Texture Classification Using Discrete Multiwavelet Transform

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Abstract

Multiwavelet, a new notion addition to wavelet theory, offer simultaneous orthogonality, symmetry, and short support, which are not possible with scalar two-band wavelet systems. This paper describes a new approach to characterize texture image at multiresolution using the discrete multiwavelet transform. Classification experiments with 20 Brodatz textures indicate that the proposed approach is superior to the method based on standard scalar wavelet transform.

1. Introduction

Textures provide important characteristics for object recognition from aerial or satellite images, biomedical images, and many other types of images. Texture classification and segmentation play an important role in several applications, such as remote sensing, computer vision, and medical diagnosis. Although various methods for texture feature extraction have been proposed during the last decades, the texture analysis problem is still considered a difficult problem and subjective to intensive research.

The earliest texture classification method was proposed by Haralick et al and was based on feature extracted from co-occurrence matrices[1]. The reported experimental results achieved an overall accuracy of 84% on 11 different types of textures. The comparative study performed by Weszka et al demonstrated that texture features based on second-order and difference statistics were superior to those extracted from 2-D power spectrum[2]. The experimental results showed a 90% accuracy on 3 different types of sample terrain images. Kashyap and Kaotanzad extracted texture features from a circular symmetric autoregressive model and reported an accuracy of 91% for the classification of 12 natural textures[3]. The Gaussian Markov Random Fields was used to classify textures by some researchers[4-5]. Derin used Gibbs distribution theory to discriminate and segment texture image and gave reasonably good performance[6-8]. Laws proposed a simple scheme used local linear transformations and energy computation to extract texture features[9]. The scheme has been studied and improved by many researchers[10-11]. However, a weakness shared by all these methods is that the images are analyzed at one single scale.

Experiments based on the human visual system indicate that the visual cortex can be modeled as a set of independent channels, each with a particular orientation and spatial frequency[12-14]. This has lead several researchers to investigate spatial frequency decompositions in the classification and segmentation of textures. In particular, Gabor filters have been used for discrimination and segmentation of textures[15-17]. However, a large combination of parameters makes texture classification using Gabor filters computationally expensive.

More recently, wavelet theory proposed by Mallat has emerged and became a mathematical framework which provided a more formal, solid and unified framework for multiscale image analysis[18-19]. Typically, the wavelet transform maps an image on a low resolution image and a series of detail images. The low resolution image is obtained by iteratively blurring the image, and the detail images contain the information lost during this operation. The energy or entropy of the detail images are the most commonly used features for texture classification and segmentation problems[19-20]. Chang and Jay performed texture analysis using the structured wavelet transform[21]. Uner used the discrete wavelet frame and characterized the texture by a set of channel variances estimated at the output of a filter bank[22]. Classification experiments on 12 Brodatz textures showed the DWF method is superior to standard critical sampled wavelet transform feature extraction. Chen and Kundu utilized rotation and gray scale transform invariant recognition scheme using a combination of wavelet decomposition and hidden Markov model and reported a 93.33% classification accuracy for 10 natural textures[23]. Lain and Fan used wavelet packets and wavelet packets frame to characterize textures at different scales and achieve very high classification accuracy[24-25]. Chitre and Dhawan investigated the classification of 20 natural textures with image of varying sizes using M-band wavelet and obtained fairly good results[26].

Multiwavelets, which are extension from scalar wavelets, have received considerable attention from the wavelets research communities both in theory as well as in applications such as signal compression and denoising[27-31]. Multiwavelets have several advantages in comparison to scalar wavelets, such features as short support, orthogonality, symmetry, and vanishing moments which are known to be important in signal processing. Scalar wavelets except the Haar system can not posses all these properties at the same time[29]. On the other hand, a multiwavelet system can simultaneously provide perfect reconstruction while preserving length (orthogonality), good performance at the boundaries (via linear-phase symmetry), and a high order of approximation (vanishing moments)[29]. Thus, multiwavelets offer the possibility of superior performance for image processing applications, compared with the scalar wavelets.

