Texture Image Classification Using Visual Perceptual Texture Features and Gabor Wavelet Features

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***Abstract*—Texture can describe a wide variety of surface characteristics and a key component for human visual perception and plays an important role in image-related applications. This paper proposes a scheme for texture image classification using visual perceptual texture features and Gabor wavelet features. Three new texture features which are proved to be in accordance with human visual perceptions are introduced. Usually, Subband statistics based on Gabor wavelet features are normally used to construct feature vectors for texture image classification. However, most previous methods make no further analysis of the decomposed subbands or simply remove most detail coefficients. The classification algorithms commonly use many features without consideration of whether the features are effective for discriminating different classes. This may produce unnecessary computation burden and even decrease the retrieval performance. This paper proposes a method for selecting effective Gabor wavelet subbands based on feature selection functions. The method can discard those subbands that are redundant or may lead to wrong classification results. We test our proposed method using the Brodatz texture database, and the experimental results show the scheme has produced promising results.**

***Index Terms*—Visual Perception Texture Features, Gabor wavelet features; Texture image classification; SVM**

I. INTRODUCTION

Texture is an important component of human visual perception and can be effectively used for characterizing different image regions. For example, the skin of a zebra can be seen as texture with black and white stripe pattern. In the past, texture features have been extensively studied in the research area of texture image classification and content-based image retrieval, as well as other fields related to pattern analysis [1, 2, 3, 4].

Basically, texture representation methods can be classified into three categories, namely structural, statistical and multi-resolution filtering methods. Typical structure-based methods include morphological and graph techniques, which describe texture using structural primitives and layout [1]. Statistical methods are commonly used and proved to be effective in texture analysis [3, 4, 5]. Methods based on Multi-resolution decompose a texture image into different scales, from which more statistics can be extracted and used to describe texture features [7, 8, 11, 12, 13]. These methods have been effectively used for solving texture recognition problems.

Due to the resemblance between multi-resolution filtering techniques (such as Gabor and wavelet transform) and human visual process, Gabor and wavelet transform techniques are often used for texture characterization through the analysis of spatial-frequency content. Many publications showed the effectiveness of using these techniques for texture analysis, segmentation, retrieval and classification [7, 8, 11, 12, 13].

However, most previous methods make no further analysis of the decomposed subbands or simply remove most detail coefficients. The classification algorithms commonly use many features without consideration of whether the features are effective for discriminating different classes. This may result in unnecessary computation and even decrease the classification performance.

Psychophysical investigation has shown that the Human Visual System (HVS) does a frequency analysis when we see images [22, 23, 24]. Texture is especially suited for this type of analysis for its intrinsic properties. In this paper, we introduce three visual perceptual features, namely directionality, contrast and coarseness, which have proved to be in accordance with human visual perception in image retrieval experiments [17, 18].

Then, a scheme for texture image classification using visual perceptual texture features and Gabor wavelet features is proposed. In contrast to previous work, our study focuses on reducing the dimensionality of feature vectors by discarding those subbands that may be irrelevant or redundant, with the aim of achieving better

texture classification performance. We introduce a procedure for selecting effective wavelet subbands [16]. The feature selection functions are used to rank all subbands, so that the problem of selecting the most "useful" subband set reduces to picking up those with highest rankings. Statistics extracted from such subbands are then used to construct feature vectors. In this way, the dimensionality of feature vectors is reduced. Experiments show the selected subbands are effective for discriminating different textures, as the classification performance is much improved.

The rest of the paper is organized as follows. In section 2, we introduce the visual perceptual texture features. Section 3 briefly describes Gabor wavelet decomposition. In section 4, a feature selection algorithm is introduced. In section 5, experimental results are presented in section 5. Finally, we conclude the paper in section 6.

II. NEW TEXTURE FEATURES DERIVING FROM WAVELET TRANSFORM

Wavelet transform has been widely used in image processing and shows tremendous advantages over Fourier transform. Wavelet transform is a multi-resolution analysis that represents image variations at different scales [6, 7, 8]. According to the definition of wavelet, a wavelet is an oscillating and attenuated function and its integrals equal to zero. It is a mathematical function useful in digital signal and image processing.

