Structured and Random Texture Patterns Characterization Using Multiscale Directional Filter Bank

K. O. Cheng, N.F. Law and W.C. Siu

Centre for Multimedia Signal Processing,
Department of Electronic & Information Engineering,
The Hong Kong Polytechnic University

ABSTRACT

The use of multiscale directional decomposition achieved by combining Laplacian pyramid and directional filter bank is studied in this paper for texture classification. We first demonstrated the importance of multiscale analysis of directional texture features. Then, it is found that directional analysis is suitable for characterizing structured textures, but not random textures. Thus, structured and random textures are separated by employing an entropy-based measure on the multiscale directional features. Through this pre-filtering step, structured textures are extracted for further classification so that the overall retrieval performance can be enhanced. Experimental results showed that this pre-filtering step can significantly improve the overall retrieval accuracy.

1. INTRODUCTION

Texture analysis has a wide application on content-based image retrieval, remote sensing and medical imaging. Recently, multiscale analysis such as wavelet transform becomes popular for texture classification because it suits the human visual system (HVS) well. Although wavelet transform allows a multi-resolution view on textures, it does not provide a fine directional analysis. Therefore, Gabor filters [1] based and directional filter bank (DFB) [2, 3] based approaches have been proposed for directional feature extraction. Compared with Gabor filtering, DFB is more computation efficient due to the properties of critical sampling and tree structure implementation. However, in contrary to wavelet transform and Gabor filtering, DFB lacks multiscale property. In [4], a Laplacian pyramid [5] is combined with DFB to achieve multiscale analysis. The use of Laplacian pyramid allows directional decomposition to be performed on different scales independently. Hence, such kind of multiscale directional decomposition is well suited for texture analysis.

The use of multiscale directional decomposition for texture analysis has been primarily studied in [6]. In general, directionality is obvious only in structured textures. In other words, classification performance using features extracted from multiscale directional decomposition is good for structured textures while that is deteriorated greatly for non-structured or random textures. This suggests that multiscale directional features should be exploited to distinguish structured from random textures. In this paper, we will first study the texture analysis using multiscale directional decomposition. After that, we will investigate the use of multiscale directional features for filtering out random textures in order to optimize the performance in texture classification.

2. DIRECTIONAL FILTER BANK (DFB)

DFB provides multidirectional analysis by partitioning the frequency plane into a set of wedge-shaped passband regions. A tree structure implementation can be adopted as described in [2]. In each stage, a two-channel filter bank splits the input image into two subband images by two complementary diamond filters. Using a quincunx down-sampling matrix $\begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix}$, the lowpass and the bandpass filters can be shown to be,

$$H_0(z_0, z_1) = 0.5[z_0^{-2N} + z_0^{-1}\beta(z_0 z_1^{-1})\beta(z_0 z_1)]$$

$$H_1(z_0, z_1) = z_0^{-4N+1} - \beta(z_0 z_1^{-1})\beta(z_0 z_1)H_0(z_0, z_1)$$

where $\beta(z)$ is a 1-D filter of even length N with linear phase [3, 7]. DFB lacks multiscale property in contrary to the wavelet transform. Also, the lowpass information spreads into multiple directional subbands. As a result, a sparse representation cannot be achieved using DFB.

3. MULTISCALE DFB (MDFB)

To introduce multiscale property, DFB can be combined with certain multiscale schemes [4, 6]. For example, three scales, which correspond to frequency ranges [π/4, π/2], [π/2, 3π/4] and [3π/4, π] respectively, can be used. The first scale sub-image is obtained by first applying a lowpass filter with passband [0, 3π/4] on an input image. Then the lowpass image is subtracted from the original image to produce the first scale sub-image. Further multiscale decomposition is performed using Laplacian pyramid on this lowpass image. Hence, the second and the third scale sub-images are the prediction residuals of the first two levels on the lowpass image. To avoid bias from DC component [3] and use the fact that textures have dominant features in mid-frequency range, the scales of frequency lower than $\pi/4$ are not considered. After obtaining the multiscale sub-images, DFB is applied on each sub-image independently. The number of directional decomposition can be different for different scales. The multiscale directional decomposition is denoted as (d_1, d_2, d_3) where d_i is the number of directional components in scale i.