This paper is organized as follows. In Section 2, we briefly review theory of multiwavelet transform. The application of the DMWT to texture analysis is described in Section 3. Experimental results of texture classification are described in Section 4. Concluding remarks are given in Section 5.

2. 2-D Discrete multiwavelet transform

Figure 1 shows the multiwavelet framework for image decomposition. The prefilter is first applied to all the rows of the image, before the first level decomposition is applied to each of the resultant rows. The first half of each row of the decomposition results contains coefficients corresponding to the first scaling function and the second half contains coefficients corresponding to the second scaling function. Then the prefilter and decomposition operations are repeated to the columns, such that the first half of each column contains coefficients corresponding to the first scaling function and the second half of each column corresponding to the second scaling function. At the end of the first of 2-D multiwavelet decomposition, we have a 16-subband intermediate image as follows,

L_1L_1	L_2L_1	H_1L_1	H_2L_1
L_1L_2	L_2L_2	H_1L_2	H_2L_2
L_1H_1	L_2H_1	H_1H_1	H_2H_1
L_1H_2	L_2H_2	H_1H_2	H_2H_2

Here a typical block H_2L_1 contains low pass coefficients corresponding to the first scaling function in the horizontal direction and high pass coefficients corresponding to the second scaling function in the vertical direction. The next step of the cascade will decompose the "low-low pass" submatrix

L_1L_1	L_2L_1
L_1L_2	L_2L_2

in a similar manner. No prefiltering is performed for these later 2-D decompositions. In this fashion, a L-level decomposition of a 2-D image will produce $4(3L+1)$ subbands. The 2-D reconstruction of a 2-D image is obtained by simply performing all the steps described above for decomposition in the reverse order. The details of DMWT can be found in [27-31].

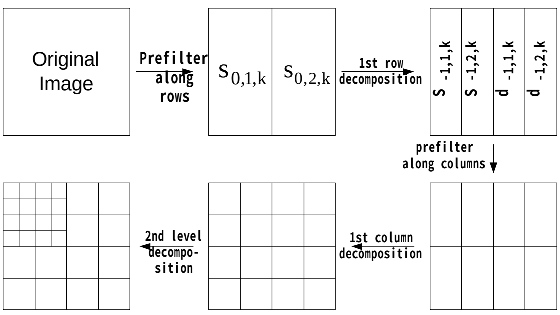


Figure 1. **One level of 2-D multiwavelet decomposition of a 2-D image**

3. Texture analysis with DMWT

3.1. Extraction of features

A 2-D DMWT with depth L typically yields J=4(3*L+1) sub-images. The normalized energy was computed on each sub-image and defined as

$$E = \frac{1}{N}\sum_{i,j} x_{i,j}^{2} \tag{1}$$

The wavelet energy features reflect the distribution of energy along the frequency axis over scale and orientation and have proven to be very powerful for texture characterization. Since most relevant texture information has been removed by iteratively lowpass filtering, the energy of the low resolution sub-images are generally not considered as texture features. An alternative feature for a texture is the entropy

$$Et = \frac{1}{N}\sum_{i,j} x_{i,j}^{2}\log(x_{i,j}^{2}) \tag{2}$$

Note that since both energy and entropy are measures of the dispersion of the wavelet coefficients, they are strongly correlated. And some experimental results showed that the performance of the energy feature was statistically the same as or better than the entropy feature alone and combination of the energy and entropy features[24,26] .

3.2. Classification procedure

Firstly, class data set is constructed by select one image for each texture class. Every texture image in the set is decomposed by DMWT into L levels. The energy feature set is consisted of the energies of the decomposed subimages except of the low-low pass subimages of every texture image. Then to an unknown texture image, the classification procedure is as follows.

1) Decompose the unknown texture image with the DMWT into L levels.

