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ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 7 (6): 883-889, 2008
ISSN 1812-5638

Texture Classification Based on Extraction of Skeleton Primitives Using Wavelets

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Abstract: A novel method for dominant skeleton extraction of textures using different wavelet transforms, is proposed in this study. The skeleton varies depending on the shape of structuring element. If the structuring element is homothetic to the object, the object is covered with only one magnification of the structuring element. By this, the skeleton is reduced to one point. The present study considers the skeleton from a binary texture. The proposed method derives from the above that a total number of pixels within the skeleton is the minimum when structuring element is homothetic to the primitive. This provides the scope that the texture is composed of one primitive, which minimizes the total number of pixels. For evaluating such skeleton primitive the present study utilized a 3×3 structuring element, as the skeleton primitives. All possible skeleton primitives combinations of 3×3 mask are evaluated on all textures. The skeleton primitive that is making the least number of skeleton points is considered as dominant skeleton primitive. Based on the extraction of skeleton primitives a classification is made on textures using Haar, Daubechies, Coiflet and Symlet wavelets. Experimental results indicate a good classification and also a comparison is made among these four wavelet results. Present method is experimented on Brodatz textures using these four wavelets.

Key words: Textures, Skeleton primitive, structuring element weight, wavelet, classification

INTRODUCTION

Analysis of texture requires the identification of proper attributes or features that differentiate the textures for classification, segmentation and recognition. The features are assumed to be uniform within the regions containing the same texture. Various feature extraction and classification techniques have been suggested in the past for the purpose of texture analysis. Initially, texture analysis was based on the first order or second order statistics of textures (Haralick *et al*., 1973; Weszka *et al*., 1976; Chen and Pavlidis, 1983). It is well known that the co-occurrence matrix features are first proposed by Haralick *et al*. (1973). However, there are 14 features to be computed for different distances at different orientations which increase the computational and time complexity. Even if all the features are used, the correct classification rate of 60-70% was only reported in the literature. Then, Gaussian Markov Random Fields (GMRF) and Gibbs random fields were proposed to characterize textures (Chellappa and Chatterjee, 1985; Cohen *et al*., 1991). Later, local linear transformations are used to compute texture features (Laws, 1980; Unser, 1986). The above traditional statistical approaches to texture analysis such as co-occurrence matrices, second order statistics, GMRF and local linear transforms 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 micro-textures only (Unser, 1995). More recently methods based on multi-resolution or multi-channel analysis such as Gabor filters and wavelet transform have received a lot of attention (Bovik *et al*., 1990; Chang and Jay Kuo, 1993; Unser, 1995). A major disadvantage in using Gabor transform is that the output of Gabor filter banks are not mutually orthogonal, which may result in a significant correlation between texture features. Moreover, these transformations are usually not reversible, which limits their applicability for texture synthesis. Most of these 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 (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

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filters of different parameters (Chang and Jay Kuo, 1993). In other words, Gabor filters require proper tuning of filter parameters at different scales.

Study of patterns on textures is recognized as an important step in characterization and classification of textures. Textures are classified recently by various pattern methods: preprocessed images (Vijaya Kumar *et al*., 2007a) long linear patterns (Krishna *et al*., 2005; Vijaya Kumar *et al*., 2007b) and edge direction movements (Eswara Reddy *et al*., 2007), Avoiding Complex Patterns (Vijaya Kumar *et al*., 2008a) marble texture description (Suresh *et al*., 2008). Textures are also described and classified by using various wavelet transforms: one based on primitive patterns (Vijaya Kumar *et al*., 2008b) and another based on statistical parameters (Raju *et al*., 2008).

