applying the dyadic wavelet transform as a traditional method with Gabor wavelet for texture extraction. It is well known that Gabor wavelets attain maximum joint space-frequency resolution which is highly significant in the process of texture extraction in which the conflicting objectives of accuracy in texture representation and texture spatial localization are both important. This fact has been explored in our results as they show that the classification rate obtained for Gabor wavelet is higher that those obtained using dyadic wavelets. Based on our experiments, the Gabor wavelet is more appropriate than dyadic wavelets for texture classification as it leads to a better discrimination of textures.**

Keywords—**Texture Classification, Gabor wavelet, dyadic Wavelet. Texture analysis.**

I. INTRODUCTION

Texture is an image feature that provides important characteristics for surface and object identification from image [1]. Texture analysis is a major component of image processing and is fundamental to many applications such as remote sensing, quality inspection, medical imaging, etc. It has been studied widely for over four decades.

Recently, multiscale filtering methods have shown significant potential for texture description, where advantage is taken of the spatial-frequency concept to maximize the simultaneous localization of energy in both spatial and frequency domains [2].

The use of wavelet transform as a multiscale analysis for texture description was first suggested by Mallat [3,4]. Recent developments in the wavelet transform provide good multiresolution analytical tool for texture analysis and can achieve a high accuracy rate.

Most of previous works on wavelet transform have focused on dyadic wavelet transform which applies one-dimensional wavelet transform to both rows and columns of image, separately[5]. In this paper we proposed using nonseparable Gabor wavelet for texture classification and we compared it's effectiveness with traditional dyadic wavelet transform.

II. REVIEW OF WAVELET TRANSFORM

A. Wavelet Transform in 1D

The wavelet transform is defined as decomposition of a signal $f(t) \in L^2(R)$ into a family of functions $y_{m,n}(t)$ obtained through translation and dilation of a kernel function $y(t)$ known as mother wavelet:

$$y(t) = 2^{-m/2} y(2^{-m} t - n) \qquad (1)$$

Where m and n are the scale and translation indices, respectively. The mother wavelet is constructed from the scaling functions $f(t)$ as follows:

$$f(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} h_0(k) f(2t - k) \qquad (2)$$

$$y(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} h_1(k) f(2t - k) \qquad (3)$$

where $h_0(k)$ and $h_1(k)$ are coefficients for low-pass and high-pass filters, respectively.

$$h_1(k) = (-1)^k \cdot h_0(1-k) \qquad (4)$$

Performing a discrete wavelet transform does not require the explicit forms of $f(t)$ and $y(t)$, but it only depends on filter coefficients $h_0(k)$ and $h_1(k)$. The DWT of $f(t)$ can be written as

$$f(t) = \sum_k c_j(k) 2^{j/2} f(2^j t - k) + \sum_k d_j(k) 2^{j/2} y(2^j t - k) \qquad (5)$$

where $c_j(k)$ and $d_j(k)$ are the j level scaling and wavelet coefficients, respectively.

These coefficients follow the recursive equations called analysis equations:

$$c_j(k) = \sum_m h_0(m - 2k) c_{j+1}(m) \qquad (6)$$

$$d_j(k) = \sum_m h_1(m - 2k) c_{j+1}(m) \qquad (7)$$

The inverse process of analysis is called synthesis.

$$c_{j+1}(k) = \sum_m h_0(k - 2m) c_j(m) + \sum_m h_1(k - 2m) d_j(m) \qquad (8)$$

Thus the 1D wavelet transform of a discrete signal is equal to passing the signal through a pair of low-pass and high-pass filters h_0 and h_1, followed by a down-sampling with factor two.

