# A New Method for Coarse Classification of Textures and Class Weight Estimation for Texture Retrieval[1]

**K. L. Lee and L. H. Chen***

*Department of Computer and Information Science, National Chiao Tung University*
*1001 Ta Hsueh Rd., Hsinchu, Taiwan 30050, Republic of China*
*e-mail:lhchen@cc.nctu.edu.tw*
** To whom all correspondence should be addressed*

**Abstract**—In this paper, a new texture classification method is provided for dividing texture images into three classes: periodic, directional, and random. The method is based on the fact that for a directional texture image, the magnitudes of its Fourier spectrum will concentrate on a certain direction; for periodic, on several directions; and for random, spread out over all directions. To use this fact, Fourier transform is, first, performed. Principal component analysis is, then, conducted on the Fourier spectrum to get the ratio of two eigenvalues, which will be used to measure the directionality of the texture image. If the texture image is not a directional one, for getting better discriminative properties for separating periodic textures from random ones, Fourier transform is applied to the Fourier spectrum to produce an enhanced Fourier spectrum. A discriminative measure based on the variance of the radial wedge distribution is, then, calculated and applied to classify the texture image as periodic or random one. Texture images from Brodatz album and Corel image database are used to demonstrate the effectiveness of the proposed method. In addition, it is shown that the intermediate results of the proposed method can be used to derive a weighting scheme used for texture retrieval. The proposed method can also be used to implement the texture browsing descriptor of MPEG-7.

## INTRODUCTION

Texture presents almost everywhere in natural and real world images and, therefore, has long been an important research topic in image processing. Successful applications of texture analysis methods have been widely found in industrial, biomedical, and remote sensing areas. In addition, the recent emerging of multimedia and the availability of large image and video archives have made content-based information retrieval a very popular research topic. Texture is also deemed as one of the most important features when performing content-based information retrieval. Various textural features have been adopted to fulfill these applications. Since there are a lot of variations among natural textures, to achieve the best performance for texture analysis or retrieval, different features should be chosen according to the characteristics of texture images. Therefore, developing an effective method for preliminary texture classification based on the textural characteristics will greatly help the design of a texture classification system or a content-based texture retrieval system.

Rao and Lohse [1] conducted a texture study based on human perception, they conclude that the most important dimensions of natural texture discrimination are periodicity, directionality, granularity, and complexity. On the other hand, texture modeling based on Wold decomposition has been proposed by Francos *et al.* [2–3]. According to Wold decomposition, a 2D homogeneous random field is decomposed into three mutually orthogonal components: periodicity, directionality and randomness which are consistent with the three most important dimensions of human texture perception. If texture images can be coarsely classified into these three categories, texture features can, then, be chosen or designed specifically for each category. To be more specific, for periodic textures, the periodic features can be extracted by the methods specifically designed for periodic textures [5–6]; for random textures, MRSAR model [7] is reported to have the best performance and can be used for texture discrimination applications. The texture retrieval method proposed by Liu and Picard [4] used this idea and demonstrate a better performance. It provides a pre-classification step assigning weights to the two classes of texture images: periodic and non-periodic. The weight of each class stands for the probability that the texture image belongs to the class. Our method also provides a weighting scheme for three classes of texture images: directional, periodic, and random. Thus, the proposed method provides a finer pre-classification than that in [4].

The properties of the Fourier spectrum of textures have been well studied [9–11], they can be summarized as follows: (1) for periodic textures, the Fourier spectrum consists of significant peaks scattered out regularly at some directions; (2) for textures with strong directionality, the directionality will be preserved in the Fourier spectrum; (3) for random textures, the distribu-

[1] This article was submitted by the authors in English.

Received June 7, 2002

tions of the responses of spectrum are not restricted to certain directions. The proposed method is developed on the basis of these properties, it consists of two phases: (1) directionality classification; (2) periodicity and randomness classification. In the phase of directionality classification, Fourier transform is, first, performed on the texture image to obtain its Fourier spectrum. Principal component analysis is, then, conducted to get two eigenvalues. If the texture image contains strong directionality, then the larger eigenvalue will be much greater than the smaller eigenvalue. Based on this phenomenon, the ratio of the larger eigenvalue to the smaller eigenvalue is used to measure the directionality of the texture image. If the texture image is not classified as a directional one, the periodicity and randomness classification phase is entered. Fourier transform is applied to the Fourier spectrum to obtain an enhanced Fourier spectrum. The enhanced Fourier spectrum has more discriminative properties in separating periodic textures from random ones than Fourier spectrum. For periodic textures, those points with high magnitude appear in some directions more clearly than those in the Fourier spectrum. Based on the properties, a discriminative measure is, then, calculated to classify the texture image as a periodic or a random texture. Texture images from Brodatz album [8] and Corel image database are used to demonstrate the effectiveness of the proposed method. It is also shown that the intermediate results of the proposed method can be used to derive the weights used for texture retrieval.

The rest of the paper is organized as follows. In Section 2, the proposed method is described in detail and a weighting scheme for texture retrieval is provided. Experimental results and discussion are presented in Section 3. Finally, in Section 4, we give a conclusion.

## 2. THE PROPOSED METHOD

The system block of the proposed method is shown in Fig. 1. Basically, the proposed method consists of two phases: (1) directionality classification and (2) periodicity and randomness classification. In directionality classification phase, Fourier transform is, first, performed on the texture image. To reduce noises, the Fourier spectrum is smoothed. A thresholding method is, then, applied on the smoothed Fourier spectrum to extract pixels with high spectral value. Principal component analysis is, then, conducted on the high spectral pixels and two eigenvalues are calculated. The ratio of the two eigenvalues is used to measure the directionality of the texture image. If the texture image is not classified as a directional one, the classification phase of periodicity and randomness is entered. Fourier transform operation is, first, performed on the smoothed Fourier spectrum to enhance the distinction between periodic and random textures. On the basis of the enhanced Fourier spectrum, a discriminative measure based on the variance of the radial wedge distribution is, then, provided to classify the texture image as a periodic or random one. In the following, the proposed method will be described in detail. Besides, we will use the intermediate results of the proposed method to provide a weighting scheme for texture retrieval.