Skeletonization is an important tool for many image processing applications. The result of the skeletonization of an image is its skeleton. Skeleton is essentially a one-pixel-thick line that passes through the centre, or medial axis, of an object. An accurate skeleton possesses significant properties that makes it suitable for pattern recognition, machine vision and image compression. Skeletonization allows the extraction of important features such as an image's topology, orientation and composition. Since its conception by Blum (1967) skeletonization has been studied extensively and there now exist many techniques and algorithms for performing skeletonization. There currently exist many skeletonization methods, each utilizing different algorithms and different information contained in an image. Recently new algorithms for skeletonizaiton and thinning for 2D images based on primitive concept approach are proposed by Vijaya Kumar *et al*. (2008c, d). Most of the methods, however, fall into one of the two broad categories: Pixel based method and Non-pixel based method. In the pixel-based method, each foreground pixel is utilized for computation in the skeletonization process. Techniques used in the pixel-based method include thinning (Lam *et al*., 1992; Unser, 1986) and distance transform (Unser, 1986). In the nonpixel based method, the skeleton of a shape is analytically derived from the border of the image. There are two types of nonpixel based methods, which are based on either cross section (Pavlidis, 1986) or Voronoi diagrams (Ogniewicz and Kubler, 1995). These methods attempt to determine the symmetric points of a shape without the intermediate step of the grassfire propagation. The fundamental concept of these methods is that the local symmetric axes of a shape are derived from pairs of contour pixels or a contour segment representing a sequence of the contour pixels. Although more than 300 skeletonization algorithms have been proposed by Lam (1992) the improvement is still required, since the existing approximation algorithms of skeletonization often suffer from one or more of the drawbacks (Chang and Yan, 1999; Ge and Fitzpatrick, 1996; Lam, 1992; Smith, 1987; Zou and Yan, 1999). To overcome these problems, a novel wavelet-based method is presented in this study.

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 (Antonini *et al*., 1992; Daubechies, 1992). There are various wavelet transforms like Haar, Daubechies, Coiflet, Symlet and etc. They differ with each other in the formation and reconstruction. The wavelet transform divides the original image into four subbands and they are denoted by LL, HL, LL and HH frequency subbands. The HH subimage represents diagonal details (high frequencies in both directions), HL gives horizontal high frequencies (vertical edges), LH gives vertical high frequencies (horizontal edges) and the image LL corresponds to the lowest frequencies. At the subsequent scale of analysis, the image LL undergoes the decomposition using the same filters, having always the lowest frequency component located in the upper left corner of the image. Each stage of the analysis produces next 4 subimages whose size is reduced twice when compared to the previous scale. i.e. for level n it gives get a total of 4+(n-1)*3 subbands. The size of the wavelet representation is the same as the size of the original. The Haar wavelet is the first known wavelet and was proposed in 1909 by Alfred Haar. Haar used these functions to give an example of a countable orthonormal system for the space of square-integrable functions on the real line. The Haar wavelet's scaling function coefficients are $h\{k\} = \{0.5, 0.5\}$ and wavelet function coefficients are $g\{k\} = \{0.5, -0.5\}$. The Daubechies (1992) are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function which generates an orthogonal multiresolution analysis.

MATERIALS AND METHODS

On a 3×3 structuring element by assuming always center pixel as one, one can have 2^8 combinations. However the present study has not considered the following structuring element as shown in Fig. 1 for extracting skeleton primitives. By this there will be a total of 255 structuring elements on a 3×3 mask. These structuring elements are used for evaluating skeleton points, means the skeleton of an object has the property that it is reduced to one point when the structuring element used for the skeletonization is exactly homothetic

0	0	0
0	1	0
0	0	0

Fig. 1: Structuring element that has not been considered for skeletonization

$p\times2^0$	$p\times2^1$	$p\times2^2$
$p\times2^4$		$p\times2^3$
$p\times2^5$	$p\times2^6$	$p\times2^7$

Fig. 2: Structuring element weight representation

to the object. This method minimizes the number of pixels contained in the skeleton. If the texture is composed of one primitive, the structuring element minimizes the number of pixels which is homothetic to the primitive because of the above property of the skeleton.

The structuring elements are represented by weight based system as shown in Fig. 2 which are called as Structuring Element Weight (SEW). Some of the skeleton structuring elements with their weights are represented in the following Fig. 3.