Given $f(x)$ is a one-dimensional input signal, a 1-Ddiscrete wavelet transform is defined as:

$$\phi_{jk}(x) = 2^{-j/2}\phi(2^{-j}x - k),$$

$$\psi_{jk}(x) = 2^{-j/2}\psi(2^{-j}x - k),$$

Where: $\phi(x)$ and $\psi(x)$ are the scaling function and wavelet function respectively, $\{\phi_{jk}(x)\}$ and $\{\psi_{jk}(x)\}$ are the two orthogonal function basis sets.

Define $P_0 f = f$, a 1-D discrete wavelet transform at the scale j decomposed $P_{j-1}f$ through orthogonal projection $P_j f$ and $Q_j f$ *as* follows:

$$P_{j-1}f = P_j f + Q_j f = \sum_k c_k^j \phi_{jk} + \sum_k d_k^j \psi_{jk};$$

and $$c_k^j = \sum_{n=0}^{p-1} h(n) c_{2k+n}^{j-1},$$

$$d_k^j = \sum_{n=0}^{p-1} g(n) c_{2k+n}^{j-1},$$

$$(j = 1,2,\ldots,L, k = 0,1,\ldots,N/2^j - 1).$$

where: {h(n)} and {g(n)} are low pass filter and high pass filter, respectively; $\{C_n^0\}$ is the input signal; N is the length of the input signal; L is the necessary progression.

Wavelet is commonly used for multi-resolution analysis and representing image variations at different scales. The computation framework of the wavelet transform of a 2D signal involves recursive filtering and sub-sampling, as shown in Fig.1. To clarify the use of symbols, we briefly describe the general process of wavelet transforms and the notations of subbands of wavelet decomposition. At each level, there are three detail images. Following [7], we denote the detail images (subband) as LH (contains the high frequency horizontal information), HL (contains the high frequency vertical information), and HH (contains the high frequency diagonal information). The decomposition/transform also produces one approximation image, denoted by LL, containing the low frequency information. The wavelet transform can recursively decompose the LL band. Since 2 level wavelet decomposition yields 6 detail images, we use LH1, HL1, HH1, LH2, HL2, HH2, and an additional approximation image LL2 to denote all the subband images.

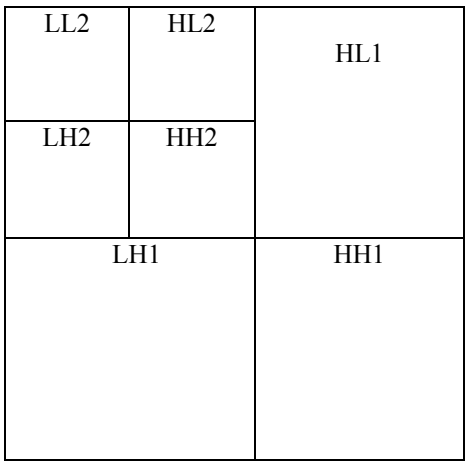
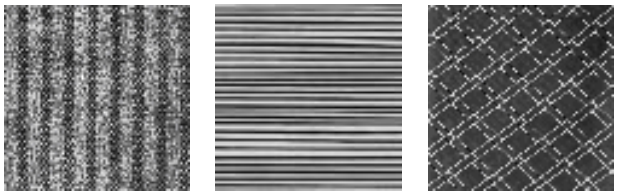


Fig.1. Two-level wavelet decomposition

A. Directionality

Directionality is an important characteristic for texture images. For example, from human perception's viewpoint, we perceive the D11 texture in Figure 2 as a "vertical" texture, D49 as a "horizontal" one and D47as "diagonal". Instead of computing a vague value of directionality, we introduce three different directionalities, namely "the vertical directionality", "the horizontal directionality" and "the diagonal directionality", to represent the directional information of a texture image.



D11 D49 D47

Fig.2 Three textures from Brodatz database.