### *2.1. Directionality Classification Phase*

Some examples of the properties of the Fourier spectra of textures are shown in Fig. 2. Figure 2a shows a periodic texture (D1, from Brodatz album). As shown in Fig. 2d, the spectral peaks are spread out regularly in horizontal and vertical directions. The texture image shown in Fig. 2b is a vertically directional texture (D106). As shown in Fig. 2e, the spectral peaks form a horizontal line-like shape. Figure 2c shows a random texture (D54). Its Fourier spectrum is shown in Fig. 2f. The distribution of the spectral values in the Fourier spectrum is not restricted to any direction. In addition to the textural features described above, it is observed that some noise exists on the Fourier spectra. To reduce the noise, a Gaussian smoothing filter is applied to the Fourier spectrum (see Figs. 2g–2i)).

From the smoothed Fourier spectrum, we can see that for directional textures, if we locate high spectral pixels and find their two principal components, the direction of the eigenvector with larger eigenvalue will be aligned with the line-like shape observed. In addition, the larger eigenvalue will be much greater than the smaller eigenvalue. Therefore, the ratio of the larger eigenvalue to the smaller eigenvalue can be used to measure the directionality of the texture image.

To get the ratio, a thresholding method is, first, designed to extract the high spectral pixels from the Fourier spectrum. Assume that the spectral values of Fourier spectrum range from 0 to $L_{\max}$. Based on the fact that the high spectral pixels contribute most of the energy, we can locate these pixels through a threshold value $l$ with the aggregated energy from $L_{\max}$ to $l$ greater than $t$% of the total spectrum.

The high spectral pixel thresholding algorithm is presented as follows.

***Algorithm 1. High spectral pixel thresholding***

**Input.** The smoothed Fourier spectrum $F'(u, v)$, $u = 1, \ldots, N$, $v = 1, \ldots, N$ of the texture image $f(x, y)$ with $0 \le F'(u, v) \le L_{\max}$.

**Output.** The high spectral pixel set, $H$.

**Step 1.** Evaluate the histogram $h(i)$, $i = 0, \ldots, L_{\max}$ of $F'$.

**Step 2.** Compute the energy $E$ of $F'$ as:

$$E = \sum_{u=1}^{N} \sum_{v=1}^{N} F'(u, v),$$

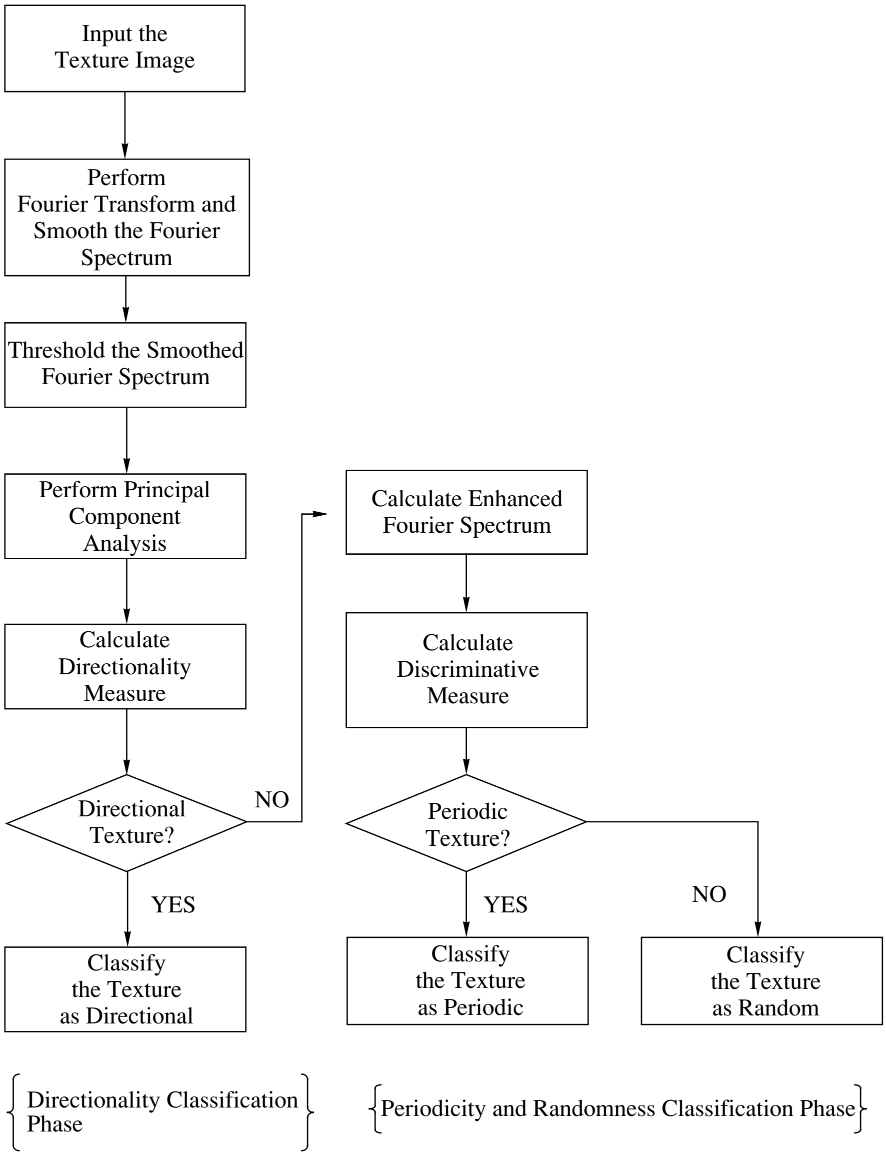



**Fig. 1.** The system block of the proposed method.

**Step 3.** Let $CE_j$ be the cumulative energy of histogram $h(i)$ from j to $L_{\max}$ and be evaluated as follows:

$$CE_j = \sum_{i=j}^{L_{\max}} h(i).$$

Determine the largest threshold $l$ which satisfies the following criterion:

$$l = \max\{j | CE_j/E > t_1\}.$$

**Step 4.** Use $l$ to threshold $F'(u, v)$ as follows:

If $F'(u, v) < l$ then $(u, v)$ is not a high spectral pixel;

else assign $(u, v)$ to $H$.

End if.

