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Pattern Recognition Letters 24 (2003) 3197–3203
Pattern Recognition Letters
www.elsevier.com/locate/patrec

Texture segmentation using wavelet transform

S. Arivazhagan [a,*], L. Ganesan [b]

[a] Department of Electronics and Communication Engineering, Mepco Schlenk Engineering College, Amathur (P.O.), Sivakasi 626 005, Tamil Nadu, India
[b] Department of Computer Science and Engineering, Government College of Engineering, Tirunelveli 627 007, India

Received 4 February 2003; received in revised form 31 July 2003

Abstract

Texture analysis such as segmentation and classification plays a vital role in computer vision and pattern recognition and is widely applied to many areas such as industrial automation, bio-medical image processing and remote sensing. This paper describes a novel technique of feature extraction for characterization and segmentation of texture at multiple scales based on block by block comparison of wavelet co-occurrence features. The performance of this segmentation algorithm is superior to traditional single resolution techniques such as texture spectrum, co-occurrences, local linear transforms, etc. The results of the proposed algorithm are found to be satisfactory.

Keywords: Texture; Texture segmentation; Feature extraction; Wavelet co-occurrence features

1. Introduction

Texture plays an important role in many machine vision tasks such as surface inspection, scene classification, surface orientation and shape determination. Texture is characterized by the spatial distribution of gray levels in a neighborhood. Though texture is widely used and intuitively obvious, it has no precise definition due to its wide variability. According to Sklansky (1978), "an image region has a constant texture if a set of its local properties in that region is constant, slowly changing or approximately periodic". This definition explains many of the textures found in natural images. The local image region, statistics or property that is repeated over the textured region, is called a texture element or texel. It must be noted that the texture has both local and global meaning, i.e., it is characterized by invariance of certain local attributes that are distributed over a region of an image.

Texture analysis is one of the most important techniques used in the analysis and interpretation of images, consisting of repetition or quasi repetition of some fundamental image elements (e.g., Raghu and Yegnanarayana, 1996, p. 1625). There are three primary issues in texture analysis, such as texture classification, texture segmentation and shape recovery from texture. In texture classification, the problem is identifying the given texture region from a given set of texture classes. As opposed to texture classification, in which the class

* Corresponding author.
E-mail address: s_arivu@yahoo.com (S. Arivazhagan).

0167-8655/$ - see front matter
doi:10.1016/j.patrec.2003.08.005

label of a single homogeneous region is determined using distinguishing features derived from the region, texture segmentation is concerned with automatically determining the boundaries between various textured regions in an image (e.g., Jain et al., 1995).

Analysis of texture requires the identification of proper attributes or features that differentiate the textures in the image for segmentation, classification and recognition. The features are assumed to be uniform within the regions containing the same textures. Initially, texture analysis was based on the first order or second order statistics of textures (e.g., Haralick et al., 1973; Weszka et al., 1976; Davis et al., 1979; Faugeras and Pratt, 1980; Chen and Pavlidis, 1983). Then, Gaussian Markov random field (GMRF) and Gibbs random field models were proposed to characterize textures (e.g., Cross and Jain, 1983; Chellappa and Chatterjee, 1986; Kashyap and Khotanzed, 1986; Derin and Elliot, 1987; Cohen et al., 1991; Manjunath and Chellappa, 1991). Later, local linear transformations are used to compute texture features (e.g., Laws, 1980; Unser, 1986). Then, texture spectrum technique was proposed for texture analysis (e.g., He and Wang, 1990). The above traditional statistical approaches to texture analysis, such as co-occurrence matrices, second order statistics, GMRF, local linear transforms and texture spectrum, are restricted to the analysis of spatial interactions over relatively small neighborhoods on a single scale. As a consequence, their performance is best for the analysis of microtextures only (e.g., Unser, 1995, p. 1549).

More recently, methods based on multi-resolution or multi-channel analysis, such as Gabor filters and wavelet transform, have received a lot of attention (e.g., Unser and Eden, 1989; Bovik et al., 1990; Chang and Jay Kuo, 1993; Unser, 1995; Teuner et al., 1995; Haley and Manjunath, 1995; Manjunath and Ma, 1996; Wu and Wei, 1996; Raghu and Yegnanarayana, 1996; Van de Wouwer et al., 1999). But, the outputs of Gabor filter banks are not mutually orthogonal, which may result in a significant correlation between texture features. Finally, these transformations are usually not reversible, which limits their applicability for texture synthesis. Most of these problems can be avoided if one uses the wavelet transform, which provides a precise and unifying frame work for the analysis and characterization of a signal at different scales (e.g., Unser, 1995). Another advantage of wavelet transform over Gabor filter is that the low pass and high pass filters used in the wavelet transform remain the same between two consecutive scales while the Gabor approach requires filters of different parameters (e.g., Chang and Jay Kuo, 1993). In other words, Gabor filters require proper tuning of filter parameters at different scales. Later, Kaplan (1999) proposed extended fractal analysis for texture classification and segmentation and Wang and Liu (1999) proposed multi-resolution MRF (MRMRF) parameters for texture classification. Wavelet statistical features (WSF) and wavelet co-occurrence features (WCF) were proposed and effectively used for texture characterization and classification (e.g., Arivazhagan and Ganesan, 2003).