To illustrate the advantage of using multiscale analysis on DFB, let's consider images shown in Table 1. After the image is decomposed into multiscale directional components, energy values of these components are computed and used to form a feature vector to reduce the dimensionality of representation. To measure the similarity between two images, Euclidean distance weighted by the global standard deviation of feature components over the whole database is used. As shown in Table 1, for images A and B, each of which consists of straight lines of similar width, high energy is found in the directional subbands corresponding to the orientations of the straight lines. However, it becomes confusing to discriminate images B and C. Image C has wider 'top-right' diagonal lines than horizontal lines. Without using multiscale features, similar feature vectors are obtained for both images. However, with the use of MDFB, the energy values for image B concentrate on the vertical and 'top-right' directional components in all scales. For image C, the higher frequency scale, i.e., the 1-st scale, has the highest energy in the 'vertical' directional subbands while the lower frequency scale, i.e., the 3-rd scale, has the highest energy in 'top-right' directional subbands. Since textures usually have features at various scales and directions, MDFB is a suitable tool for texture feature extraction.

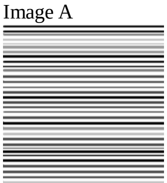
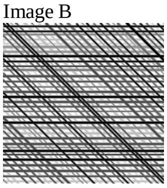
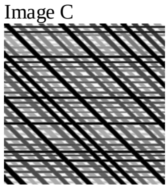
Images	Scale	Energy values
Image A 	No	(0.067, 0.033, 0.049, 0.443, 0.874, 0.095, 0.066, 0.133)
	1-st	(0.021, 0.013, 0.057, 0.447, 0.885, 0.106, 0.016, 0.033)
	2-nd	(0.015, 0.007, 0.008, 0.448, 0.893, 0.012, 0.013, 0.027)
	3-rd	(0.026, 0.013, 0.014, 0.539, 0.840, 0.015, 0.027, 0.050)
Image B 	No	(0.124, 0.066, 0.113, 0.347, 0.709, 0.497, 0.252, 0.186)
	1-st	(0.117, 0.107, 0.199, 0.381, 0.744, 0.425, 0.190, 0.139)
	2-nd	(0.104, 0.057, 0.098, 0.336, 0.703, 0.529, 0.265, 0.137)
	3-rd	(0.176, 0.105, 0.141, 0.402, 0.623, 0.540, 0.277, 0.139)
Image C 	No	(0.098, 0.082, 0.175, 0.295, 0.604, 0.609, 0.305, 0.190)
	1-st	(0.115, 0.115, 0.195, 0.403, 0.751, 0.382, 0.191, 0.164)
	2-nd	(0.070, 0.078, 0.173, 0.323, 0.676, 0.555, 0.278, 0.117)
	3-rd	(0.096, 0.105, 0.218, 0.242, 0.356, 0.763, 0.387, 0.120)

Table 1. Multiscale directional features of straight lines images.

'No', '1-st', '2-nd' and '3-rd' refers to the directional components for frequency range $[0, \pi]$ (no scale), $[\pi/4, \pi/2]$ (1-st scale), $[\pi/2, 3\pi/4]$(2-nd scale) and $[3\pi/4, \pi]$ (3-rd scale).

3.1 Textural Retrieval Using MDFB

Brodatz texture album, which consists of 111 512×512 8-bit gray level images, is used to construct the texture database used in the simulation. The center part of each of the album images is divided into 9 non-overlapping 128×128 sub-images. The sub-images extracted from the same album image are considered to be from the same texture type. The resulting database thus contains a total of 999 images with 111 texture types. The simulations are performed with different filters in the multiscale decomposition and different combinations of directional decompositions in the 3 scales. To reduce the intensity correlation between images derived from the same parent image, all the images are normalized to have zero mean and unit variance. The retrieval results are summarized in Table 2. It can be seen that a large improvement in retrieval rate is obtained when the number of directional decompositions increases from 2 to 8 in each scale. For example, the retrieval accuracy increases from 63.0% to 69.6% when the decomposition changes from (2, 2, 2) to (8, 8, 8) for the Binomial (15) filter. However, further directional decompositions only have little improvements.