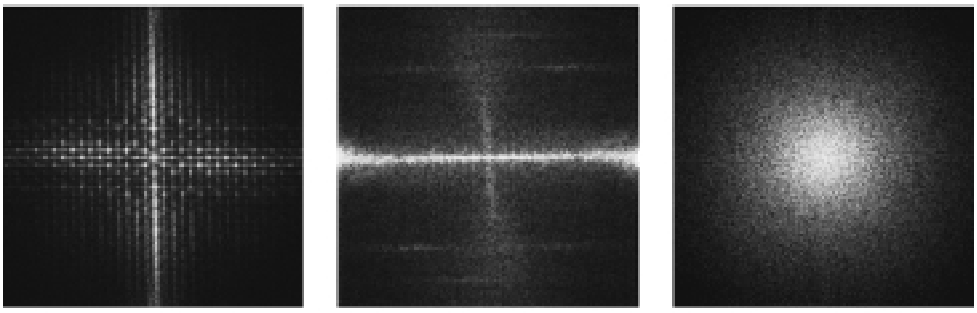
End of algorithm 1.

We, then, calculate the principal components of $H$. To emphasize the importance of pixels with higher spectral value in the calculation of principal component, we use the spectral values of pixels as weights when calculating the principal components. First, the co-variance matrix is calculated as

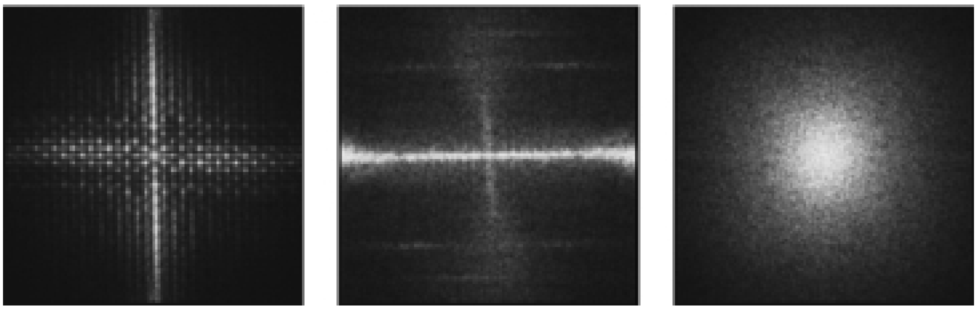
$$C = \begin{bmatrix} c_{uu} & c_{vu} \\ c_{uv} & c_{vv} \end{bmatrix}. \tag{1}$$

where $c_{uu} = \frac{1}{W}\sum_{(u,v)\in H} F'(u, v)(u - \bar{u})^2$, $c_{vv} = \frac{1}{W}\sum_{(u,v)\in H} F'(u, v)(v - \bar{v})^2$, $c_{uv} = \frac{1}{W}\sum_{(u,v)\in H} F'(u, v)(u - \bar{u})(v - \bar{v})^2$, $c_{uv} = c_{vu}$ and

(a) A periodic texture (D1).　(b) A directional texture (D106).　(c) A random texture (D106).



(d) The Fourier spectrum of (a).　(e) The Fourier spectrum of (b).　(f) The Fourier spectrum of (c).



(g) The smoothed Fourier spectrum of (d).　(g) The smoothed Fourier spectrum of (e).　(g) The smoothed Fourier spectrum of (f).

**Fig. 2.** Some examples for the Fourier spectra of periodic, directional, and random textures.
(a) Periodic texture (D1).
(b) Directional texture (D106). (c) Random texture (D54).
(d) Fourier spectrum of (a). (e) Fourier spectrum of (b). (f) Fourier spectrum of(c).
(g) Smoothed Fourier spectrum of (d). (h) Smoothed Fourier spectrum of (e). (i) Smoothed Fourier spectrum of (f).

$W = \sum_{(u,v) \in H} F'(u, v)$, $\bar{u} = \sum_{(u,v) \in H} F'(u, v)u$, $\bar{v} = \frac{1}{W} \sum_{(u,v) \in H} F'(u, v)\bar{v}$ .

Then the two eigenvalues of $C$ are evaluated, and let them be $\lambda_1$ and $\lambda_2$ with $\lambda_1 > \lambda_2$. The eigenvalue ratio $EV = \lambda_1/\lambda_2$ is, then, used to measure the directionality of textures.

The directionality classifier is designed using a Bayesian approach. To design the classifier, some sample images from Brodatz album are used as training set. Then, $EV$ ratio is computed for each image in the training set. The distributions of $EV$ ratios for the non-directional and directional images in the training set are shown in Figs. 3a and 3b, respectively. We model the distribution of $EV$s in each class by a Gaussian distribution. The directional class is denoted by $w_d$ and the non-directional class is denoted by $w_{nd}$. The prior probabilities are denoted by $p(w_d)$ and $p(w_{nd})$, respectively. The conditional probability density functions of $EV$'s are denoted by $p(EV|w_d)$ and $p(EV|w_{nd})$. And their mean and variance are estimated by the unbiased sample mean and sample variance of the $EV$'s of the training set.

Given a texture, the posterior probability of $w_d$ is computed as

$$p(w_d|EV) = \frac{p(EV, w_d)}{p(EV)} = \frac{p(EV|w_d)p(w_d)}{p(EV)}. \quad (2)$$

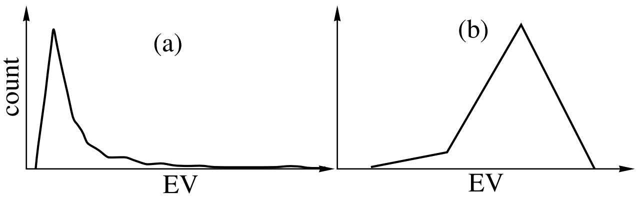



**Fig. 3.** The distributions of the *EV*'s of the images in the training set.
(a) EV distribution of non-directional class. (b) EV distribution of directional class.

We can then design the directionality classifier as follows:

If $p(w_d|EV)p(w_{nd}|EV)$, classify the texture as directional; otherwise classify the texture as non-directional.

Through Eq. (2), the inequality equation in the if condition of the classifier can be replaced by $p(EV|w_d)p(w_d) \geq p(EV|w_{nd})p(w_{nd})$. If the texture image is classified as non-directional, the classification process enters into periodicity and randomness classification phase.

