International Journal of Soft Computing 3 (4): 293-296, 2008
ISSN: 1816-9503

Texture Classification Using Wavelet Based Laws Energy Measure

[1]S. Suresh Kumar and [2]L. Ganesan
[1]Department of Information Technology, N.I College of Engineering,
Kumaracoil, Tamilnadu, India
[2]Department of Computer Science and Engineering,
A.C. College of Engineering and Technology, Karaikudi, Tamilnadu, India

Abstract: Texture analysis plays a vital role in many tasks, ranging from remote sensing to medical imaging and query by content in large image data bases. The main difficulty of texture analysis in the past was the lack of adequate tools to extract the features for classification and segmentation. Although there are many techniques available they are not capable of classifying the universal textures because of their inherent limitations. In this study, a novel approach of feature extraction by combining the texture features at multiple scales based on block by block comparison of wavelet based Laws features. The performance of this classification is superior to traditional techniques. The efficiency of the proposed method is found to be better.

Key words: Texture, wavelet, laws, wavelet laws energy measure, feature extraction, texture classification

INTRODUCTION

Texture analysis is important in many applications of computer image analysis for classi?cation, detection, or segmentation of images based on local spatial patterns of intensity or color. Essentially, textures are replications, symmetries and combinations of various basic patterns or local image functions, usually with some random variation. There are many characteristics and local measures of such patterns which can be employed, depending on the application and textured imagery which must be discriminated. Important applications include industrial and biomedical surface inspection, for example of defects or disease and ground classification and segmentation of satellite or aerial imagery (Besag, 1974; Eom and Kashyap, 1990; Chellappa and Chatterjee, 1985; Kashyap and Khotanzad, 1986; Mao and Jain, 1992; Todd and Du Buf, 1993). Analysis of textures requires the identification of proper attributes or features that differentiates the textures in the image. The features are assumed to be uniform within the regions containing the same textures. A good texture feature must allow us to determine both similarities and dissimilarities in intensity variation patterns present in different region. It is well known that texture of regions cannot be characterized by intensity statistics alone (Julesz *et al.*, 1978). The features have to represent statistical as well as structural characteristics of the texture using any mathematical measure or rule. Some of the most popular texture feature extraction methods are based on the gray level co-occurrence statistics (Gotlieb and Kreysig, 1990; Haralick, 1979), texton gradients, edge gradients (Marr and Hildreth, 1980), filtering methods like morphological filters, Fourier filters, random field models (Chellappa and Chatterjee, 1985), Gabor filters (Fogel and Sagi, 1989), Wavelet packets approaches (Chang and Kuo, 1993; Laine and Fan, 1993), wavelet frames (Unser, 1995), wavelets like Gaussian (Cheriet *et al.*, 1998; Charalampidis and Kasparis, 2002), fractal dimension (Kapalan, 1999) and local binary patterns (Ojala *et al.*, 2002). Each method is superior in discriminating its texture characteristics and there is no universal method available for all textures. Randen and Husoy (1999) observed that the particular texture classification technique is restricted to a limited real texture. Arivazhaga and Ganesan (2003) proposed wavelet co-occurrence features (WCF). Every texture has a band of filter banks for extracting the features becomes a non-trivial task.

In this study, the DWT is applied on a set of texture images and Laws energy measure features are extracted from the approximation and the detail regions of DWT decomposed images, at different scales. The various features are applied for texture classification, in order to improve the success of classification.

Corresponding Author: S. Suresh Kumar, Department of Information Technology, N.I College of Engineering, Kumaracoil, Tamilnadu, India

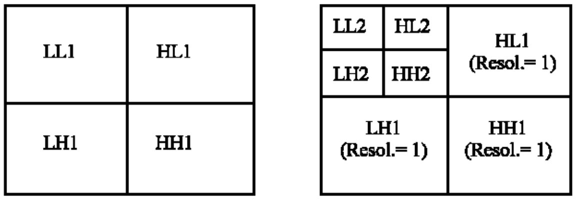

Fig. 1: Image decomposition (a) One Level (b) Two level

DISCRETE WAVELET TRANSFORM

The image is actually decomposed i.e., divided into four sub-bands and critically sub-sampled by applying DWT as shown in Fig. 1a. These sub-bands labeled LH1, HL1 and HH1 represent the finest scale wavelet coefficients i.e., detail images while the sub-band LL1 corresponds to coarse level coefficients i.e., approximation image.