	QMF (5)	QMF (13)	Binomial(5)	Binomial(15)
(2, 2, 2)	57.3	57.8	62.3	63.0
(4, 4, 4)	61.9	61.4	64.5	66.5
(8, 8, 8)	65.3	65.2	68.2	69.6
(16, 16, 16)	65.6	65.4	69.1	69.6
(32, 32, 32)	65.7	65.7	69.1	69.3
(8, 8, 16)	64.6	65.0	68.0	68.2
(8, 16, 8)	65.4	65.2	68.6	69.9
(16, 8, 8)	65.6	65.3	68.3	69.7
(8, 8, 32)	63.3	64.1	66.4	65.4
(8, 32, 8)	64.9	64.5	68.6	69.6
(32, 8, 8)	65.2	64.3	67.6	68.9
(16, 16, 32)	64.8	65.3	68.1	67.8
(16, 32, 16)	65.6	65.4	69.4	69.8
(32, 16, 16)	65.5	65.2	68.8	69.9

Table 2. Retrieval accuracy (%) for multiscale directional features.

4. USE OF MDFB AS TEXTURE PRE-FILTERING

In structured textures, patterns are regularly arranged so that the orientations of the patterns are consistent throughout. However, it is not the case in non-structured (random) textures as they would give a roughly uniform distributed orientation pattern. This suggests that directional analysis can be applied to distinguish structured and non-structured patterns. First, the energy of each directional subband is computed. Then the similarity of these energies is measured as an estimation of the uniformity of pattern orientations. Shannon entropy, which provides a measure of the sequence "concentration" [7], is used as a measure of uniformity. For a directional energy sequence, $\{v_i\}$, the similarity S is given by

$$S(\{v_i\}) = -\sum_i (v_i / v)^2 \ln(v_i / v)^2 , \quad \text{where } v = \sqrt{\sum_i v_i^2}$$

The measure gives a large value for roughly the same energy values. To determine whether the texture is structured or non-structured, a threshold of the entropy is set for each scale. In this paper, the global mean is used as the threshold. However, if training is employed, the thresholds can be set to maximize the retrieval performance on the training set. If the entropy of the query texture is greater than the threshold, it is regarded as non-structured with respect to that scale. Otherwise, it is considered as structured. The texture is classified to be structured if there exists one scale, in which it is regarded as structured.

4.1 Finding Structured and Non-structured Content

In this part, we would investigate the classification performance of structured and non-structured textures using MDFB. Table 3 gives the classification results for 6 texture images. Images D001, D052, D083 and D102 are considered to be structured while D002 and D091 are regarded as non-structured. The simple structured texture, D001 and non-structured texture, D002 can be classified successfully in all decompositions. However, for complicated structured textures like D052, D083 and D102, more scales and directional decompositions are required for successful classification. For instance, LP (8) and LP (16) misclassify D052 as non-structured because they mix up the structured patterns of D052 in different scales. Decomposition LP (8) even misclassifies D091 as structured. The misclassification is due to the insufficient radial and angular resolutions. With enough resolutions like decomposition (16, 16, 16), 100% classification can be obtained. The results also show that the mid-frequency components are important for the classification. For example, decomposition (16, 8, -) misclassifies D052 as non-structured but decomposition (8, 16, -) does not due to the finer directional resolution in mid-frequency range.

4.2 Pre-filtering Structured Textures Before Retrieval

MDFB could not characterize the random textures well due to the lack of directionality in their patterns. To optimize the performance of the retrieval system using MDFB on more general texture classes, i.e. the one including structured and non-structured textures, the textures are first classified into structured and non-structured groups using the scheme as described in Section 4. The structured textures are handled by MDFB and the non-structured textures are processed by some other approach specialized for random texture characterization. On the other hand, as shown in 4.1, multi-scale directional features can distinguish structured textures and non-structured textures. Therefore, the multi-scale directional features are used for pre-filtering structured textures as well as in the similarity measurement for classified structured textures.