2) Calculate the energy of decomposed subimage except of the low-low pass subimage and construct the feature set. Denote this feature set by

$\mathbf{E} = (E_1, E_2, \ldots, E_j, \ldots, E_J)$, J=12*L.

3) Calculate the distance measure between energy of the unknown texture image and that of the texture i in the feature set by

$$D(i)=\text{distance}(\mathbf{E}\ ,\ \mathbf{E}_i) \tag{3}$$

Four such distance functions are as follows.

Euclidean Distance

$$D_1 = \sum_{j=1}^{J}\left(E_j - E_{i,j}\right)^2 \tag{4}$$

Bayes Distance

$$D_2=(\mathbf{E}-\mathbf{E}_i)^T C_i^{-1}(\mathbf{E}-\mathbf{E}_i)+\ln|C_i| \tag{5}$$

Mahalanobis Distance

$$D_3=(\mathbf{E}-\mathbf{E}_i)^T C_i^{-1}(\mathbf{E}-\mathbf{E}_i) \tag{6}$$

Simplified Mahalanobis Distance

$$D_4=\sum_{j=1}^{J}\frac{\left(E_j - E_{i,j}\right)^2}{c_{i,j}} \tag{7}$$

where $c_{i,j}$ is the covariance of feature j and class i, and C_i is the covariance matrix of the feature set for texture i.

4) Assign the unknown texture to texture i if D(i)<D(j) for all $i \neq j$.

4. Experimental results

The efficiency of DMWT to discriminate between textures was evaluated on a set of 20 textures selected from the Brodatz album, which is a benchmark database for texture analysis[33]. The 20 textures are shown in Figure 2. A database of

1280 image regions are constructed by randomly choosing 64 image regions of size 128×128 from each original texture image.

Various sets of scalar wavelets and multiwavelets are chosen from the current literatures. They are listed as follows.

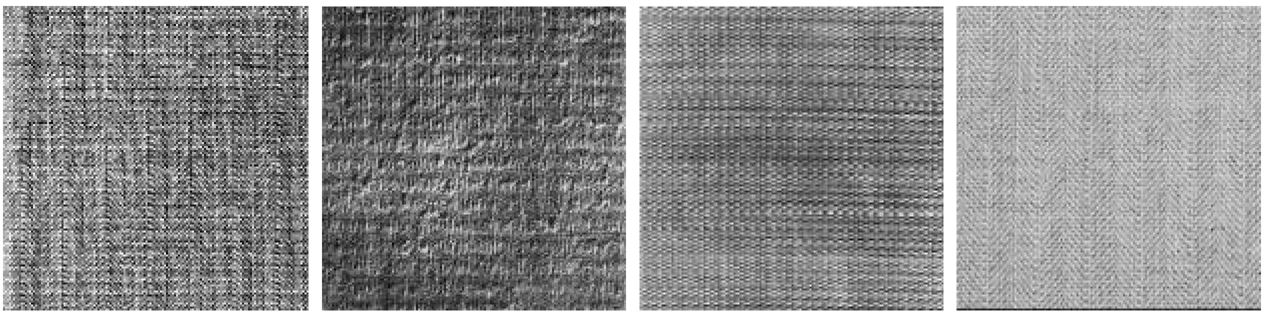
1. 'd4' -- Daubechies' 4 coefficient orthogonal scalar filter bank[32]
2. 'la8' -- Daubechies' 8 coefficient least asymmetric orthogonal scalar filter bank[32]
3. 'ghm'-- GHM orthogonal symmetric multifilter bank, with biorthogonal interpolation prefilter[29]
4. 'cl'-- CL orthogonal symmetric multifilter bank, with biorthogonal interpolation prefilter[28]
5. 'cardbal4' --orthogonal cardinal 4-balanced multifilter bank, with the identity prefilter[30]
6. 'sa4' -- orthogonal symmetric multi-filter bank with orthogonal prefilter[31]