### 2.2. Periodicity and Randomness Classification Phase

In this phase, each input texture image is assumed to be non-directional, we will classify it as periodic or random. As mentioned previously, the properties of the Fourier spectra of textures can be further enhanced by performing Fourier transform on the Fourier spectrum again. The obtained Fourier spectrum is called an enhanced Fourier spectrum in this paper. The textural features of the enhanced Fourier spectrum are more prominent than those of the original Fourier spectrum. Two examples are shown in Fig. 4. Figure 4a shows a periodic texture from D1. Figure 4b shows the Fourier spectrum of Fig. 4a, the spectral peaks, each of which comes from the contribution of those pixels with the same period in the original image, spread out regularly along certain directions. This property is enhanced in the enhanced Fourier spectrum, because those peaks in the Fourier spectrum are periodic, through applying Fourier transform again, peaks with the same period will contribute to the same frequency, thus, the peaks in the enhanced Fourier spectrum will be more prominent. On the other hand, regarding the remaining pixels (not peaks) in the Fourier spectrum, since they are not periodic, after the second applying of the Fourier transform, they do not contribute to the same frequency. This phenomenon also relatively enhances those peaks. Figure 4c shows the enhanced Fourier spectrum of Fig. 4a. Figure 4d is the image obtained by adding 30% of Gaussian noise in Fig. 4a. Figure 4e is the smoothed Fourier spectrum of Fig. 4d, the frequencies to which the periodic patterns contribute, are mixed with noise in the Fourier spectrum. This is the reason of heavy non-periodic noise. Thus, it is difficult to extract textural features from the Fourier spectrum. By applying Fourier transform to Fig. 4e, the spectral peaks appear more prominent on the enhanced Fourier spectrum shown in Fig. 4f. Figure 4g shows a random texture. Its Fourier spectrum is shown in Fig. 4h. The spectral responses in the Fourier spectrum are not periodic and do not concentrate on certain frequencies but scatter around the frequency plane. That is why pixels of a random texture are not of certain periods, thus, they will not contribute to certain frequencies and form periodic spectral peaks. This also makes the spectral responses in the enhanced Fourier spectrum (see Fig. 4i) spread over all directions. According to the above-mentioned properties, the enhanced Fourier spectrum is adopted to discriminate periodic textures from random ones.

Based on enhanced Fourier spectrum, Radial Wedge Distribution Variance (*RWDV*) will be defined and used to design a discriminative measure. In the following, we will explain *RWDV* in details.

Given an enhanced Fourier spectrum, $E(u, v)$, its radial wedge distribution is first calculated. Figure 5 shows the radial wedges used in the proposed method. Let the radial wedges be denoted by $RW_i$, $i = 1, \ldots, m$, $m = 360/\Delta\theta$, where $\Delta\theta$ is the size of each wedge. For each $E(u, v)$, we accumulate it to $RW_i$ if it satisfies

$$\theta_i \leq \tan^{-1}\left(\frac{u}{v}\right) < \theta_{i+1}.$$

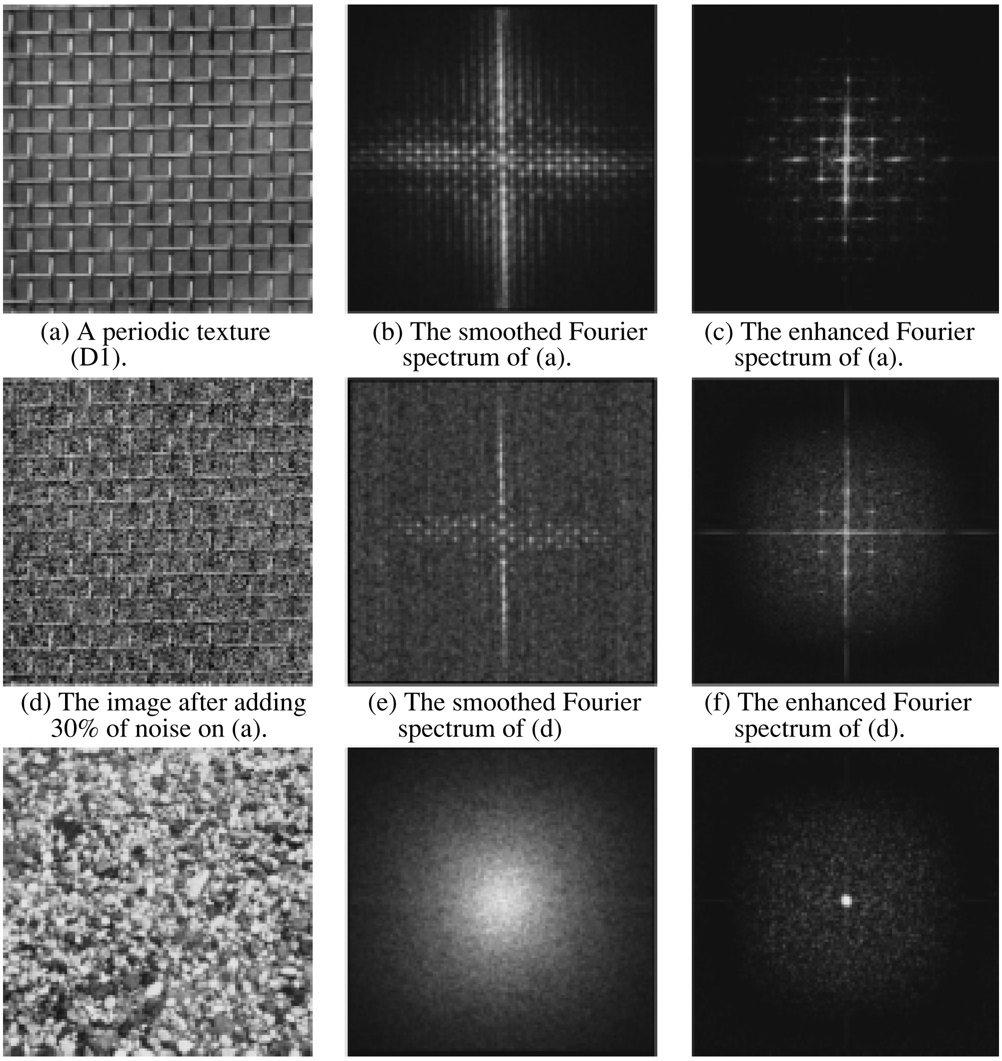
The energy of each wedge is, then, normalized by the total energy of all wedges. Let $ERW_i$, $i = 1, \ldots, m$ denote the normalized energy of radial wedges $RW_i$, then the *RWDV* is defined as:

$$RWDV = \frac{1}{m}\sum_{i=1}^{m}(ERW_i - \overline{ERW})^2, \qquad (3)$$

where $\overline{ERW} = \frac{1}{m}\sum_{i=1}^{m}(ERW_i)$.