The Horizontal Directionality

In allusion to every HL (contains the high vertical frequency information) subband of wavelet decomposition, we compute the horizontal directionality. Let *M, N* be the sizes of HL subband, and $x(j,k)$ be the subband's coefficient of wavelet decomposition, where j and *k* represent the row and column values of the subband images respectively. Firstly, the subband image is convoluted with a template $\begin{pmatrix} 1 & 0 & 1 \\ 1 & 0 & 1 \\ 1 & 0 & 1 \end{pmatrix}$ at each wavelet decomposition coefficient in order to enhance the direction contrast. Let $h(j,k)$ represent the result of convolution. For every row, the normalized convolution result is computed as:

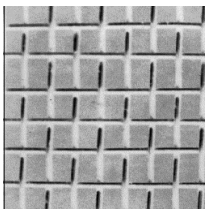
$$p_{jk} = \frac{|h(j,k)|}{\sum_{k=1}^{N} |h(j,k)|} \quad ;$$

The horizontal directionality is then defined as :

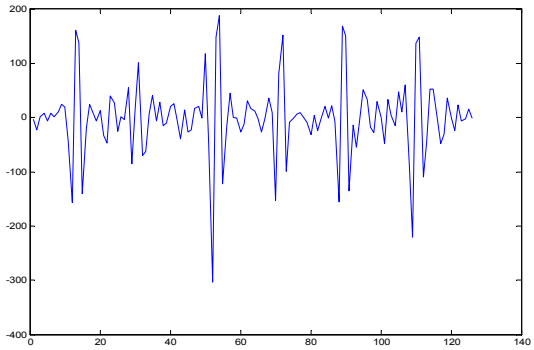
$$Dir_H = \frac{1}{MN} \sum_{j=1}^{M} \sum_{k=1}^{N} p_{jk}^{\ 2} \quad ,$$

Where *M, N* are the sizes of HL subband.

Fig. 3 (a) is the D1 texture from the Brodatz database and (b) shows the 10th row's coefficient convolution result of HL1 subband .



(a)



(b)

Fig.3 (a) The D1 texture from Brodatz database. (b). The coefficient convolution result of the 10th row's HL1 subband .

The Vertical Directionality

Similar to the definition of the horizontal directionality, the LH subband is convoluted with a different template $\begin{pmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{pmatrix}$ for each coefficient produced by wavelet decomposition. Let $v(j,k)$ represent the result of convolution; *j* and *k* represent the row and column values of the subband. Then for every column, normalized coefficient convolution result is computed as:

$$q_{jk} = \frac{|v(j,k)|}{\sum_{j=1}^{M} |v(j,k)|} \quad ;$$

The vertical directionality is defined as :

$$Dir_V = \frac{1}{MN} \sum_{j=1}^{M} \sum_{k=1}^{N} q_{jk}^{\ 2} \quad ,$$

Where *M, N* are the sizes of HL subband.

The Diagonal Directionality

Compared to the horizontal and vertical directionality, the computation of the diagonal directionality is more complex. We should take two diagonal directions into account, namely, $\pi/4$ and $3\pi/4$.

When we consider the diagonal directionality of $\pi/4$, convolution is performed with a template $\begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix}$ at the HH subband. Similarly, when the diagonal directionality of $3\pi/4$ is considered, convolution is computed with a template $\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$. Then we sample $\pi/4$ diagonals and

$3\pi/4$ diagonals for computing the diagonal directionality. The calculation process is the same as the horizontal and vertical directionality. The diagonal directionality in the same wavelet decomposition level is defined as the average of the diagonal directionality of $\pi/4$ and $3\pi/4$:

$$Dir_D = \frac{1}{2}(Dir_{D1} + Dir_{D2}),$$

Where Dir_{D1} represents the Diagonal Directionality of $\pi/4$ and Dir_{D2} represents the Diagonal Directionality of $3\pi/4$, respectively.

B. Contrast

For the purpose of denoting the change of grey levels in a texture, contrast is commonly defined for each pixel as an estimate of the local variation in a neighborhood. The calculation of the contrast is implemented in the wavelet decompose approximation subband, denoted as LL, which contains the low frequency and reflecting the global information of the texture.