To obtain the next coarse level of wavelet coefficients, the sub-band LL1 alone is further decomposed and critically sampled. This results in a two-level wavelet decomposition as shown in Fig. 1b. Similarly, to obtain further decomposition, LL2 will be used. This process continues until some final scale is reached. The values or transformed coefficients in approximation and detail images (sub-band images) are the essential features, which are shown here as useful for texture analysis and discrimination. As micro-textures or macro-textures have non-uniform gray level variations, they are statistically characterized by the features in approximation and detail images. In other words, the values in the sub-band images or their combination or the derived features from these bands uniquely characterize a texture. The features obtained from these wavelet transformed images are shown to be used for texture analysis.

LAWS METHOD

Laws texture measures have been used for many diverse applications. The measure seeks to classify each pixel of an image by transforming each pixel into a texture energy plane. The transform is fast, requiring only convolutions and simple moving window techniques. Laws (1980) developed a set of two-dimensional masks that are derived from five simple one-dimensional filters,

L5 (1, 4, 6, 4, 1)-Level Detection.
E5 (-1, -2, 0, 2, 1)-Edge Detection.
S5 (-1, 0, 2, 0, -1)-Spot Detection.
W5 (-1, 2, 0, -2, 1)-Wave Detection.
R5 (1, -4, 6, -4, 1)-Ripple Detection.

The (1×5) zero sum vectors form the basis for the larger vector sets. These (1×5) vectors with each other to provide a set of symmetric center-weighted mask were convolved by him. Each of these 1-D arrays is associated with an underlying microstructure which is the level detection, edge detection, spot detection, wave detection and ripple detection, respectively. These were convolved in turn with transposes of each other to give a set of 25 different two-dimensional convolution masks. As an example, the L5E5 mask is found by convolving a vertical L5 mask with a horizontal E5 mask. From the one-dimensional masks above, 25 two dimensional convolution masks can be generated, 24 of them are zero sums and L5L5 is a non-zero summed mask. Basically, this approach to texture characterization consists of two steps (Ching-Fen *et al*., 1998). The first step involves convolving the whole image by a zero sum mask. The 2D convolution of the image I (i, j) and mask A (i, j) With size $(2a+1)$ by $(2a+1)$ is given by the relation:

$$F(i,j) = A(i,j) * I(i,j) \tag{1}$$

$$= \sum_{p=-a}^{a} \sum_{l=-a}^{a} A(p,l) I(i+p, j+l) \tag{2}$$

For i =0, 1…N-1 and j=0, 1…N-1, where * denotes 2D convolution.

The second step involves determining the difference between the convolved image F (i, j) and the real image I (i, j). For the zero sum mask, the local texture measures are determined as statistical variances of the filtered image by computing the squared signal values in the filtered image. From the computational efficiency point of view, the sample mean deviation of the filtered image, Called ABSAVE, is introduced as the most useful statistics by Laws. The ABSAVE E (i, j) is defined as the mean deviation within a $(2n+1)$ by $(2n+1)$ window at point (i, j) and is given by

$$E(i,j) = \frac{1}{(2n+1)^2} \sum_{p=i-n}^{i+n} \sum_{l=j-n}^{j+n} |F(p,l) - M(i,j)| \tag{3}$$

Where the mean is given by

$$M(i,j) = \frac{1}{(2n+1)^2} \sum_{p=i-n}^{i+n} \sum_{l=j-n}^{j+n} F(p,l) \tag{4}$$

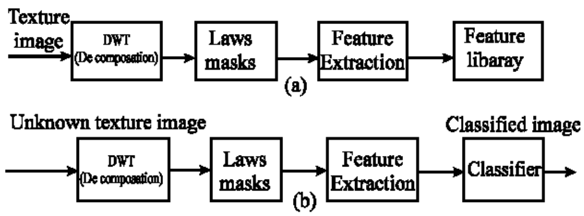

Fig. 2: (a) Texture training (b) Texture classification

the mean is zero over a large window, the ABSAVE E (i, j) becomes

$$E(i, j) = \frac{1}{(2n+1)^2} \sum_{p=i-n}^{i+n} \sum_{l=j-n}^{j+n} |F(p, l)| \qquad (5)$$

Which Laws called the texture energy measure, which is used in this test as a texture feature. The similar features are combined and normalized.