The present study proposes a novel method of the texture primitive description that requires no assumption on the distribution of grain sizes or the granulometric moments of the primitives. The present study employs the morphological skeleton for this method. The most commonly employed morphological skeleton of a binary object is explained intuitively as follows: At first it locate the largest magnification included within the object and cover the object by sweeping the magnification within the object. Then gradually smaller magnifications are employed for covering the residual area until the whole object is covered. The skeleton varies depending on the shape of the structuring element. If the structuring element is homothetic to the object, the object is covered with only one magnification of the structuring element. In this case the skeleton is reduced to one point. The present study consider here obtaining the skeleton from a binary texture. It is derived from the above property that the total number of pixels within the skeleton is the minimum when the structuring element is homothetic to the primitive, if the present paper assumes that the texture is composed of one primitive, i.e., contains grains that are magnifications of the primitive. This indicates that the primitive is described by the optimal structuring element minimizing

1	1	0
0	1	0
0	0	0

(a)

1	0	1
0	1	0
0	0	0

(b)

1	1	1
0	1	0
0	0	0

(c)

1	1	1
1	1	0
0	0	0

(d)

1	1	1
1	1	0
0	0	0

(f)

1	1	1
1	1	1
1	0	0

(f)

1	0	1
0	1	0
1	0	1

(g)

1	1	1
0	1	1
0	1	1

(h)

1	1	1
1	1	1
1	1	1

(i)

Fig. 3: Representation of structuring element with corresponding weights (a) 3 (b) 5 (c) 7 (d) 23 (e) 31 (f) 63 (g) 165 (h) 207 and (i) 255

the total number of pixels within the skeleton. This primitive description method has an advantage that no assumption on the sizing distribution of grains in the texture is required.

The entire process is explained in Algorithm 1 and 2. The present study have used four wavelet transforms namely, Haar, Daubechies (Db6), Coiflet (Cf6) and Symlet (Sym8) Wavelet transform.

Algorithm 1: To find Skeleton of an image
Begin

- Let k = 1 and A be the image
- E(A, kB)Erode the image k number of times with structuring element B
- O(A, B) Open the image with structuring element B
- Find the k^{th} Skeleton Subset S_k = E(A, kB)-O(E(A, kB)
- k = k+1
- T(A) = E(A, kB)
- If (T(A)≠ϕ) go to 4
- SK(A, B) is the union of all the Skeleton Subsets S_k(A)

End

Algorithm 2: Texture skeleton primitive extraction
Begin

- Initialize i = 1
- Read the Texture image T_i

- Decompose T_i using one of the wavelet transform and name it as WT_i
- Assign an initial value for structuring element with SEW = 1 and generate the structuring element with weight SEW
- Skeletonize the WT_i using Algorithm 1 and store the result in RES i.e., RES = SK (WT_i, SEW)
- Evaluate the Number of skeleton points in RES and assign it to NSP_1
- SEW = SEW+1, generate the structuring element with weight SEW
- Evaluate RES = SK (WT_i, SEW)
- Find the number of skeleton points in RES and assign it to NSP_2
- If (NSP_1 = NSP_2), then make NSP_1 = NSP_2
- If (SEW = 255) goto 7
- Keep the NSP_1 and the corresponding SEW in the Table
- Apply the corresponding skeleton primitive on WT_i and display it
- i = i+1
- If i = 24 goto 2

End

RESULTS

The Table 1-4 indicate the dominant skeleton primitives on all 24 Brodatz textures (Brodatz, 1966) using Haar, Db6, Cf6 and Sym8 wavelet transforms, respectively. Based on this the dominant skeleton subset is applied on all 24 Brodatz textures for skeletonization purpose using Haar, Db6, Cf6 and Sym8 wavelet transforms. Due to lack of space the present paper is presenting three Brodatz skeletonized textures using Haar, Db6, Cf6 and Sym8 in Fig. 4-6, respectively.