Given $x(j,k)$ as the coefficient of LL subband, where j and k represent the row and column values of the subband images, respectively, let the pixel at the point (j, k) be $x(j,k)$ and the neighborhood of size $W \times W$ be a mask of the pixel. Then local contrast is computed as:

$$l\_con(i,j) = \frac{\max_{x \in W \times W}(x) - \min_{x \in W \times W}(x)}{\max_{x \in W \times W}(x) + \min_{x \in W \times W}(x)}.$$

The global contrast is defined as the mean of all the local contrast values:

$$Con = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N} l\_con(i,j).$$

Since the wavelet decomposition results in a smaller size for the approximation subband compared with that of the original texture's size, we recommend a neighborhood window with a size of 3x3, instead of using the size 7x7 as introduced in [20].

C. Coarseness

Coarseness is the granularity measurement of texture and the most fundamental texture feature. Researchers usually identify the texture by "coarseness". The coarseness defined by Tamura etc. in [3] coincides well with the psychological measurements for human perception, so we also use it in the wavelet decompose approximation subband to calculate the granularity of texture. The computational definition of coarseness is briefly described as follows:

The moving average $A_z(s,t)$ over the neighborhood of size $2^z \times 2^z$ (z=0, 1, 2, 3, 4, 5) at the point *(s, t)* is

$$A_z(s,t) = \sum_{j=s-2^{z-1}}^{j=s+2^{z-1}} \sum_{k=t-2^{z-1}}^{k=t+2^{z-1}} x(j,k) \Big/ 2^{2z}.$$

Where $x(j,k)$ is the coefficient of the LL subband at *(j, k)*.

Then, the differences between pairs of non-overlapping moving averages in the horizontal and vertical directions for each pixel are computed,

$$E_{z,h}(s,t) = | A_z(s+2^{z-1},t) - A_z(s-2^{z-1},t) |;$$

$$E_{z,v}(s,t) = | A_z(s,t+2^{z-1}) - A_z(s,t-2^{z-1}) |.$$

At each point, the value of Z that maximizes E in either direction is used to set the best size:

$$S_{best}(s,t) = 2^z;$$

The global coarseness is calculated by averaging S_{best} over the entire LL subband:

$$Conse = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N} S_{best}(j,k)$$

More details on the Visual Perception Texture Features can be found in [17, 18].

III. Gabor Wavelet Features

Similar to the wavelet transform, Gabor filtering, which is also called Gabor wavelet, can also produce a multi-resolution representation of the sample texture image. Gabor filtering provides a flexible scheme for designing efficient algorithms to capture more orientation and scale information. A two dimensional Gabor function g(x, y) is defined as

$$g(x,y) = \frac{1}{2\pi\sigma_X\sigma_y}\exp\left(-\frac{1}{2}\left(\frac{x^2}{\sigma_X{}^2} + \frac{y^2}{\sigma_y{}^2}\right) + 2\pi jWx\right)$$

where σ_X and σ_y are the standard deviations of the Guassian envelopes along the x and y direction [1].

Then a set of Gabor filters can be obtained by appropriate dilations and rotations of g(x, y):

$$g_{mn}(x,y) = a^{-m} g(x', y');$$

$$x' = a^{-m}(x\cos\theta + y\sin\theta)$$
$$y' = a^{-m}(-x\sin\theta + y\cos\theta)$$

where a >1, θ = nπ/K, n = 0, 1, …, K-1, and m = 0, 1, …, S-1. K and S are the number of orientations and scales. The scale factor a^{-m} is to ensure that energy is independent of m.
Given an image I(x, y), its Gabor transform is defined as:

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

Where * indicates the complex conjugate. A bank of filters at different scales and orientations can extract the texture frequency and orientation information effectively. Then the mean μ_{mn} and the standard deviation σ_{mn} of the magnitude of $W_{mn}(x,y)$ can be used to construct feature vectors, denoted by $f = [\mu_{11}, \sigma_{11}, ..., \mu_{mn}, \sigma_{mn}, ..., \mu_{SK}, \sigma_{SK}]$. The features can be used to characterize the texture image.

IV. SUBBAND SELECTION ALGORITHM

A feature selection algorithm that can reduce the dimensionality of feature vectors is often desirable. In the context of wavelet transform, feature selection can be treated as subband selection. However, the problem of finding an optimal feature subset is NP-hard [9, 10]. In general, the fewer classes to be dealt with, the simpler the problem can be. For texture image classification, we may divide all the candidate images into two classes. Those candidates similar to the sample image can be considered as one class, because they have similar feature vectors. The remaining images can be treated as the other class, as their feature vectors can be quite different from that of the sample image. Thus, we may set a "threshold" that can be used to select effective subbands, so that the two classes can be well separated.
The basic idea is to rank all the subbands according certain criteria so that the problem of selecting the effective subset reduces to picking the first few subbands. Such subbands can be defined as effective and discriminating ones, offering the benefit that only the effective and discriminating features are involved in computation during texture image classification.

