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Classification of Texture Images using Multiresolution Transform

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Abstract: This paper proposed a scheme to identify appropriate wavelet basis function using multiresolution approach based on pyramidal wavelet transform (to extract relevant information from the texture images) for classification of the textures in various classes. In this work, for characterizing texture images at multiple scales, we have considered various wavelet basis functions such as Haar, Daubechies, Coiflet, Symlet, biorthogonal and reverse biorthogonal wavelets. They differ with each other in the formation and reconstruction. The Discrete wavelet transform is used for three level decomposition of the texture image into sub-bands. The first order statistical features are then derived from original texture image and subsequent sub-images. For classifying unknown image data to corresponding classes, minimum distance classifier is used. Experiments were carried out to compare the performance of various wavelet basis functions, which identify Haar wavelet as the best wavelet basis functions for texture classification.

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Keywords: Texture classification, Multiresolution transform

I. INTRODUCTION

Textures are important visual cues, which possess various important characteristic for the analysis of different types of images. The different regions of an image are identified based on its textural characteristics by using an image processing technique known as texture classification. Texture classification plays an important role in many applications range from industrial automation and biomedical image processing to crop classification and Remote sensing applications. Texture classification process is a way of assigning a given texture region to one of the known set of the texture classes. Texture classification can be either supervised or unsupervised. If the class information is known or defined through the use of training textures, then it is referred as supervised texture classification. Whereas, the number of classes have not been defined a priori, then it is referred as unsupervised texture classification. In this work, supervised texture classification is considered.

A wide variety of texture analysis approaches have been investigated over the past three decades, the problem of texture analysis remains a challenging area of research. It is difficult to analyse a wide variety of both natural and artificial textures using a single method [1], as the natural texture in real world are often not uniform, due to changes in orientation, scale and difficulty in determining appropriate resolutions for texture analysis. Texture analysis techniques can be loosely divided for visual inspection into four categories: statistical, structural, model based and signal processing methods [2]. Statistical methods analyse the spatial distribution of gray values, by computing local features at each point in the image. Some statistical methods used are co-occurrence matrix features [3] and autocorrelation function [4]. In structural methods, textures are considered to be composed of texture primitives, which appear in quasi-periodic spatial arrangements. Tomita *et al* introduce a structural analysis system for describing natural textures [5]. Model based methods such as Markov Random field [6,7] and fractal representation [8] are based on the construction of an image model that can be used to describe texture and also to synthesize it, such as Autoregressive model [9], Gaussian Markov Random Field model [10] and Gibbs model. Signal processing methods analyse the frequency content of the image either in spatial domain [11] or in frequency domain [12].

A common weakness of all these methods is that, the textures are analysed on only a single scale; this limitation can be overcome by the use of multiresolution analysis method. Multiresolution approach is justified by the studies of human visual system, which tells that certain cells in the visual cortex respond only to particular spatial frequencies and orientations [13]. The use of filter bank instead of single filter has been proposed, giving rise to several multi-channel texture analysis systems such as Gabor filters and wavelet transforms [14].

The multichannel Gabor filter has characteristics which allow to analyse textured images with special orientation and frequency in both spatial and spatial frequency domains [15,

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16]. Gabor filter based methods were successfully applied to texture segmentation [17], and fabric defect inspection [18, 19]. But these methods have disadvantages of high computational complexity. Also, the output of Gabor filter is not mutually orthogonal, this disadvantage may result in a significant correlation between texture features. Recently, wavelet transforms have been an alternative for the extraction of textural features. The 2D wavelet transform was defined in [20], and the use of wavelets for texture analysis was pioneered by Mallat [21]. Wavelet transform provides a precise and unifying framework for the analysis and characterization of a signal at different scales [22]. Another advantage of wavelet transform over Gabor filters is that the lowpass and highpass filters used in the wavelet transform remain the same between two consecutive scales while the Gabor approach requires filters of different parameters at different scales [23].