FEATURE EXTRACTION AND TEXTURE CLASSIFICATION

The steps involved in texture training and texture classification are shown in Fig. 2 (a) and (b), respectively.

Texture training: In the texture training, the known texture images are decomposed (i.e., LL1, LH1, HL1 and HH1) using Wavelet Transformation DWT. The texture energy measures are calculated and stored in the features library which is further used in the texture classification phase after the convolution by the Laws masks of approximation and details sub-bands.

Texture classification: Here, the unknown texture is decomposed using DWT and Laws texture energy measures are extracted and compared with the corresponding feature vector stored in the features library using a distance measure, given in Eq. 6.

$$D(i) = \sum_{j=1}^{\text{no of feature}} \text{abs}[fj(x) - fj(i)] \qquad (6)$$

where, f_j (x) represents the features of unknown texture while f_j (i) represents the features of known ith texture in the library. Then, the unknown texture is classified as ith texture, if the distance D (i) is minimum among all texture, available in the library.

RESULTS

The proposed approaches are conducted with images of size 512×512, stitched from Brodatz (1966) textured publicly available album. Initially the wavelet transform is applied for the decomposition of four sub-bands (LL1, HL1, LH1, HH1) of size 256 × 256. Now the decomposed images are convoluted with the Laws masks. Then the texture energy measure features are extracted and stored in a feature database. The same procedure is repeated for

Table 1: Correct classification

Image	DB4	DB7	DB10
D001	100.0	99.9	99.9
D003	87.6	77.7	69.8
D004	87.3	76.8	68.0
D014	100.0	100.0	100.0
D016	84.8	79.3	73.6
D020	94.1	89.7	84.4
D026	91.8	87.0	80.5
D031	91.1	85.6	80.9
D036	93.0	85.2	81.8
D041	83.2	85.4	74.1
D043	88.8	87.6	87.3
D046	91.0	97.7	96.9
D047	95.3	87.8	83.0
D048	99.2	99.4	100.0
D051	92.3	87.6	83.2
D074	88.6	86.6	79.3
D075	93.7	90.5	84.3
D076	92.4	83.5	73.6
D086	100.0	100.0	100.0
D088	85.3	80.1	76.0
D101	99.1	98.8	99.9
D103	95.9	91.0	84.9
D104	98.7	99.4	99.6
D105	95.6	89.7	84.4
D109	85.8	83.1	76.9
Average	92.584	89.176	84.892

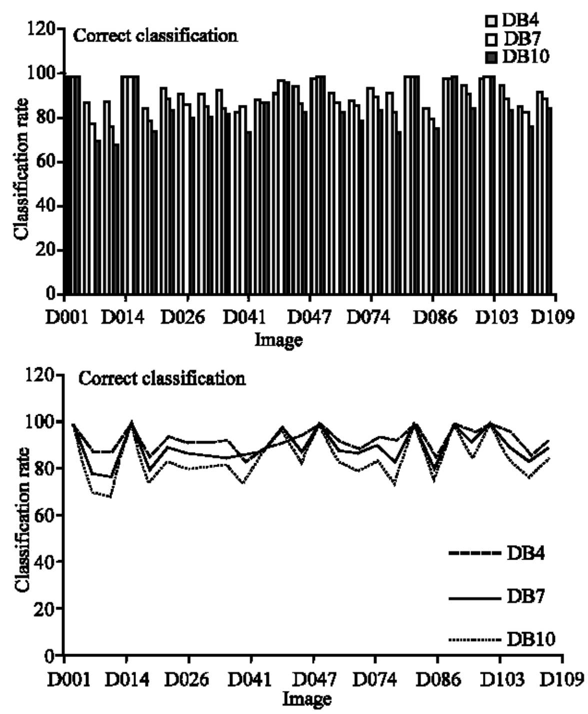

Fig. 3a and b: Correct classification-graphical analysis all the next level approximation images. Daubechies and Haar wavelets are used for decomposition. We observe that Haar wavelets are not feasible for the proposed method.

Instance of Texture energy measure features extraction and classification is done with Daubechies wavelets transform family 1-10. The correct classifications of Daubechies wavelets DB4, DB7, DB10 based Laws features are shown in the Table 1 and Fig. 3. They have achieved a better rate of classification than other traditional methods. It is observed that the mean classification rates are 92.584, 89.176, 84.892, respectively.