The wavelet transform is a multi-resolution technique, which can be implemented as a pyramid or tree structure and is similar to sub-band decomposition. In this paper, texture segmentation is carried out by comparing co-occurrence matrix features derived from discrete wavelet transformed overlapping but adjacent sub-blocks of size 32×32, both horizontally and vertically. The results are found to be satisfactory.

This paper is organized as follows: In Section 2, the theory of discrete wavelet transforms is briefly reviewed. The texture segmentation system is explained in Section 3. In Section 4, texture segmentation experimental results for various texture mosaic images are discussed in detail. Finally, concluding remarks are given in Section 5.

2. Discrete wavelet transform (DWT)

Wavelets are functions generated from one single function Ψ by dilations and translations. The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of wavelets. Any such superposition decomposes the given function into different scale levels where each level is further decomposed with a resolution adapted to that level (e.g., Antonini et al., 1992).

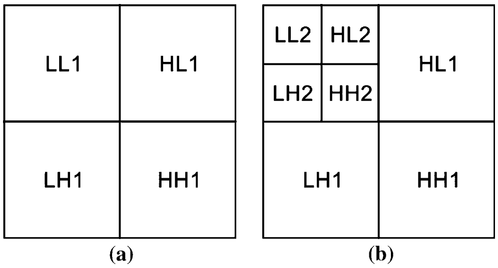


Fig. 1. Image decomposition: (a) one level, (b) two level.

The discrete wavelet transform (DWT) is identical to a hierarchical sub band system where the sub-bands are logarithmically spaced in frequency and represent an octave-band decomposition. By applying DWT, the image is actually divided i.e., decomposed into four sub-bands and critically sub-sampled as shown in Fig. 1(a). These four sub-bands arise from separate applications of vertical and horizontal filters. The 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 two level wavelet decomposition as shown in Fig. 1(b). 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 as useful for texture discrimination and segmentation. Since textures, either micro or macro, have non-uniform gray level variations, they are statistically characterized by the values in the DWT transformed sub band images or the features derived from these sub-band images or their combinations. In other words, the features derived from these approximation and detail sub-band images uniquely characterize a texture. The features obtained from these DWT transformed images are shown here as useful for texture analysis, namely segmentation, and are discussed in Section 3.

3. Texture segmentation system

The steps involved in texture segmentation is shown in Fig. 2.

Here, texture mosaic images of size $N \times N$ are considered. The analysis is carried out by considering sub-images (i.e., block) of size 32×32. Each 32×32 sub-image, taken from top left corner of the original image, is decomposed using one level DWT and co-occurrence matrices (C) are derived for sub-image and detail sub-bands (i.e., LH1, HL1 & HH1 sub-bands) of wavelet decomposed sub-image. Then, from these co-occurrence matrices (C), significant WCFs, such as contrast, cluster shade and cluster prominence, are computed using formulae given in Eqs. (1)–(3), as texture features. In our implementation, the contrast feature values, calculated over all the blocks, are subjected to linear normalization in the scale of 0–255, while the cluster shade and cluster prominence features, which found to have very large dynamic ranges, are subjected to logarithmic normalization in the scale of 0–255 for computational

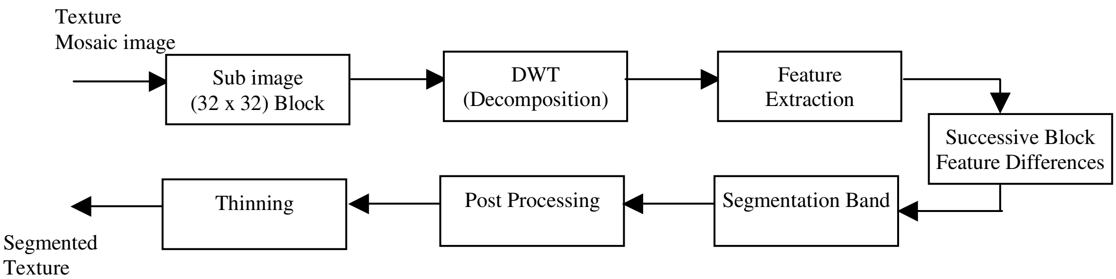


Fig. 2. Texture segmentation system.