II. DISCRETE WAVELET TRANSFORM

According to the psychovisual studies, human visual system processes an image in a multiscale manner. The multiresolution representation gives a hierarchical framework for analysing the information content of images at various resolutions, to get the details of different physical structures of the image (scene). These details analysed at different resolutions are regrouped into a pyramidal structure called a pyramidal transform. To achieve this, many types of techniques were developed, including wavelets, Gaussian, and Laplacian pyramids [24]. The use of Wavelet Transform (WT) as a framework of multiresolution signal decomposition for texture description was first suggested by Mallat [25]. The WT can be designed as a pyramid or a tree structure. However, pyramidal algorithm has down sampling, which in turn saves a large amount of computational time. Earlier, in the field of texture analysis, wavelet transform has been applied with great success. Discrete wavelet transform (DWT) decomposition (pyramid structured) can be performed by passing the original image first through the low-pass and high-pass decomposition filters to generate four lower resolution components: one low–low (LL1) sub-image, which is the approximation of the original image and is also called smooth image, and three detailed sub-images, which represent the horizontal (LH1), vertical (HL1), and diagonal directions (HH1) of the original image. The sub-band LL1 alone is further decomposed to obtain (LL2, LH2, HL2 and HH2) the next coarse level of discrete wavelet coefficients, similarly, further decomposition of LL2 is done to obtained the next coarse level. This decomposition process continues until some fine scale is reached [26]. Figure 1 shows the 3-level wavelet decompositions.

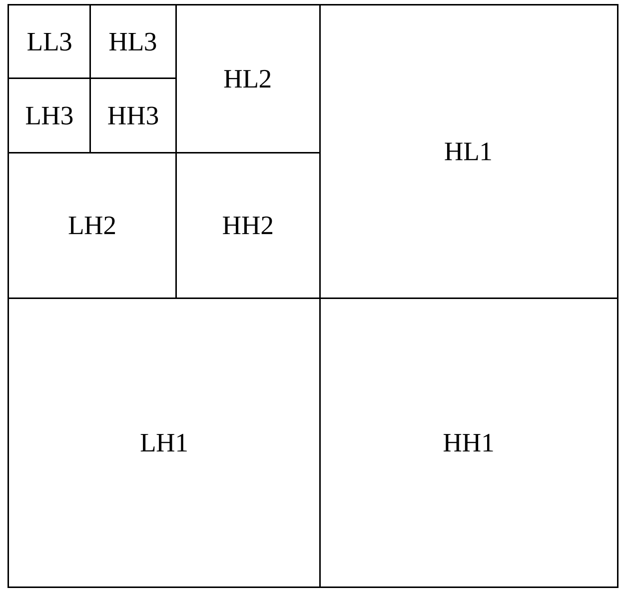

Figure1 Three level image decomposition using DWT

Wavelet decomposition of images using DWT provides an alternative to the Discrete Fourier Transform (DFT) for signal analysis resulting in signal decomposition into two-dimensional functions of time and scale. Also, DWT has multi-resolution time-scale analysis ability, which is an advantage over DFT. As, in wavelet transform, scaling property is used to create different lengths of wavelet functions by compressing or dilating the mother wavelet, in order to capture different frequency resolutions in the entire sample data. Whereas, translation property is used to translate or move every generated wavelet function over the entire sample data, in order to capture the spatial localization information. These two important properties have actually explained the capability of multiresolution analysis in wavelet transform.

III. TEXTURE TRAINING AND CLASSIFICATION

Knowledge about the class distributions is compiled from the training set in a training stage. The classifier then uses this knowledge by transforming it into a classification rule (decision rule). The classifier is a system that takes a new sample of unknown classification and assigns it as one of the known pattern classes according to the decision rule.