We employ the feature selection functions for choosing effective Gabor wavelet subbands. First, let us define the subband selection problem as follows. Given a texture image that has been decomposed into *n* subbands, the goal is to select a set of *l* (*l<n)* subbands that can be effectively used to produce the minimal retrieval error. Obviously, the number of the selected subbands should be kept as small as possible without affecting the final classification accuracy.

The subband selection scheme comprises the following steps:

(1) Suppose there are *m* texture images in the database. Compute the *J*-level Gabor wavelet decomposition of all images to obtain *n* subbands.

(2) Calculate the values of feature selection functions using the ith-subbands of the query texture and the *m* candidate images:

$$G^s_{i1}, \ldots G^s_{ij}, \ldots, G^s_{im};$$

where $s = L_2$, G^s_{ij} is the Fisher's discriminant which is a commonly used quantity for feature selection. The basic idea is to select a feature that maximizes the separation of the means of two classes scaled according to the variance. The quantity for measuring the separation is defined as:

$$G_k = \frac{(\mu_{ik} - \mu_{jk})^2}{\sigma_{ik}^2 + \sigma_{jk}^2}; \quad k=1, 2, \ldots, n$$

where: μ_{ik} and μ_{jk} are the mean values of the kth features of class ω_i and ω_j respectively.
σ_{ik} and σ_{jk} are the standard deviations of the kth features of class ω_i and ω_j respectively.
A greater G_k indicates that class ω_i and ω_j has a better separateness (discrimination) with the kth features.
Corresponding to the weighted L_2 distance, we define the new discriminants based on Fisher's discriminant :

$$G_k^{L2} = \frac{|\mu_{ik} - \mu_{jk}|^2}{\sigma_{ik}^2 + \sigma_{jk}^2};$$

We name the discriminants as "feature selection functions" respectively.

(3) Calculate the mean of all values computed using the ith-subband's feature selection functions:

$$\mu^s_{i1} = \sum_{i=1}^{m} \frac{1}{m} G^s_{ij}; \quad (j=1,2,\ldots,m)$$

In this way we obtain altogether *n* mean values of the feature selection functions corresponding to *n* subbands :

$$\mu^s_{i1}, \ldots \mu^s_{ij}, \ldots, \mu^s_{in};$$

(4) Sort the mean values ($\mu^s_{i1}, \ldots \mu^s_{ij}, \ldots, \mu^s_{in}$) in a decreasing order. Select *l(l <n)* subbands corresponding to the first *l* mean values.

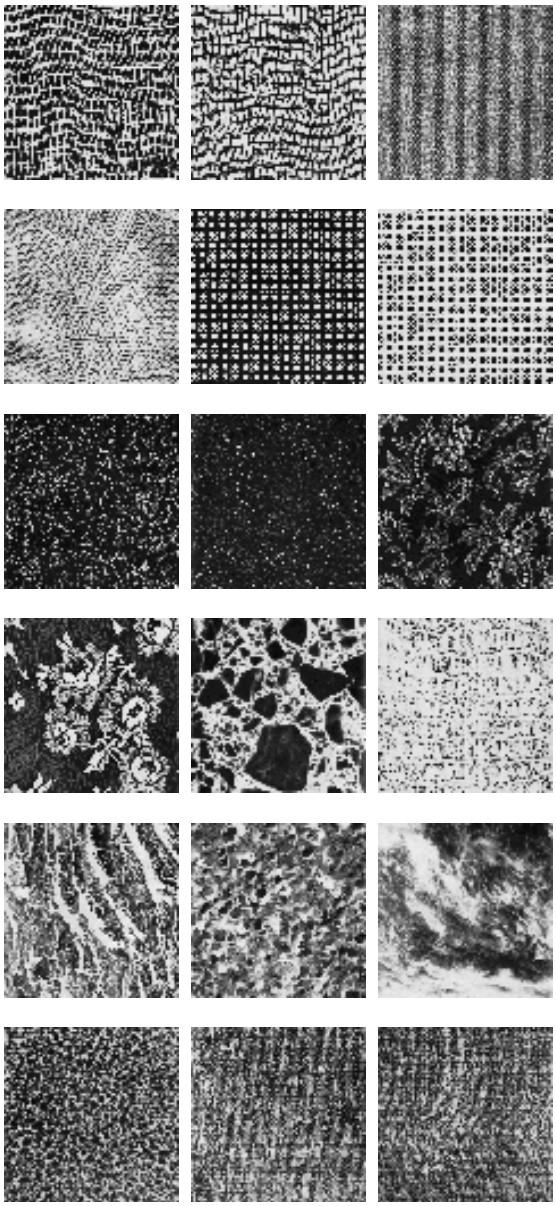
The selected *l* Gabor wavelet subbands can be effectively used for texture image classification. In this paper, we used the statistics (mean and standard deviation) extracted from the selected subbands to construct texture feature vectors for classification.