For periodic textures, as the spectral peaks spread out regularly along certain directions while the spectral values of random textures appear in all directions, the variance of all radial wedge energies of a periodic texture will be larger than that of a random texture. Therefore, *RWDV* can be used to separate periodic textures from random ones.

The classification follows the same Bayesian approach proposed in Section 2.1. *RWDV* is computed for each image in the training set. The distributions of *RWDV*'s for the random and periodic images in the training set are shown in Figs. 6a and 6b, respectively. Each distribution of *RWDV*'s is approximated by a Gaussian distribution. The periodic class is denoted by $w_p$ and the random class is denoted by $w_r$. Then, the tex-



(a) A periodic texture (D1). (b) The smoothed Fourier spectrum of (a). (c) The enhanced Fourier spectrum of (a).

(d) The image after adding 30% of noise on (a). (e) The smoothed Fourier spectrum of (d) (f) The enhanced Fourier spectrum of (d).

(g) A random texture (D54). (g) The smoothed Fourier spectrum of (g). (g) The enhanced Fourier spectrum of (g).

**Fig. 4.** Two examples of the enhanced Fourier spectra for periodic and random textures.
(a) Periodic texture (D1). (b) The smoothed Fourier spectrum of (a). (c) The enhanced Fourier spectrum of (a). (d) Image (a) after adding 30% of noise. (e) The smoothed Fourier spectrum of (d). (f) The enhanced Fourier spectrum of (d). (g) Random texture (D54). (h) The smoothed Fourier spectrum of (g). (i) The enhanced Fourier spectrum of (g).

ture periodicity and randomness classifier is designed as follows:

If $p(RWDV|w_p)p(w_p) \geq p(RWDV|w_r)p(w_r)$, then classify the texture as periodic; otherwise, classify the texture as random.

By processing the texture image through the two phases of the proposed method, we can successfully classify the texture image as directional, periodic, or random. The intermediate results of the proposed method can be used to develop a weighting scheme for texture retrieval. This idea has been used in the texture retrieval method proposed by Liu and Picard [4], the details will be explained in the following section,

### 2.3. Weighting Scheme for Texture Retrieval

First, we will briefly describe the texture retrieval system proposed in [4]. Given a query image, the system uses a pre-classification method to evaluate the probabilities ($P_i$, $i$ = 1, 2) of the query image belonging to each of the two classes: periodic and non-periodic textures. Next, the periodic and non-periodic features are extracted. By using the $i$th kind of feature for retrieval, the ordering vector $O_i$ for all images in database is determined. The joint ordering vector $O$ for all images is finally obtained by summing the results of multiplying the ordering vectors $O_1$ and $O_2$ by the weights $P_1$ and $P_2$. That is, $O = P_1O_1 + P_2O_2$. The system can get better performance without using the weights.

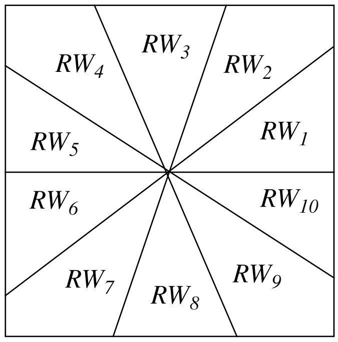



**Fig. 5.** The radial wedges used in the proposed method.

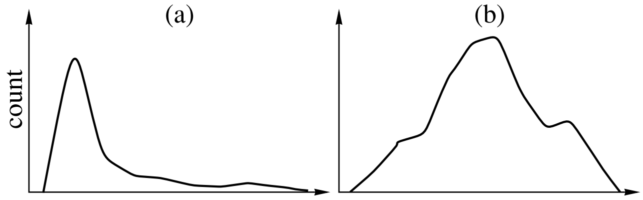



**Fig. 6.** The distributions of the *RWDV*'s of the images in traming set.
(a) The RWDV distribution of the random class. (b) The RWDV distribution of the periodic class.

As illustrated in the previous sections, the proposed method provides a coarse classification of texture images into three classes: periodicity, directionality, and randomness. In the following, a weighting scheme associated with this coarse classification will be provided. For a texture image, in the directionality classification phase, two probabilities of the texture image, $p(w_d|EV)$ and $p(w_{nd}|EV)$ standing for the posterior probability of $w_d$ and $w_{nd}$, respectively, will be calculated. If the texture image is non-directional, in the periodicity and randomness classification phase, two additional probabilities $p(w_p|RWDV)$ and $p(w_r|RWDV)$ standing for the posterior probability of $w_p$ and $w_r$, respectively, will be computed. Let $wt_d$, $wt_p$, and $wt_r$ denote the probabilities of the texture image belonging to the classes of directional, periodic, and random, respectively. Then, the vector $(wt_d, wt_p, wt_r)$ can be evaluated as

$$wt_d = p(w_d|EV),$$

$$wt_p = p(w_{nd}|EV) * p(w_p|RWDV),$$

$$wt_r = 1 - wt_d - wt_p.$$

Since the proposed method provides a finer preclassification than that in [4], this should help to improve the performance of a texture retrieval system. The reason is that the final performance of a texture retrieval system heavily depends on the textural features related to the texture classes. The system flow of a texture retrieval system using the weight vector $(wt_d, wt_p, wt_r)$ is shown in Fig. 7.

## 3. EXPERIMENTAL RESULTS

Texture images of Brodatz album and Corel Gallery image database were used to test the proposed method. To build up the Brodatz album database, eight patches for each of the 112 textures in Brodatz album were scanned and 896 texture images were obtained for experiments. Four out of the eight patches of each texture were used as training set to obtain the empirical values for parameters used, while the remaining images were used as a testing set. To further validate the performance of the proposed method, 1896 natural color texture images from Corel Gallery image database were selected and used as a testing set as well, including abstract textures, bark textures, creative textures, food textures, light textures, etc. Some examples of Corel Gallery database are shown in Fig. 8. We will report the experimental results of Brodatz database and Corel database, respectively.