The skeleton images of dominant primitive skeleton with weight 255 is not showing any difference for textures D_2 and D_{10} in all four wavelet transforms. However the skeletoned image D_{25} with weight 255 is not similar in the

Table 1: Textures with least skeleton points corresponding to their SEW by using Haar wavelet transform

Texture	No. of skeleton points	Dominant skeleton primitive weight
D_1	4140	255
D_2	4226	255
D_3	7267	115
D_4	7279	251
D_5	4498	255
D_6	5069	153
D_7	3540	255
D_8	1967	255
D_9	6600	255
D_{10}	5710	255
D_{11}	5985	255
D_{12}	5200	255
D_{13}	3937	255
D_{15}	6402	255
D_{16}	6128	255
D_{17}	7177	182
D_{18}	4034	255
D_{19}	5436	255
D_{20}	3646	255
D_{21}	6076	24
D_{22}	6019	206
D_{23}	3399	255
D_{24}	7382	206
D_{25}	2200	255

Table 2: Textures with least skeleton points corresponding to their SEW by using Db6 Wavelet Transform

Texture	No. of skeleton points	Dominant skeleton primitive weight
D_1	4442	255
D_2	4302	255
D_3	7508	115
D_4	7329	143
D_5	4594	255
D_6	6053	124
D_7	3407	255
D_8	1978	255
D_9	6657	255
D_{10}	5700	255
D_{11}	6091	255
D_{12}	5261	255
D_{13}	4128	255
D_{15}	6330	255
D_{16}	6147	255
D_{17}	6691	182
D_{18}	4023	255
D_{19}	5465	255
D_{20}	3782	255
D_{21}	6000	24
D_{22}	6035	115
D_{23}	3534	255
D_{24}	7219	206
D_{25}	2510	255

Table 3: Textures with least skeleton points corresponding to their SEW by using Cf6 Wavelet Transform

Texture	No. of skeleton points	Dominant skeleton primitive weight
D_1	4164	255
D_2	4456	255
D_3	7562	206
D_4	7274	223
D_5	4674	255
D_6	5953	217
D_7	3507	255
D_8	1952	255
D_9	6751	255
D_{10}	5726	255
D_{11}	6048	255
D_{12}	5233	255
D_{13}	4122	255
D_{15}	6405	255
D_{16}	6208	255
D_{17}	6831	109
D_{18}	4107	255
D_{19}	5415	255
D_{20}	3743	255
D_{21}	5793	24
D_{22}	5927	115
D_{23}	3505	255
D_{24}	7272	206
D_{25}	2396	255

Table 4: Textures with least skeleton points corresponding to their SEW by using Sym8 Wavelet Transform

Texture	No. of skeleton points	Dominant skeleton primitive weight
D_1	4399	255
D_2	4316	255
D_3	7366	115
D_4	7270	251
D_5	4637	255
D_6	5765	217
D_7	3512	255
D_8	1983	255
D_9	6748	255
D_{10}	5829	255
D_{11}	6246	255
D_{12}	5299	255
D_{13}	4150	255
D_{15}	6467	255
D_{16}	6105	255
D_{17}	6701	109
D_{18}	4124	255
D_{19}	5619	255
D_{20}	3810	255
D_{21}	6081	24
D_{22}	5908	115
D_{23}	3538	255
D_{24}	7260	115
D_{25}	2456	255

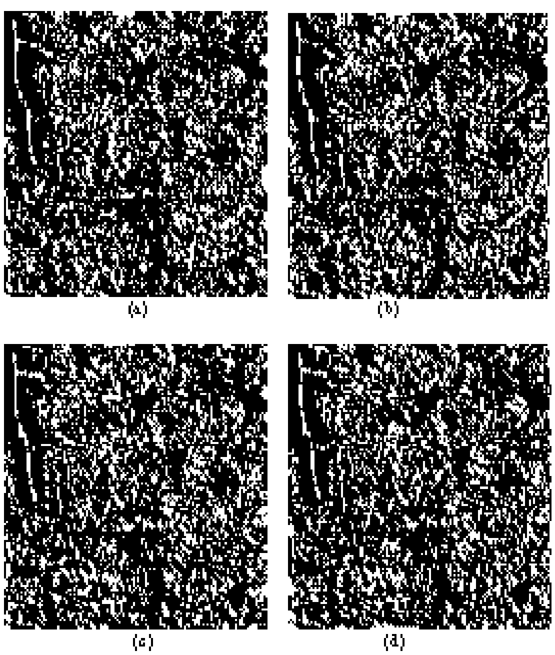

Fig 4: The skeletonization of the Texture D_2 using (a) Haar wavelet (b) Db6 wavelet (c) Cf6 wavelet and (d) Sym8 wavelet

four wavelet transformed images. Textures are also grouped by the skeleton primitive weight. The groups are listed in the following Table 5.