More details about the feature selection algorithm can be seen in [16].

V. EXPERIMENTAL RESULTS

A variety of experiments are performed to verify the effectiveness of the combining scheme. Fig. 4 shows some texture samples from the Brodatz texture database [21].

All the texture images are transformed by wavelet decomposition and Gabor wavelet decomposition to extract texture feature for classification. The introduced texture features are tested using the Brodatz texture database [21]. In our experiments, our implementation of the Gabor wavelet is based on Manjunath et al's work [7, 8]. In our experiment, the feature is computed by filtering the texture image with 6 orientations and 4 scales and computing the mean and standard deviation of the output in the frequency domain. In our experiments, we select the 12 subbands out of the total 24 subbands. Every texture is represented by a 24-dimensional feature vector



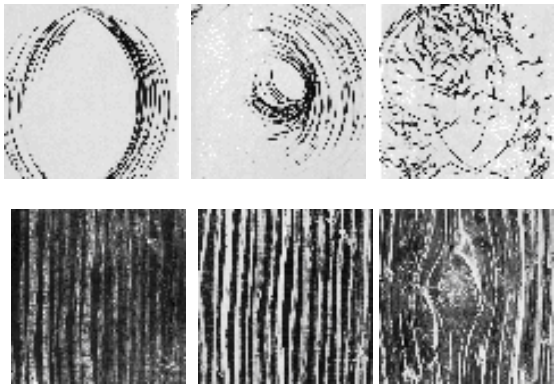


Fig4. Some texture samples from the Brodatz texture database.

(comprising mean and variance values), whereas the traditional texture feature vector is 48-dimensional [7, 8].

Then, Support Vector Machine algorithm, which is developed from optimal classification in the sense of linear separation [14, 15], is used as the classifier. Kernel functions are introduced in order to construct non-linear decision surfaces. They map the data to some higher dimensional feature space and construct a separation hyper-plane in this space. Radial basis function kernel, also called RBF:

$$K(x, x_i) = \exp\left\{-|x - x_i|^2 / \gamma^2\right\};$$

This is a radial basis classifier. For most pattern recognition applications, using different parameters may have more effects on the correct recognition rate than using different kernel functions [14, 15].The RBF kernel can be used in applications related to human vision characteristics such as license plate recognition.

The SVM algorithm, using the RBF kernel functions, employed for classification was as described in the above section. The experiments results for various experimental training samples are listed in Table 1. Every sample was divided into 24 sub-images to perform the classification.

For every class, we random selecting 14 textures used for training and the rest 10 textures for testing. Another experiment is 18 textures used for training per class, and the rest 6 textures were used for testing.