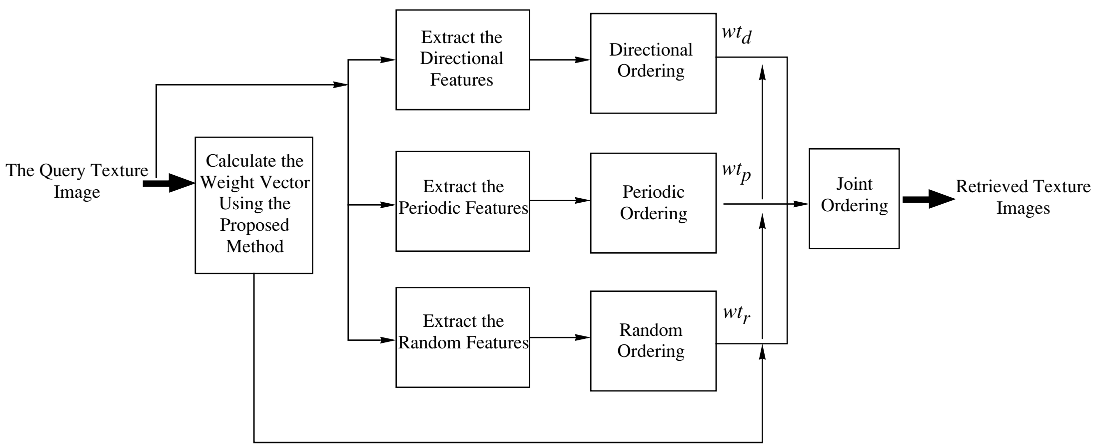
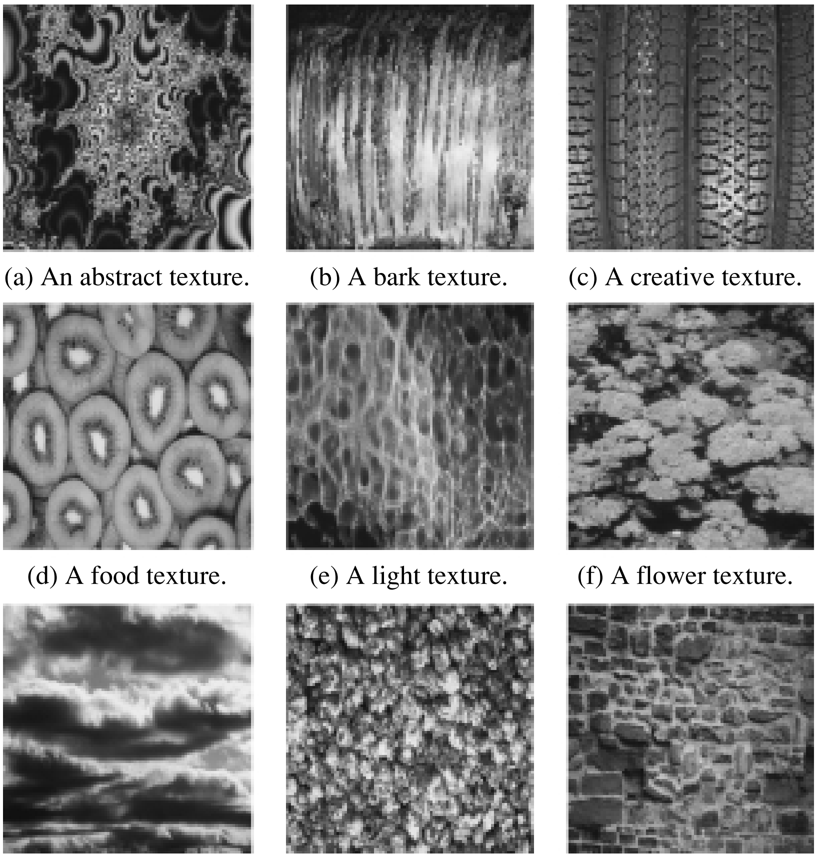



**Fig. 7.** The revised system flow of the texture retrieval system presented in [4] using the proposed method.



(a) An abstract texture. (b) A bark texture. (c) A creative texture.

(d) A food texture. (e) A light texture. (f) A flower texture.

(g) A cloud texture. (h) A candy texture. (i) A brick texture.

**Fig. 8.** Some textures of Corel Gallery image database used in the experiments.
(a) Abstract texture. (b) Bark texture. (c) Creative texture. (d) Food texture. (e) Light texture. (f) Flower texture. (g) Cloud texture. (h) Candy texture. (i) Brick texture.

To classify the texture images in the testing set into directional, periodic, or random, we, first, classify the textures into directional or non-directional ones (step 1). Those classified as non-directional are then further classified into periodic or random (step 2). By inspecting the images in the testing set, the classification rate of each step as well as the estimated and actual classification rates are reported. The estimated classification rate is obtained by multiplying the classification rates of both steps. The actual classification rate is the total number of correctly classified images via both steps divided by the total number of images in the testing set. The classification result of Brodatz database and Corel database are summarized in Tables 1 and 2, respectively. Figure 9 shows some examples of correctly classified directional, periodic, and random texture images. Four images are shown for each category, the first two images are from Brodatz database and the latter two images are from Corel database.

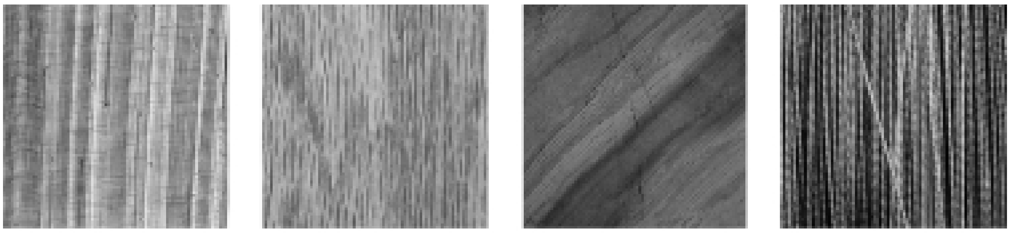
Tables 1 and 2 both show that the classification rates of step 1 (99.3% and 99.8%) are quite high, this demonstrates the effectiveness of the proposed method in discriminating directional textures from non-directional textures. Some of the misclassified textures in step 1 are shown in Fig. 10. Figure 10a is a periodic texture image classified as directional. It can be noticed that although both vertical and horizontal lines are present in the image, the horizontal lines are not signif-