B. Wavelet Transform in 2D

The simplest way to generate 2D wavelet transform is to apply two 1D transforms separately. This transform called dyadic wavelet transform is characterized by 2D scaling function

$$f(x,y)=f(x)f(y) \qquad (9)$$

and three wavelet functions :

$$\begin{aligned} y_1(x,y) &= f(x)y(y) \\ y_2(x,y) &= y(x)f(y) \qquad (10) \\ y_3(x,y) &= y(x)y(y) \end{aligned}$$

To compute dyadic wavelet transform of an image, we should apply 1D wavelet transform to both dimension of an image, separately.

Another solution for 2D wavelet transform is to use nonseparable sampling and filtering. One of the most widely used nonseparable wavelets is the Gabor wavelet.

C. Gabor Functions and Wavelets

A 2D Gabor function g(x,y) and its Fourier transform G(u,v) can be written as [6]

$$g(x,y)=\frac{1}{2ps_x s_y}\exp\left(\frac{-1}{2}\left(\frac{x^2}{s_x^2}+\frac{y^2}{s_y^2}\right)+2pjWx\right) \qquad (11)$$

$$G(u,v)=\exp\left(\frac{-1}{2}\left(\frac{(u-W)^2}{s_u^2}+\frac{v^2}{s_v^2}\right)\right) \qquad (12)$$

where

$$s_u=\frac{1}{2ps_x} \quad , \quad s_v=\frac{1}{2ps_y} \qquad (13)$$

Gabor functions form a complete but non-orthogonal basis set. Expanding a signal using this basis provides a localized frequency description.

A class of self-similar functions referred to as *Gabor wavelets*, is now considered. Let *g(x,y)* be the mother Gabor wavelet, then this self-similar filter dictionary can be obtained by appropriate dilations and rotations of g(x,y) through the generating function :

$$g_{mn}(x,y)=aG(x',y') \qquad (14)$$

$$a>1$$

$$m,n=\text{Integers}$$

and

$$x'=a^{-m}(xCosq+ySinq) \qquad (15)$$

$$y'=a^{-m}(-xSinq+yCosq) \qquad (16)$$

where $q=\frac{np}{k}$

and k is the total number of orientations. The scale factor a^{-m} is meant to ensure that the energy is independent of *m*.

D. Gabor Filter Design

The non-orthogonality of the Gabor wavelets implies that there is redundant information in the filtered images, and the following strategy is used to reduce this redundancy. Let U_l and U_h denote the lower and upper center frequencies of interest. Let K be the number of orientations and S be the number of scales in decomposition. Then the design strategy is to ensure that the half-peak magnitude support of the filter responses in the frequency spectrum touch each other as shown in figure (1).

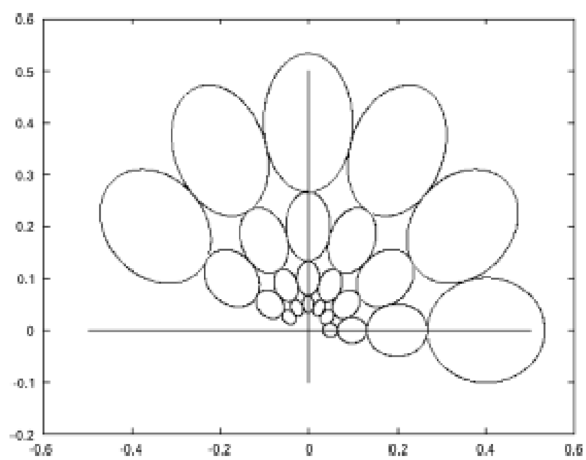

Figure 1: The contoursindicate the half-peak magnitude of filter responses in Gabor filter dictionary

This results in the following formulas for computing the filter parameters s_u and s_v.

$$a=\left(\frac{U_h}{U_l}\right)^{\frac{-1}{S-1}} \qquad (17)$$

$$s_u=\frac{(a-1)U_h}{(a+1)\sqrt{2\ln 2}} \qquad (18)$$

In order to eliminate sensitivity of filter response to absolute intensity values the real components of 2D Gabor filters are biased by adding a constant to make them zero mean.