A. Texture training

In texture training phase, three level decomposition of input texture image is achieved using Discrete Wavelet Transform (DWT). Then, the first order statistical features such as mean, variance, entropy and energy were calculated

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from original image as well as from approximation and the detail sub-images of every level of decomposition using the formulas, using the formulas,

$$Mean = \sum_{g=0}^{G-1} gH(g) \quad (1)$$

$$Variance = \sum_{g=0}^{G-1} (g-\mu)^2 H(g) \quad (2)$$

$$Entropy = -\sum_{g=0}^{G-1} H(g)\log_2(H(g)) \quad (3)$$

$$Energy = \sum_{g=0}^{G-1} H^2(g) \quad (4)$$

where,

g is the gray level value (i.e. $g = 0,1, \dots, G-1$),
G is the highest gray level value,
μ is the mean value of the image,
$H(g)$ is the probability of certain pixel occurring in an image (i.e. $H(g) = \frac{n_g}{N}$, $n_g$is the of pixels of value g in an image, and N is the number of all pixels in an image

Thus, the resulting four set of feature vectors (of size 13×1) is stored in the features library which is further used for texture classification phase.

B. Texture classification:

In this phase, the test sample texture image X is decomposed using DWT and a similar set of wavelet statistical features are extracted and then compared with the corresponding feature values of all the classes stored in the features library using a distance vector formula as given in (5),

$$D(M) = \sqrt{\sum_{j=1}^{N} [f_j(X) - f_j(M)]^2} \quad (5)$$

where,

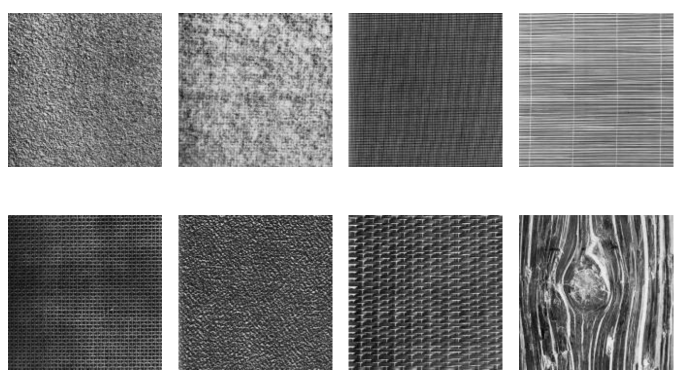
N is the number of features in feature vector,
$f_j(X)$ represents the jth texture feature of the test sample X, and
$f_j(M)$ represents the jth feature of the Mth texture class in the feature library.

Then, the unknown texture is classified as Mth texture, if the distance $D(M)$ is minimum among all textures, available in the library

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

Performance of the proposed texture classification algorithm is analysed using sixteen different textured images each of size 512×512 (as shown in Figure 2), out of which, twelve natural textural images are taken from Brodatz album [27] and the remaining four synthetic texture images are self generated synthetic texture images. Each texture image is subdivided into 16 equal sized sub-images of size 128 × 128. Among these sixteen texture sample images, eight randomly chosen sub-images (from each texture class) have been chosen to train the classification algorithm and the remaining eight sub-images (from each texture class) have been presented to the algorithm for classification. Thus, a set of 256 samples have been used for experimentation.

Dyadic wavelet decomposition of every input texture image is achieved, using various wavelet basis functions such as Haar, Daubechies (db2, db4, db8 and db10), Biorthogonal (bior3.3, bior4.4 and bior5.5), Symlet (sym4), Coiflet (coif4), and Reverse biorthogonal wavelets (rbior2.2). Each texture image is decomposed into various sub-bands with three level wavelet decomposition. Figure 3 shows three level sub-band decomposition using Haar wavelet of natural texture images D101 from Brodatz texture album. Four statistical features such as mean, variance, energy and entropy were computed for original and each sub-band image. Thus, four feature vectors of size 13 × 1 is obtained for three levels of wavelet decomposition. The performance of each feature was tested independently. Here we have tested use of various features as well as different basis functions for texture classification. Classification efficiency of this proposed algorithm is tested using minimum distance classifier along with various wavelet basis functions. Table 1 shows the percentage classification results of the database image classes using various wavelet basis functions. The highest mean success rate (91.66%) is obtained using Haar wavelet which is higher than the classification rate obtained for other wavelets.