**Table 1.** The performance for the classification of Brodatz database

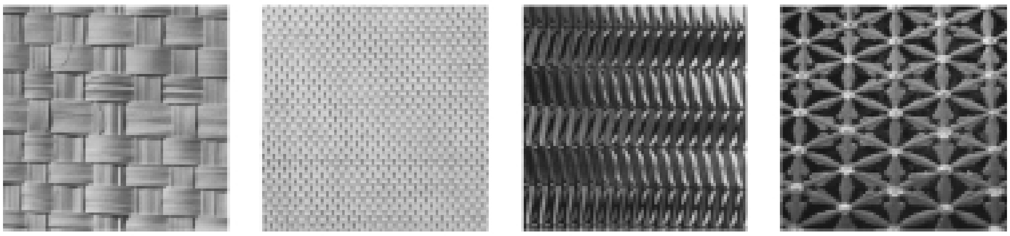
| | Step 1 | Step 2 |
|---|---|---|
| Step Classification Rate | 99.3% | 96.1% |
| Estimated Classification Rate | 95.4% | |
| Actual Classification Rate | 95.5% | |

**Table 2.** The performance for the classification of Corel database

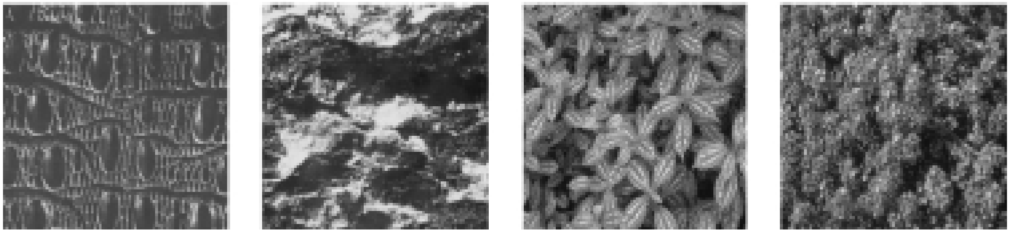
| | Step 1 | Step 2 |
|---|---|---|
| Step Classification Rate | 99.8% | 98.8% |
| Estimated Classification Rate | 98.6% | |
| Actual Classification Rate | 98.8% | |



(a) Some correctly classified directional textures.



(b) Some correctly classified periodic textures.



(c) Some correctly classified random textures.

**Fig. 9.** Some correctly classified texture images from Brodatz database and Corel database.
(a) Some correctly classified directional textures. (b) Some correctly classified periodic textures. (c) Some correctly classified random textures.

(a) (b) (c) (d)

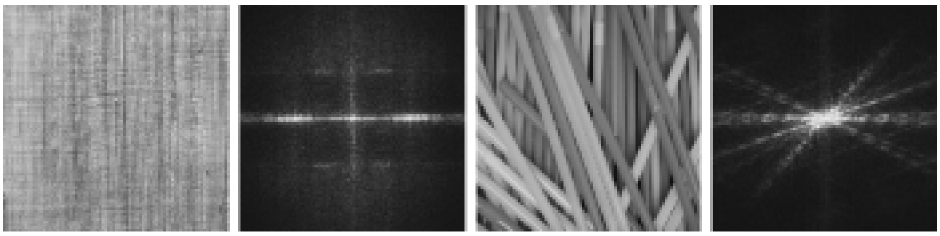


**Fig. 10.** Some misclassified textures and their Fourier spectra of step 1.

icant enough. Thus, the high spectral pixels of its Fourier spectrum (Fig. 10b) form a horizontal line-like region, making it misclassified. Figure 10c shows a directional texture classified as non-directional. Since there are only three classes used, we consider Fig. 10e as a directional texture. However, there are actually groups of straws arranged in four different directions. Therefore, its Fourier spectrum shown in Fig. 10d also presents four lines distributed in different directions. This makes Fig. 10c be classified as non-directional in step 1, and in step 2, Fig. 10c will be further classified as periodic. This classification error is caused by a small number of classes used. In fact, Fig. 10c is neither directional nor periodic, it is multi-directional. Thus, to be more accurate in classifying textures, we can introduce additional classes named multi-directional to cope with diversity of natural textures. Some examples of multi-directional textures from Corel database are shown in Fig. 11.

Similarly, some of the misclassified textures of step 2 are shown in Fig. 12. Figure 12a shows a wave texture and is classified as periodic; however, we consider it as a random texture. It is observed that, in addition to most of the homogeneous areas, there are directional wave-like patterns present in the image. The classification error is due to the fact that, although Fig. 12a is not close to any class, it has to be classified to one of the three classes used. Fortunately, the class probabilities

(a) (b) (c) (d)

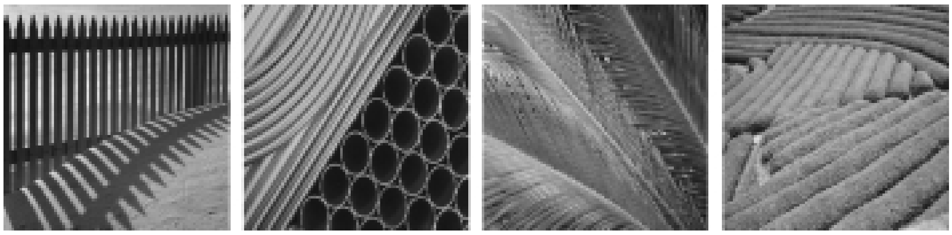


**Fig. 11.** Some examples of multidirectional textures from Corel database.

(a) (b) (c)

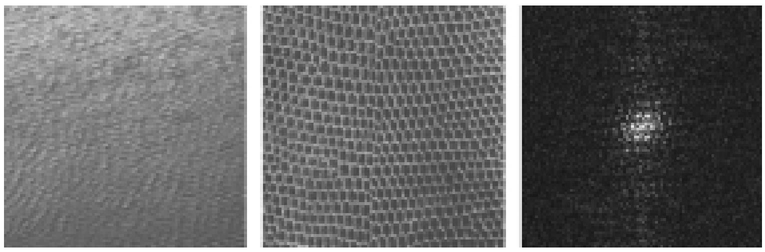
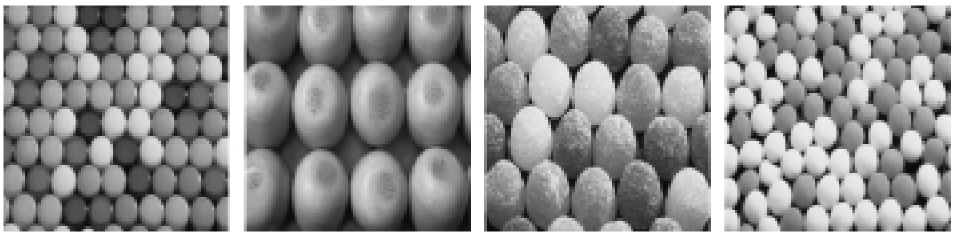