simplicity, without affecting their original variations.

$$\text{Contrast} = \sum_{i,j=1}^{N} (i-j)^2 C(i,j), \tag{1}$$

$$\text{Cluster shade} = \sum_{i,j=1}^{N} (i - M_x + j - M_y)^3 C(i,j), \tag{2}$$

$$\text{Cluster prominence} = \sum_{i,j=1}^{N} (i - M_x + j - M_y)^4 C(i,j), \tag{3}$$

where

$$M_x = \sum_{i,j=1}^{N} iC(i,j) \quad \text{and} \quad M_y = \sum_{i,j=1}^{N} jC(i,j).$$

Then, texture segmentation is carried out by comparing the normalized co-occurrence features of discrete wavelet transformed adjacent but overlapping 32×32 sub-image blocks, both horizontally and vertically. Each successive block is differ from the previous one in its spatial location by one column or one row, depending on whether the successive block is taken in horizontal or vertical direction, respectively. Here, the sum of the above normalized features of one block is compared with the corresponding sum of features derived from the next block. The difference in feature values is less when successive blocks belong to the same texture region and it increases in the texture border region while it is high when the successive blocks are from two different texture regions.

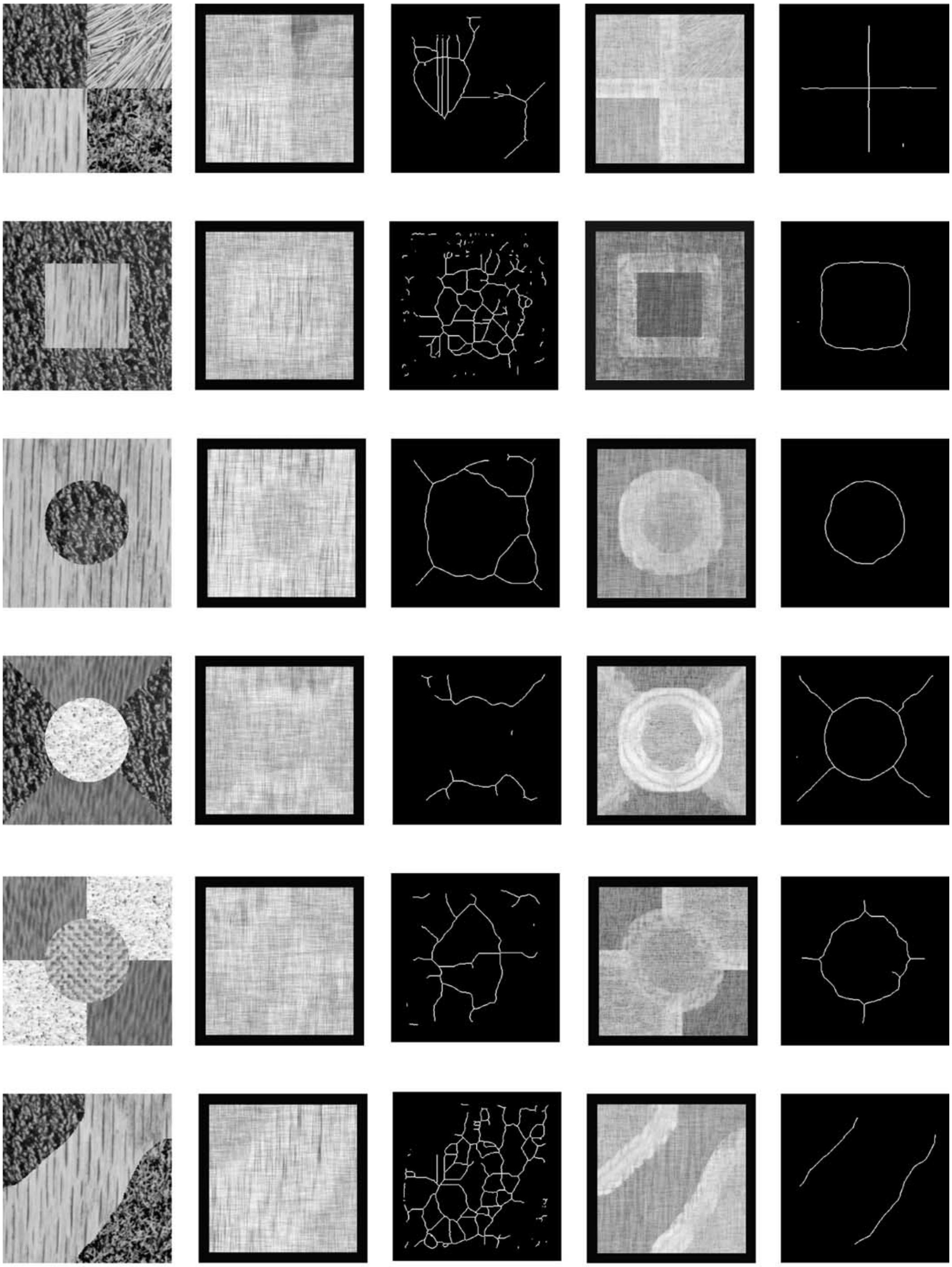
By carrying out the above block by block feature comparison both in horizontal and vertical directions, a segmentation band is formed across the texture boundaries. When the difference in feature values within the same texture region is high, noise like artifacts or spurious spots appear in the segmented image. This spurious spots are removed by applying disk filtering and thresholding techniques (i.e., post processing). Then, the post processed segmented band is thinned using a skeletonizing algorithm to get segmented line of one pixel thickness. The thinned result gives the line of demarcation among the different textures present in the image i.e., thinned lines are exactly aligned with texture boundaries. The texture segmentation algorithm is given as follows.