Table 1. **Classification results with the test database**

Wavelet and multiwavelet	Level of decomposition	Distance functions			
		D1	D2	D3	D4
d4	1	0.9446	0.9689	0.9712	0.9707
	2	0.9495	0.9719	0.9768	0.9756
	3	0.9545	0.9801	0.9812	0.9807
la8	1	0.9476	0.9693	0.9719	0.9715
	2	0.9500	0.9731	0.9786	0.9791
	3	0.9567	0.9797	0.9827	0.9831
ghm	1	0.9553	0.9802	0.9822	0.9812
	2	0.9668	0.9967	0.9987	0.9954
cl	1	0.9632	0.9812	0.9824	0.9809
	2	0.9798	0.9921	0.9976	0.9951
cardbal4	1	0.9671	0.9814	0.9819	0.9812
	2	0.9765	0.9932	0.9986	0.9965
sa4	1	0.9667	0.9811	0.9865	0.9847
	2	0.9789	0.9957	0.9985	0.9970

Table 1 indicates the classification results over the test sets using the minimum distance classifier as described in the previous section. The overall classification results were obtained by averaging the results over the 20 different partitions of the data set into sample and test sets. A performance index of 100% indicates a perfect classification.

The first observation to Table 1 is that the DMWT methods always outperform the DWT, which is consistent with our expectation. It can be seen that multiresolution decomposition with two or three levels is superior to with one level only. A comparison of the results between several different distance metrics indicates that Euclidean distance has the worst performance and the other three distance measures perform well with similar performance. Table 1 also indicates that the different multiwavelets give a similar performance.