III. FEATURE EXTRACTION & CLASSIFICATION

A. Feature Extraction& classification with dyadic wavelet transform

First every input image is transformed to wavelet domain. Then the energy of each subimage is calculated from

$$E_i = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} I_i^{\,2}(x, y) \qquad (19)$$

where, $I_i(x,y)$ denotes an image obtained in $\boldsymbol{i}^{th}$ subband , with resolution $M \times N$.
The distance vector D between test image and $\boldsymbol{i}^{th}$ reference texture is

$$\vec{D}_i = \left| \vec{E}_i - \vec{E}_t \right| \qquad (20)$$

where E_i and E_t are the energies of $\boldsymbol{i}^{th}$ reference texture and test texture. The distance number d is calculated from

$$d_i = \sum_j D_i(j) \qquad (21)$$

The test image is referred to class k if d_k is the minimum value of d_i for test image.

B. Feature Extraction& classification with Gabor wavelet transform

Given an image $I(x,y)$, its Gabor wavelet transform is defined as

$$W_{mn}(x, y) = \int I(x_1, y_1) g^{*}_{mn}(x - x_1, y - y_1) dx_1 dy_1 \qquad (22)$$

where * indicates the complex conjugate. We assume the local texture regions are spatially homogeneous. The mean μ_{mn} and standard deviation s_{mn} of the magnitude of transform coefficients are used to represent the regions for classification :

$$m_{mn} = \iint \left| W_{mn}(x, y) \right| dxdy \qquad (23)$$

$$s_{mn} = \sqrt{\iint \left(\left| W_{mn}(x, y) \right| - m_{mn} \right)^2 dxdy} \qquad (24)$$

A feature vector is now constructed using μ_{mn} and s_{mn} as feature components.
Let $\bar{f}^{\,i}$ and $\bar{f}^{\,j}$ represent the feature vector of test and reference texture, respectively. Then the distance between two textures in the feature space is defined to be

$$d(i, j) = \sum_i \sum_j d_{mn}(i, j) \qquad (25)$$

where

$$d_{mn}(i, j) = \left| \frac{m^{(i)}_{mn} - m^{(j)}_{mn}}{a(m_{mn})} \right| + \left| \frac{s^{(i)}_{mn} - s^{(j)}_{mn}}{a(s_{mn})} \right| \qquad (26)$$

The test image is referred to class k if d_k is the minimum value of d_i for test image.

IV. EXPERIMETNAL RESULTS

We performed our experiments using 15 Brodatz textures as reference textures. These textures are shown in figure (2).