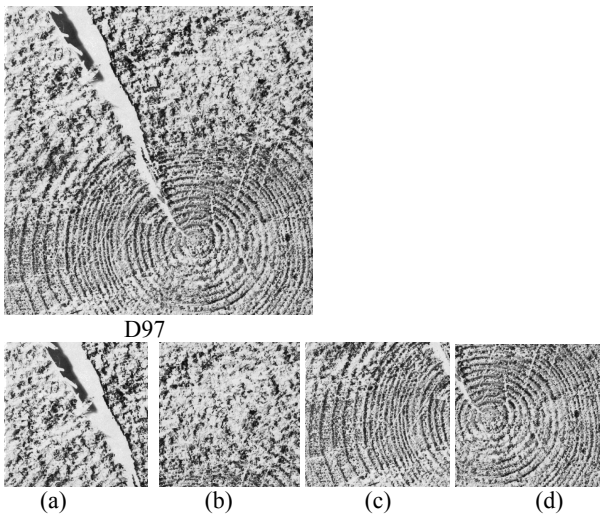
As the Table 1 shows, the method using feature selection algorithm outperforms the method using all the Gabor wavelet subbands features and visual perceptual texture features. The feature selection algorithm successfully selected effective Gabor wavelet subbands that can improve correct classification rates. Our experiments show that if we do not carried out the subband selection procedure, although Gabor wavelet can capture more orientation information of the sample texture than selected effective subbands, the classification performance is worse. We deduce that many subbands are not effective and discriminating or redundant when used as texture features. After the subband selection procedure, although the dimensionality of the texture feature vector is lower, the classification accuracy is raised. The average accuracy produced in different ways is shown in Table 1.

It can be seen that our proposed method is not only effective but also efficient.

Table 1. Experiments results for various experimental trainning samples.
Method A: using all the Gabor wavelet subbands features and visual perceptual texture features.
Method B: selected Gabor wavelet subbands features and visual perceptual texture features using feature selection algorithm.

Training samples number	Testing samples number	Average Accuracy Of Method A	Average Accuracy Of Method B
14 x 102	10 x 102	81.6%	83.7%
18 x 102	6 x 102	89.1%	91.3%

In addition, we analyzed the cases which have low classification accuracy and misclassifications. We discovered that the cause of misclassification was that some sub-images in a same class were not perceptually similar at all. Because some texture images in the Brodatz texture database are anisotropic, in the phase of dividing each texture into 24 overlapping sub-texture-images, sub-images in the same class are not similar ultimately, such as sub-images (b) and (c) derived from the D43 texture, sub-images (a) and (d) from the D97 texture image (shown in Fig.5). These misclassifications of sub-texture-images are observed dissimilar from human visual perception. The experimental results are therefore reasonable if these cases are discarded.



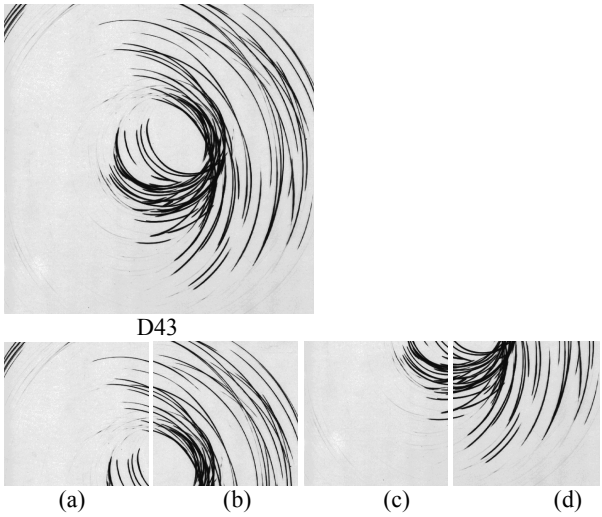


Fig.5 Some texture images (D97, D43) in the Brodatz texture database and result of are the sub-texture-images producing by divide the same texture into 4 ((a), (b), (c), (d)) sub-images.

VI. Conclusion and Discussion

In this paper, we propose a scheme for texture image classification using visual perceptual texture features and Gabor wavelet features. Then, a simple feature selection procedure based on a modification of Fisher's discriminant for texture classification. Subbands are first sorted according to the mean value of proposed feature selection functions. Then the first few subbands are selected. Our experiments show that while the dimensionality of feature vectors is reduced (for Gabor wavelet: from 48 down to 24), the classification accuracy is raised. Many experiments have tested the effectiveness of the proposed scheme.
Furthermore, more experiments based on different image database will be tested in the future.

Acknowledgment

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