**Fig. 12.** Some misclassified textures and their enhanced Fourier spectra of step 2.



(a) [0.98] (b) [0.73] (c) [0.15] (d) [0.11]

**Fig. 13.** Four textures with clear primitives but different displacements.

of Fig. 12a for periodic and random are 0.53 and 0.47, respectively. Since these two probabilities are quite close, Fig. 12a can be considered as an ambiguous texture. In practice, all images of this kind can be considered as ambiguous. Figure 12b shows a periodic texture misclassified as random. Although Fig. 12b is perceived as havinge clear directionality and some periodicity, some local variations are present and distort the directionality and periodicity. Thus, the high spectral pixels of its enhanced Fourier spectrum (Fig. 12c) do not concentrate at certain directions. This makes Fig. 12b be classified as random.

Figure 13 shows four textures from Corel database. They are all textures with clearly defined texture primitives but different in the regularity of displacement. The regularity of their displacements is decreasing from Fig. 13a to Fig. 13d. The corresponding class probability for periodic is listed under each figure. These values are also in decreasing order. This reveals that the class weights calculation scheme proposed in Section 2.3 is consistent with human perception. In addition, a descriptor for measuring the regularity of textures has been specified in the texture browsing descriptor of MPEG-7 [12]. The calculated periodic weight can also be used to implement this regularity descriptor.

## 4. CONCLUSION

In this paper, we propose a new method for coarse classification of textures and a weighting scheme for texture retrieval. The eigenvalue ratio obtained by performing principal component analysis on the Fourier spectrum of the texture image is, first, used to determine the directionality measure. If the texture image is not a directional one, Fourier transform is applied to the Fourier spectrum image to produce an enhanced Fourier spectrum. A discriminative measure based on the variance of the radial wedge distribution is, then, calculated and applied to classify the texture image as periodic or random one. The proposed method provides a coarse classification of textures based on the three most important dimensions of human texture perception, i.e., periodicity, directionality, and randomness. The proposed method can be used to implement the texture browsing descriptor of MPEG-7. Furthermore, for different classes, system designers can design their own texture features and use the immediate results, class probabilities, of the proposed method as weights for classes to perform texture retrieval. In the future, we will develop texture classification methods to cope with multi-directional textures in the Corel database.

## ACKNOWLEDGMENTS

This research was supported in part by the National Science Council of Republic of China, contract no. NSC-87-2213-E-009-060.)

## REFERENCES

1. Rao, A.R. and Lohse, G.L., Toward a Texture Naming System: Identifying Relevant Dimensions of Texture, *Proc. IEEE Conf. Visualization*, 1993, pp. 220–227.
2. Francos, J.M., Zvi Meiri, A., and Porat, B., A Unified Texture Model Based on a 2D Wold Like Decomposition, *IEEE Trans. on Signal Processing*, 1993, pp. 2665-2678.
3. Sriram, R., Francos, J.M., and Pearlman, W.A., Texture Coding Using a Wold Decomposition Model, *Proc. ICPR*, 1994, vol. 3, pp. 35–39.
4. Liu, F. and Picard, R., Periodicity, Directionality, and Randomness: Wold Features for Image Modeling and Retrieval, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 1996, vol. 18, no. 7, pp. 722–733.
5. Kim, H.B. and Park, R.H., Extracting Spatial Arrangement Of Spectral Textures Using Projection Information, *Pattern Recognition*, 1992, vol. 25, no. 3, pp. 237–247.
6. Lin, H.C., Wang, L.L., and Yang, S.N., Extracting Periodicity Of A Regular Texture Based On Autocorrelation Functions, *Pattern Recognition Letters*, 1997, vol. 18, pp. 433–443.
7. Mao, J. and Jain, A.K., Texture Classification and Segmentation Using Multiresolution Simultaneous Autoregressive Models, *Pattern Recognition*, 1992, vol. 25, no. 2, pp. 173–188.
8. Brodatz, P., *Textures–A photographic for Artists and Designers*, New York: Dover, 1966.
9. Levine, M.D., *Vision in Man and Machine*, New York: McGraw Hill, 1985.
10. Chen, C.H., A Study of Texture Classification Using Spectral Features, *Proc. 6th Int. Conf. on Pattern Recognition*, Munich, 1982, pp. 1074–1077.
11. Connors, R.W. and Harlow, C.A., A Theoretical Comparison of Texture Algorithms, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 1980, vol. 2, no. 3, pp. 204–222.
12. *Text of ISO/IEC 15938-3 Multimedia Content Description Interface–Part 3: Visual. Final Committee Draft*, ISO/IEC/JTC1/SC29/WG11, Doc. N4062, 2001.

**Ling-Hwei Chen.** Born in Taiwan, Republic of China, in 1954. Received her BSci Degree in Mathematics, her Msci Degree in Applied Mathematics from National Tsing Hua University, Hsinchu, Taiwan in 1975 and 1977, respectively, and her PhD Degree in Computer Engineering from National Chiao Tung University in 1987. In 1977-1979, was a Research assistant in the Chung-Shan Institute of Science and Technology, Taoyan, Taiwan. In 1979-1981, was a Research associate in the Electronic Research and Service Organization, Industry Technology Research Institute, Hsinchu, Taiwan. In 1981-198, worked as an Engineer in the Institute of Information Industry, Taipei, Taiwan. Professor of the Department of Computer and Information Science at the National Chiao Tung University. Her current research interests include image processing, pattern recognition, document processing, image compression, and image cryptography.

**Kuen-Long Lee.** Received both his BSci and MSci Degrees in Computer and Information Science from National Chiao Tung University, Taiwan, in 1988 and 1990, respectively. He is currently a PhD student in the Department of Computer and Information Science at National Chiao Tung University. His research interests include image processing, pattern recognition, texture analiysis, and image retrieval.

SPELL: directionality, thresholding, co-variance, misclassified, wave-like, havinge, analiysis, lighttexture