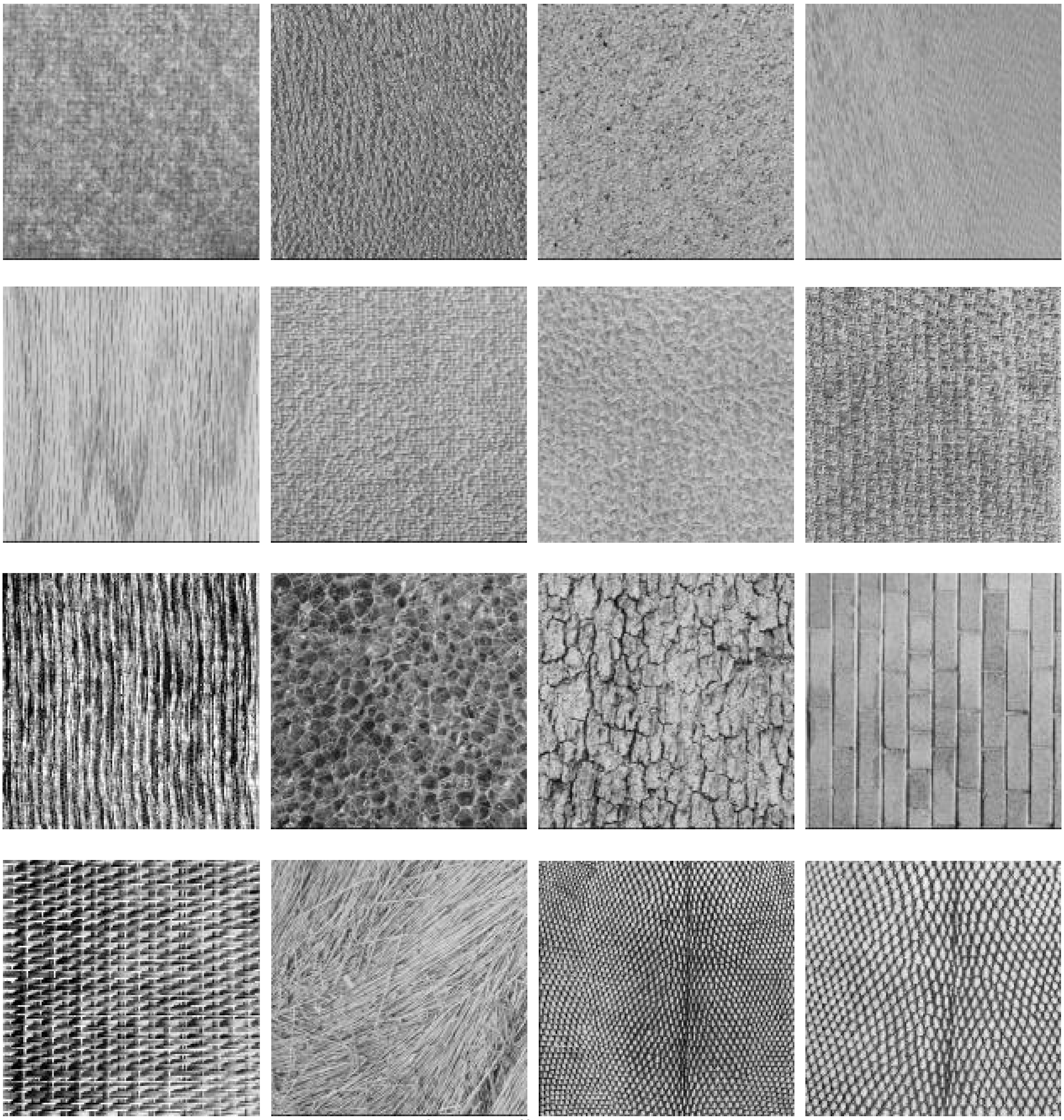


Figure 2. **Samples of the 20 different textures used in the test**

5. Conclusions

We have presented a discrete multiwavelet method for the classification of texture image. Multiwavelets offer the advantages of combining symmetry, orthogonality, and short support, which can not be achieved by scalar two-channel wavelet systems at the same time. 20 different types of textures were decomposed using different DMWT and features were computed on the decomposed sub-images. The minimum distance classifier using several different metrics was used to classify the textures. The experimental results demonstrate that DMWT have the efficiency to discriminate different textures with a near perfect classification accuracy.

References

[1] R. M. Haralick, K. Shanmugam and I. Dinstein, "Textural features for image classification", *IEEE Transactions on System, Man and Cybernetics* **3** (1973) 610-621.

[2] J. S. Weska, C. R. Dyer and A. Rosenfield, "Comparative study of texture measures for terrain classification", *IEEE Transactions on System, Man and Cybernetics* **26** (1986) 118-125.

[3] R. L. Kashyap and A. Khotanzad, "A model-based method for rotation invariant texture classification", *IEEE Transactions on Pattern Analysis and Machine Intelligence* **8** (1986) 472-481.

[4] R. L. Kashyap and R. Chellappa, "Texture synthesis using 2-D noncausal autoregressive models", *IEEE Transactions on Acoustics Speech and Signal Processing* **33** (1985) 194-203.

[5] F. S. Cohen, Z. Fan and M. A. Patel. "Classification of rotated and scaled textured images using Gaussian Markov random filed model", *IEEE Transactions on Pattern Analysis and Machine Intelligence* **13** (1991) 192-202.

[6] H. Derin, "Segmentation of textured image using Gibbs random fields", *Computer Vision, Graphics and Image Processing* **35** (1986) 72-98.

[7] H. Derin and H. Elliot, "Modeling and segmentation of noisy and textured images using Gibbs random fields", *IEEE Transactions on Pattern Analysis and Machine Intelligence* **9** (1987) 39-55.

[8] S. Lakshman and H. Derin, "Simultaneous parameter estimation and segmentation of Gibbs random fields using simulated annealing", *IEEE Transactions on Pattern Analysis and Machine Intelligence* **11** (1989) 799-813.

[9] K. L. Laws, "Texture image segmentation", Ph.D. dissertation, Image Processing Inst. Univ. Of Southern California, 1980.

[10] J. Y. Hsiao and A. A. Sawchuk, "Supervised textured image segmentation using feature smoothing and probabilistic relaxation techniques", *IEEE Transactions on Pattern Analysis and Machine Intelligence* **11** (1989) 1279-1292.