CONCLUSION

In this study, the novel method of combining the distribution of spatial and signal processing responses to extract texture feature is presented for the classification. It has tested with Daubechies wavelets transform family 1-10. The good result has obtained from DB4, DB7 and DB10. The idea behind this proposed method is to exhibit the usage of wavelet based Laws energy measure for texture classification perceived better results. Daubechies 4 wavelet based laws features achieved a higher rate of classification. Also the proposed method has high classification efficiency and the computation time is less comparable with other methods.

REFERENCES

Arivazhagan, S. and L. Ganesan, 2003. Texture classification using Wavelet transform. Pattern Recog. Lett., 24: 3197-3203.

Besag, J., 1974. Spatial interaction and the statistical analysis of lattice Systems. J.R. Statist. Soc. B. (Methodological), 48: 192-226.

Brodatz, P., 1966. Textures: A Photographic Album for Artists and Designers. Dover, New York.

Chang, T. and C-CJ. Kuo, 1993. Texture analysis and classification with tree-structure wavelet transform. IEEE. Trans. Image Proc., 2 (4): 429-441.

Charalampidis, D. and T. Kasparis, 2002. Wavelet-based rotational invariant roughness features for texture classification and segmentation. IEEE. Trans. Image Proc., 11 (8): 825-837.

Chellappa, R. and S. Chatterjee, 1985. Classification of textures using gaussian markov random fields. IEEE. Trans. Acoust. Speech Signal Process. ASS, 33 (4): 959-963.

Cheriet, M. *et al.*, 1998. A recursive thresholding technique for image segmentation. IEEE. Trans. Image Proc., 7 (6): 918-921.

Ching-Fen, J. and M.L. Chen, 1998. Segmentation of ultrasonic ovarian images by texture features. IEEE. Conf. Med. Biol. Soc., 20: 2.

Eom, K.B. and R.L. Kashyap, 1990. Robust image models for image restoration and texture edge detection. IEEE. Trans. Sys. Man Cybern., 20: 81-93.

Fogel, I. and D. Sagi, 1989. Gabor filters as texture discriminator. Biol. Cybern., 61: 103-113.

Gotllieb, C.C. and H.E. Kreysig, 1990. Texture descriptors based on co-occurrence matrices. Comput. Vis. Graph. Image Proc., 51: 70-86.

Haralick, R.M., 1979. Statistical and structural approaches to texture. Proc. IEEE., 67: 786-804.

Julesz, B. *et al.*, 1978. Visual discrimination of texture with identical third-order statistics. Biol. Cyben., 31: 137-140.

Kaplan, L.M., 1999. Extended fractal analysis for texture classification and segmentation. IEEE. Trans. Image Process, 8 (11): 1572-1585.

Kashyap, R.L. and R. Chellappa, 1983. Estimation and choice of neighbors in spatial-interaction models of images. IEEE. Trans. Inform. Theory, 19: 60-72.

Kashyap, R. L. and A. Khotanzad, 1986. A model-based method for rotation invariant texture classification. IEEE. Trans. Pattern Anal. Mach. Intell., 8: 472-480.

Laine, A. and J. Fan, 1993. Texture classification by wavelet packet signatures. IEEE. Trans. Pattern Recog. Mach. Intell., 15: 1186-1191.

Laws, K.I., 1980. Textured image segmentation. PhD. Thesis, University of Southern California.

Mao, J. and A.K. Jain, 1992. Texture classification and segmentation using multi-models. Pattern Recog., 2 (25): 173-188.

Marr, D. and E.C. Hildreth, 1980. Theory of edge detection. In: Proceedings of the Royal Society, Londres. B., 207: 187-217.

Ojala, T. *et al.*, 2002. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE. Trans. Pattern Anal. Mach. Intell., 24 (7): 971-987.

Randen, T. and J. Husoy, 1999. Filtering for texture classification: A comparative study. IEEE. Trans. Pattern Anal. Mach. Intell., 21 (4): 291-310.

Todd, R.R. and J.M.H. Du Buf, 1993. A review of recent texture segmentation and feature extraction techniques. CVGIP: Image Understanding, 57 (3): 359-372.

Unser, M., 1995. Texture classification and segmentation using wavelet frames. IEEE. Trans. Image Proc., 4: 1549-1560.