Decomposition	Images					
	D001	D002	D052	D083	D091	D102
LP(8)	O	X	X	X	O	X
LP(16)	O	X	X	O	X	X
(8, 16, -,)	O	X	O	O	X	X
(16, 8, -,)	O	X	X	X	X	X
(8, 8, 8)	O	X	O	O	X	X
(16, 16, 16)	O	X	O	O	X	O

Table 3.(a) Structured texture classification results for six textures. Symbols 'O' and 'X' denote the classified result as structured and non-structured respectively. LP(n) refers to n number directional decompositions performed on the image with the content in frequency range $[0, \pi/4]$ filtered out. The unused scale k is indicated by '-'.

4.3 Retrieval results

Simulations have been performed to study the retrieval scheme using MDFB with pre-filtering. The retrieval results for the textures, which are classified to be structured, are given in Table 4. Compared the retrieval accuracy with and without using pre-filtering (Table 2), the retrieval accuracy with per-filtering is higher for all the decompositions regardless of the type of filter used. For example, in the case of Binomial (15) filter, the retrieval accuracies for decompositions (8, 8, 8) and (16, 16, 16) are 78.9% and 79.0% respectively as shown in Table 4. They are significantly higher than those in Table 2, which are 69.6% and 69.6% respectively. The best result with pre-filtering is 80.5% for Binomial (5) with decomposition (16, 32, 16) while the best result without pre-filtering is 69.9% using Binomial (15) with decomposition (8, 16, 8) or (32, 16, 16). These improvements justify the use of pre-filtering for retrieval based on MDFB.

4.4 Retrieval performance vs feature size

Beside the retrieval rate, another main concern in texture retrieval is the computational time. Actually, the computational time greatly depends on the number of features used. Reduction in features is thus required to reduce the processing time [8]. In this paper, only the m highest energy values are preserved while all others are set to zero. The reason is that non-dominant features usually have little directional information. Therefore, only the *m* highest energy values in a query texture will be included in distance measure of texture retrieval.

Simulations are conducted to investigate the relation between retrieval performance and number of features used in the retrieval scheme with per-filtering together with the above feature reduction method. The filter used in multi-scale decomposition is Binomial (15). Figure 1 shows the graph of retrieval rate vs number of features for MDFB. The decomposition (8, 16, 8) has relatively high performance for few number of features. Its highest retrieval accuracy of 80.3% is achieved for 24 features. The retrieval accuracy is better than those of other finer decompositions. This shows that the radial frequency range [π/2, 3π/4] contains the most significant directional features. It can also be seen that for finer decomposition, more number of features are required for the decomposition to achieve their maximum retrieval accuracies. This is caused by the use of overly fined angular resolution for some textures. For such kind of features, two or more directional components are usually required to represent one single texture directional feature. This thus introduces redundancy in the characterization of the textures and lowers the efficiency.

	QMF (5)	QMF (13)	Binomial(5)	Binomial (15)
(2, 2, 2)	65.0	64.8	70.3	67.4
(4, 4, 4)	70.6	70.1	69.9	71.1
(8, 8, 8)	76.5	76.8	76.4	78.9
(16, 16, 16)	78.2	78.7	79.7	79.0
(32, 32, 32)	78.4	80.1	79.1	79.2
(8, 8, 16)	76.6	77.4	79.2	78.9
(8, 16, 8)	77.7	77.8	77.0	79.5
(16, 8, 8)	76.7	76.9	75.7	78.1
(8, 8, 32)	77.0	78.8	78.4	78.3
(8, 32, 8)	78.1	78.0	77.8	79.8
(32, 8, 8)	76.9	76.5	74.5	76.4
(16, 16, 32)	78.4	80.3	79.0	79.0
(16, 32, 16)	78.5	79.1	80.5	79.4
(32, 16, 16)	78.0	78.4	78.4	77.9

Table 4. Retrieval accuracy (%) for the retrieval approach with pre-filtering.