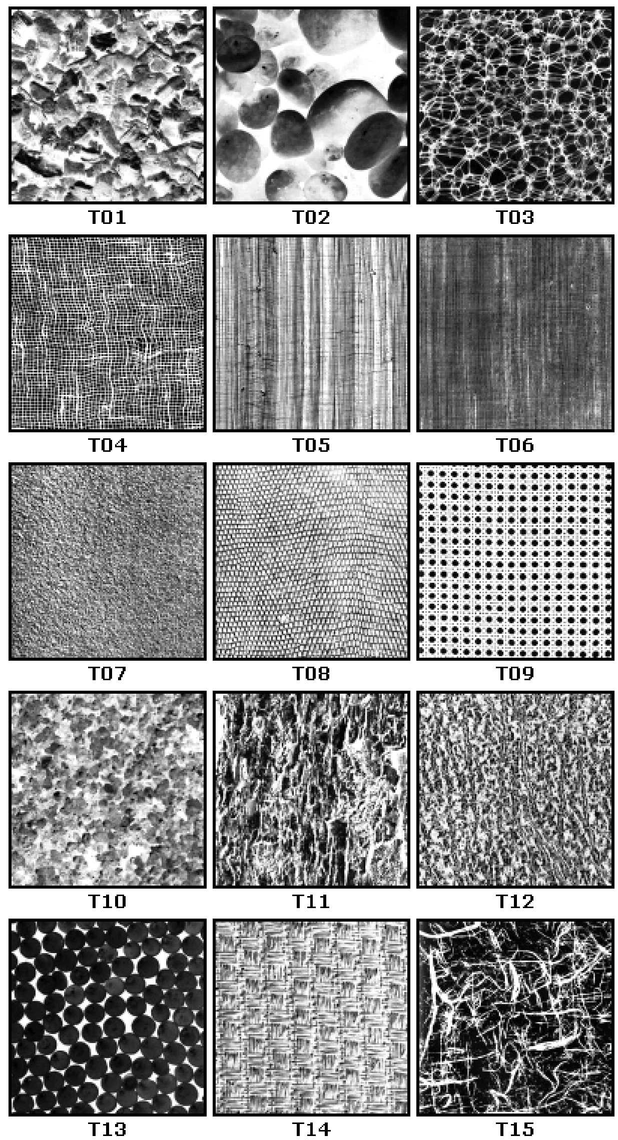

Figure 2: Brodatz textures used for classification algorithms

In the first step we applied dyadic wavelet transform (Daubechies and Symlet wavelet filters) for classification algorithm. The wavelet filter parameters were tuned to achieve the best result. We have already shown that the wavelet filter parameters such as regularity, phase linearity, etc have a great impact on the performance of the classification algorithms [7].

We used the quantity named "classification rate" defined as below to compare the results.

$$\text{Classification rate} = \frac{\text{Number of Textures Classified Truely}}{\text{Total Number of Classified Textures}} \quad (27)$$

The classification rate achieved by dyadic wavelet was about 86%.

In the second step we applied Gabor wavelet to the textures. To get the best result, the Gabor parameters were tested for different values of the number of scales *(S)* and the number of orientations *(K)*. The classification rate computed for each setting. The results are presented in Table (1). As it suggests the total number of bands at all orientations is important for texture classification since it improves the process of texture discrimination by using more features. Obviously, the cost for this improvement is an increase in computational time.

In order to see the effect of image rotation and changing in brightness on the performance of the algorithm we compared the classification rate for a small (10^o) rotation in an image and 20% changes in brightness of the image for both Gabor and dyadic wavelets.

For rotated textures, the dyadic wavelet transform results 73% classification rate, while Gabor wavelet leads to an 86% classification rate. When the test textures are made brighter, the classification rate of dyadic wavelet was 73%, while for Gabor wavelet it was 86%. These results are summarized in Table (2).

Number of Scales (S)	***Number of Orientations (K)***	***Classification Rate***
6	6	86%
8	6	93%
6	8	93%

Table 1: Classification rate obtained for different values of *S* and *K*.

Input images	***Dyadic wavelet classification rate***	***Gabor wavelet classification rate***
Original Textures	86%	93%
Brightened Textures	73%	86%

Table 2: Results of Rotation, and Brightening of input images on classification rate for dyadic and Gabor wavelet

V. DISCUSSION

Comparing the above results clearly shows that the Gabor wavelet is more effective for texture classification.

One main reason for this is because the dyadic wavelet loses some middle-band information, while the Gabor wavelet dose not. We observed that texture features are mainly located in middle bands therefore, the behavior of any algorithm on these bands can have an impact on the performance of the classification.

For rotated textures, we know that dyadic wavelet is not rotation-invariant and it makes failures in classification process. But, Gabor wavelet is rotation –invariant and has led to a better classification rate.

In brightened textures, the energy of input images has been changed which causes failures for dyadic wavelets. Gabor wavelet eliminates the DC-component of input image and therefore it gives a better classification rate.

VI. CONCLUSION

Nonseparable Gabor wavelet performs better characteristics for texture classification than traditional dyadic wavelet. It is well known that Gabor wavelet decomposition achieves the theoretical lower bound of the uncertainty principle. They attain maximum joint space-frequency resolution which is significant for texture extraction. This algorithm can be used widely for texture analysis applications including texture classification and segmentation.

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