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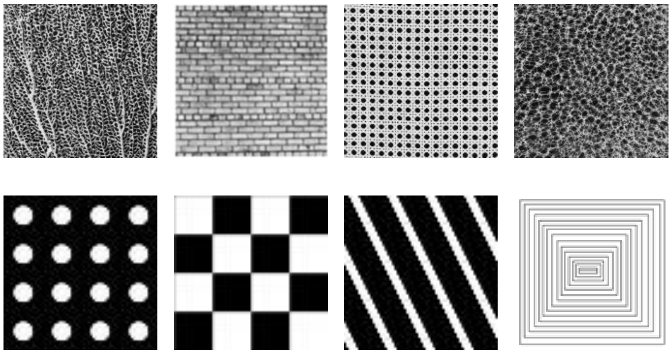
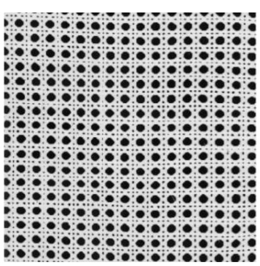


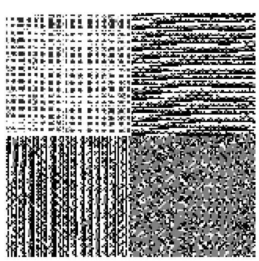
Figure 2 Sixteen textured images used in our experiment, Row 1: D4, D19, D21, D49, Row 2: D52, D57, D65, D72, Row 3: D87, D95, D101, D111, Row 4: disc-lattice, checkerboard, square-grating, S22.

V. CONCLUSIONS

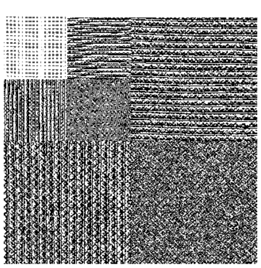
Texture classification problem is investigated using multiresolution features computed through dyadic wavelet decomposition. For classifying unknown image data to corresponding classes, minimum distance classifier is used, which minimize the distance between the image data and the class in multi-feature space. The distance is defined as an index of similarity so that the minimum distance is identical to the maximum similarity. Experiments were conducted on the above database, to compare the performance of various wavelet basis functions. Among it, Haar wavelet is identified as the best wavelet basis functions for texture classification. The proposed scheme using multiresolution approach is computationally efficient.



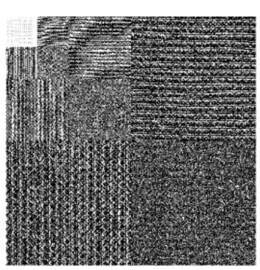
(a)



(b)



(c)



(d)

Figure 3 Three level wavelet decomposition using Haar wavelet (a) Texture image D101, (b) Output of DWT (first level decomposition), (c) Output of DWT (second level decomposition) and (d) Output of DWT (third level decomposition).

Table 1 Texture classification results using various wavelet basis functions.

Wavelet	Mean success rate
Haar	91.66%
db2	87.24%
db4	85.49%
db8	84.22%
db10	78.55%
bior3.3	78.30%
bior4.4	84.19%
bior5.5	82.16%
sym4	83.91%
coif4	81.19%
rbio2.2	78.69%