5. CONCLUSION

Texture retrieval using multiscale directional filter bank for feature extraction is studied. It has been shown that multiscale directional feature is important for texture retrieval since textures have directional features at different scales. With the use of entropy as a measure of uniformity, these multiscale directional features can also be used to separate structured texture pattern from random texture pattern. Simulations have shown that this step of pre-filtering of structured textures can significantly improve the overall retrieval performance on a texture database. The retrieval accuracy with reduction of features is also studied. Fine directional decomposition in mid-frequency range is found to be efficient for retrieval.

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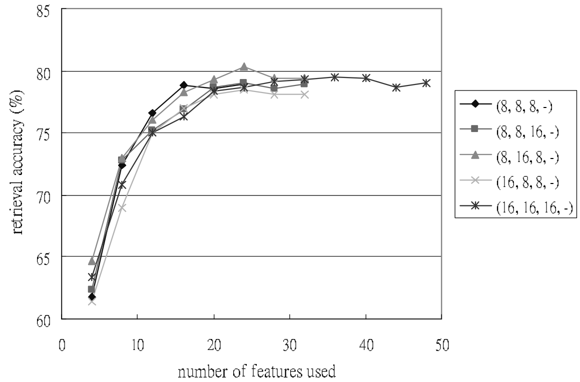

Figure 1. Retrieval accuracy (%) vs number of features used of different multiscale directional decompositions for the retrieval scheme with pre-filtering. The filter used in multiscale decomposition is Binomial (15) filter.

7. REFERENCES

[1] B. S. Manjunath and W. Y. Ma, 'Texture Features for Browsing and Retrieval of Image Data', IEEE Trans. Pattern Anal. Machine Intell., vol. 18, no. 8, pp. 837-842, Aug. 1996.

[2] R. H. Bamberger and M. J. T. Smith, 'A Filter Bank for the Directional Decomposition of Images: Theory and Design', IEEE Trans. Signal Processing, vol. 40, no. 4, pp. 882-893, Apr. 1992.

[3] J. G. Rosiles and M. J. T. Smith, 'Texture Classification with a Biorthogonal Directional Filter Bank', Proc. IEEE Int. Conf. Acoustics, Speech and Signal Processing, vol. 3, pp. 1549-1552, May 2001.

[4] M. N. Do and M. Vetterli, 'Pyramidal Directional Filter Banks and Curvelets', Proc. Int. Conf. on Image Processing, vol. 3, pp. 158-161, Oct. 2001.

[5] P. J. Burt and E. H. Adelson, 'The Laplacian Pyramid as a Compact Image Code', IEEE Trans. Commun., vol. 31, no. 4, pp. 532-540, Apr. 1983.

[6] W. Y. Chan, N. F. Law and W. C. Siu, 'Multiscale Feature Analysis Using Directional Filter Bank', Proc. 2003 Joint Conf. of 4th Int. Conf. Information, Communication and Signal Processing, 2003 and 4th Pacific Rim Conf. on Multimedia, vol. 2 , pp. 822-826, Dec. 2003.

[7] S.-M. Phoong, C. W. Kim, P. P. Vaidyanathan and R. Ansari, 'A New Class of Two-Channel Biorthogonal Filter Banks and Wavelet Bases', IEEE Trans. Signal Processing, vol. 43, no. 3, pp. 649-665, Mar. 1995.

[8] R. R. Coifman and M. V. Wickerhauser, "Entropy-Based Algorithms for Best Basis Selection", IEEE Trans. Inform. Theory, vol. 38, No. 2, Mar. 1992.

[9] M.-C. Lee and C.-M. Pun, "Texture Classification Using Dominant Wavelet Packet Energy Features", Proc. 4th IEEE Southwest Symp. on Image Analysis and Interpretation, 2000, pp.301-304, Apr. 2000.