Segmentation algorithm:
Input: Texture mosaic image of size $N \times N$.
Output: Texture segmented image.

Step 1. Read the texture mosaic image.
Step 2. Obtain 32×32 sub-image blocks, starting from the top left corner.
Step 3. Decompose sub-image blocks using 2-D DWT.
Step 4. Derive co-occurrence matrices (C) for original image, and detail sub-bands of DWT decomposed sub-image blocks.
Step 5. Calculate WCFs such as contrast, cluster shade and cluster prominence from co-occurrence matrices.
Step 6. Calculate the difference between the sums of WCFs of adjacent sub-image blocks. This results in segmentation band.
Step 7. Apply disk filtering and thresholding techniques to remove noise like artifacts, if any, in the segmentation band.
Step 8. Apply skeletonizing algorithm to get thinned or segmented line of one pixel thickness.

4. Experimental results and discussion

The segmentation technique discussed in the previous section is applied on six different texture mosaic images of size 256×256, stitched from texture images of Brodatz (1966) texture album. The stitched texture mosaic images, shown in Fig. 3(a), consist of (i) leather, straw, grass and wood textures of square shape in clockwise direction; (ii) wood texture of square shape at the center of leather texture; (iii) leather texture of circular shape at the center of wood texture; (iv) leather and water textures of triangular shape with sand texture at the center; (v) water and sand textures of square shape with weave texture of circular shape



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

Fig. 3. Texture segmentation results. (a) Texture mosaic images. Texture spectrum technique: (b) segmented band, (c) thinned results. Proposed method: (d) segmented band, (e) thinned results.

at the center and (vi) an irregular texture mosaic image consisting of leather, wood, and grass textures. The segmented band images are obtained for the above six images by applying the segmentation algorithm, given in Section 3, and are shown in Fig. 3(d). Then, thresholding and disk filtering techniques are applied to remove spurious noise spots. Since the image windows of larger width are considered for computation of features from the texture, the localization of the segmentation bands are poor. As a result, the detected boundary lines between different textured regions are thickened. A pattern matching thinning algorithm is applied for thinning the detected segmented band images. The thinned results are shown in Fig. 3(e). In addition, for the purpose of comparison, the texture segmentation bands and the thinned results, obtained using texture spectrum technique, proposed by He and Wang (1990) are given in Fig. 3(b) and (c), respectively. From the figures, it is observed that the segmentation bands, shown in Fig. 3(b), are not very clear and hence, the thinned results are very poor while the thinned lines, obtained for the segmentation bands, shown in Fig. 3(d) are exactly aligned with the boundaries of texture mosaic images.

5. Conclusion

In this paper, the concept of discrete wavelet transform is presented for applying to textured images for decomposing them into detail and approximation regions. Co-occurrence features, computed out of the wavelet decomposed images, are used for texture segmentation. The idea behind this proposed method is to exhibit the usage of co-occurrence features computed from discrete wavelet transformed images (i.e., WCF) for texture segmentation. The features are approximately the same when the windows or subimages considered are from the same texture and different if they are from different textures. Varieties of textures, collected from standard album, are stitched to form target images which are used for experimentation and it is found that the proposed method yield better results than the texture spectrum method, a single resolution technique.

Acknowledgements

The authors are grateful to the Management, Principal and Head of the Department of Electronics and Communication Engineering of our college for their constant support and encouragement. The authors also extend their gratitude to the anonymous reviewers who have given very good suggestions for this better presentation of our manuscript.

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