VI. REFERENCES

[1] A. Busch and W. Boles, “Texture Classification Using multiple Wavelet Analysis,” Digital Image Computing Techniques and Applications (DICTA2002), PP. 1-5, 2002.
[2] M. Tuceyran and A. K. Jain, “Texture analysis,” Handbook of Pattern Recognition and Computer Vision (2nd edition), pp. 207-248, 1998.
[3] R. M. Haralick, K. Shanmugam and I. Dinstein, “Texture features for image classification,” IEEE Transactions on System Man Cybernetic, vol.8, no.6, pp. 610-621,1973.
[4] H. Lin, L. Wang and S. Yang, “Extracting Periodicity of a Regular Texture-Based on Autocorrelation Functions,” Pattern Recognition Letters, vol.18, no.5, pp. 433-443, 1997.
[5] F. Tomita, Y. Shirai and S. Tsuji, “Description of textures by a structural analysis,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 4, No. 2, pp 183-191,1982.
[6] S. Li, “Markov Random Field Modeling in Computer Vision,” New York: Springer-Verlag, 2001.
[7] B. Manjunath, R. Chellappa, “Unsupervised texture segmentation using Markov random fields,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.13, pp.478-482.
[8] B. Mandelbrot, “The Fractal Geometry of Nature,” W.H. Freeman, San Francisco, 1983.
[9] S. Lu and H. Xu, “Textured image segmentation using autoregressive model and artificial neural network,” Pattern Recognition, Vol. 28, No. 12, pp 1807-1817, 1995.
[10] F. Cohen, Z. G. Fan, and M. A. Patel, “Classification of Rotated and Scaled Textured Images Using Gaussian Markov Random Field Models,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 13, No. 2, pp 192-202, 1991.
[11] M. Unser, “Local linear transforms for texture measurements,” signal Processing, vol.11, no.1, pp. 61-79, 1986.
[12] R.Bajcsy and L.Lieberman, Texture gradient as a depth cue, Computer Graphics and Image Processing, 5(1), 1976, 52-67.

[13] D. pollen and S. Ronner, "Visual Cortical Neurons as Localized Spatial Frequency Filters," IEEE Transactions on Systems, Man, and Cybernetics, Vol. 13, pp 907-916,1983.
[14] M. Unser, M. Eden, "Multiresolution feature extraction and selection for texture segmentation," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 11, No. 7, pp 717-728, 1991.
[15] M. Rallo, M. Milan, J.Escofet and R.Navarrao, "Wavelet based techniques for textile inspection," Wavelets and applications, Lecture Notes Vol.1, pp.435-466, 2002.
[16] C. Chan and K. Pang, "Fabric defect detection by Fourier analysis," IEEE Transactions on Industry Applications, Vol. 36, pp.1267-1276, 2000.
[17] D. Tsai, S. Wua and M. Chenb, "Optimal Gabor filter design for texture segmentation using stochastic optimization," Image and Vision Computing, Vol.19, pp. 299-316, 2001.
[18] K. Mak and P. Peng, "An automated inspection system for textile fabrics based on Gabor filters," Robotics and Computer-Integrated Manufacturing, Vol.24, no.3, pp.359-369, 2008.
[19] A. Kumar and G. Pang, "Defect detection in textured materials using Gabor filters," IEEE Transaction on Industry Application,Vol.38, no.2, pp.425-440, 2002.
[20] P. Lemarie and Y. Meyer, "Ondelettes et bases Hilbertiennes," Revista Matematica lbero Americana, vol.2, 1986.
[21] S. Mallat, "A theory for multiresolution signal decomposition: The Wavelet representation," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 11, No. 7, pp 674-693, 1989.
[22] M. Unser, "Texture classification and segmentation using wavelet frames," IEEE Transactions on Image Processing, vol. 4, no. 11, pp. 1549–1560, 1995.
[23] T. Chang and C. Kuo, "Texture analysis and classification with tree-structured wavelet transform," IEEE Trans. Image Processing, vol. 2, no. 4, pp. 429–441, 1993.
[24] C. Mandriota, M. Nitti, N. Ancona, E. Stella, A. Distante, " Filter-based feature selection for rail defect detection," Machine Vision and Applications, vol.1, pp. 179–185, 2004.
[25] S. Mallat, "A theory for multiresolution signal decomposition: The Wavelet representation," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 11, No. 7, pp 674-693, 1989.
[26] S. Arivazhagan, L. Ganesan, Texture classification using wavelet transform, Pattern Recogn. Lett. 24 (2003) 1513–1521.
[27] P. Brodatz, Textures: A Photographic Album for Artists and Designers. New York: Dover Publications Inc., 1966.