[11] P. Cohen, C. T. Ledinh and V. Lacasse, "Classification of natural textures by means of two-dimensional orthogonal masks" *IEEE Transactions on Acoustics Speech and Signal Processing* **37 (**1989) 125-128.

[12] S. Marceljia, "Mathematical descriptions of the responses of simple cortical cells", *Journal of Optical Society American A* **70** (1980) 1297-1300.

[13] B. Julesz, "A theory of preattentive texture description based on first-order statistics of textons", *Biological Cybernetics* **41** (1981) 131-138.

[14] R. De Valios and K. De Valois. *Spatial vision*, New York, Oxford, 1988

[15] M. R. Turner, "Texture discrimination by Gabor functions", *Biological Cybernetics* **55** (1986) 71-82.

[16] M. Porat and Y. Y. Zeevi, "Localized texture processing in Vision: Analysis and synthesis in Gaborian space", *IEEE Transactions on Biomedical Engineering* **36** (1989) 115-129.

[17] A. K. Jian and F. Farrokhnia, "Unsupervised texture segmentation using Gabor filters", *Pattern Recognition* **24** (1991) 1167-1186.

[18] S. G. Mallat, "Multiresolution approximations and wavelet orthogonal bases of $L^2(R)$", *Transactions on American Mathematics Society* **315** (1989) 69-87.

[19] S. G. Mallat, "A theory of multiresolution signal decomposition: The wavelet representation", *IEEE Transactions on Pattern Analysis and Machine Intelligence* **11 (**1989) 674-693.

[20] S. Mallat, " Wavelets for a vision", *Proceedings of the IEEE* **84 (**1996) 604-614.

[21] T. Chang, K. Tianhrong and C. C. Jay, "Texture analysis and classification with tree-structured wavelet transform", *IEEE Transactions on Image Processing* **2** (1993) 429-441.

[22] M. Uner, "Texture classification and segmentation using wavelet frames", *IEEE Transactions on Image Processing* **4** (1995) 1549-1560.

[23] J. Y. Chen and A. Kundu, "Rotation and gray scale transform invariant texture identification using wavelet decomposition and Hidden Markov model", *IEEE Transactions on Pattern Analysis and Machine Intelligence* **16** (1994) 208-214.

[24] A. Laine and J. Fan, "Texture classification by wavelet packet signatures", *IEEE Transactions on Pattern Analysis and Machine Intelligence* **15** (1993) 1186-1191.

[25] A. Laine and J. Fan, "Frame representations for texture segmentation", *IEEE Transactions on Image Processing* **5** (1996) 771-780.

[26] Y. Chitre and A. P. Dhawan, "M-band wavelet discrimination of natural textures", *Pattern Recognition* **32 (**1999) 773-789.

[27] J. Y. Tham, L.X. Shen, S. L. Lee, et al, "A general approach for analysis and application of discrete multiwavelet transforms", *IEEE Transactions on Signal Processing* **48** (2000) 457-464.

[28] C.K. Chui and J.A. Lian, "A study of orthogonal multiwavelets", CAT Report 351,Texas A&M University, 1995.

[29] V. Strela, N. Heller, G. Strang, et al., "The application of multiwavelet filters banks to signal and image processing", *IEEE Transactions on Image Processing* **8** (1999) 548-563.

[30] I. Selesnick, "Interpolating multiwavelet bases and the sampling theorem", *IEEE Transactions on Signal Processing* **47** (1999) 1615-1621.

[31] L. X. Shen, H. H. Tan, and J. Y. Tham, "Symmetric-antisymmetric orthogonal multiwavelets and related scalar wavelets", *Applied and computational Harmonic Analysis* **8** (2000) 258-279.

[32] I. Daubechies, "Ten lectures on wavelets", SIAM, Technical Reports/CBMS-NSF Lecture Notes vol.61, 1992.

[33] P. Brodatz, *Textures-A photographic album for artists and designers*, Dover, New York, 1965.