From Table 5, it is clearly evident that a total of 17 textures are having a common structuring element weight of 255. One texture is having a common structuring element weight of 24. That is 18 out of 24 textures are showing a common classification in all four wavelets, which results a 75% correct classification.

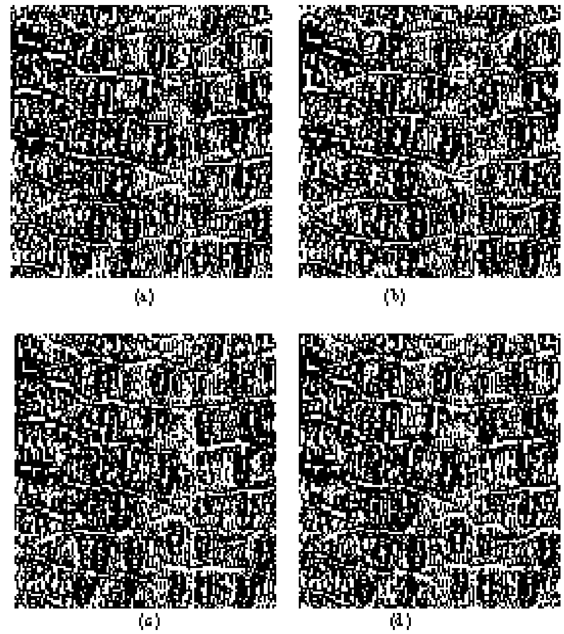

Fig 5: The skeletonization of the Texture D_{10} using (a) Haar wavelet (b) Db6 wavelet (c) Cf6 wavelet and (d) Sym8 wavelet

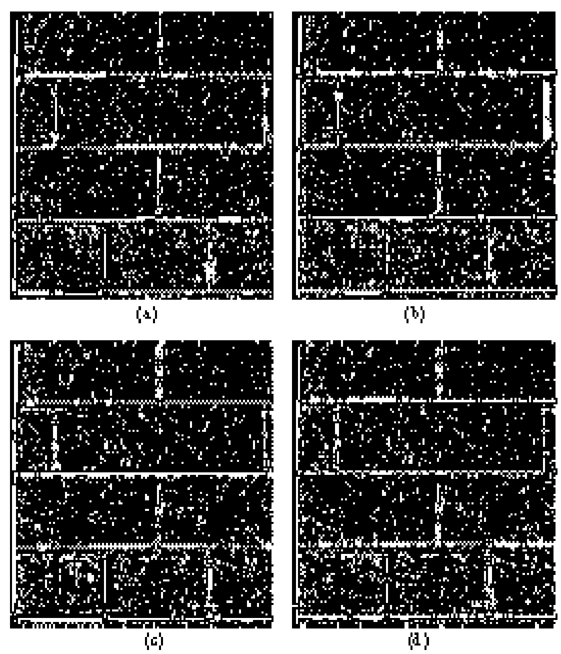

Fig 6: The skeletonization of the Texture D_{25} using (a) Haar wavelet (b) Db6 wavelet (c) Cf6 wavelet and (d) Sym8 wavelet

Table 5: Texture groups according to SEW

Wavelet name	Group	Dominant skeleton primitive weight	Brodatz texture grouping
Haar	1	255	$\{D_1, D_2, D_5, D_7, D_8, D_9, D_{10}, D_{11}, D_{12}, D_{13}, D_{15}, D_{16}, D_{18}, D_{19}, D_{20}, D_{23}, D_{25}\}$
	2	251	$\{D_4\}$
	3	206	$\{D_{22}, D_{24}\}$
	4	182	$\{D_{17}\}$
	5	153	$\{D_6\}$
	6	115	$\{D_3\}$
	7	24	$\{D_{21}\}$
Db6	1	255	$\{D_1, D_2, D_5, D_7, D_8, D_9, D_{10}, D_{11}, D_{12}, D_{13}, D_{15}, D_{16}, D_{18}, D_{19}, D_{20}, D_{23}, D_{25}\}$
	2	206	$\{D_{24}\}$
	3	182	$\{D_{17}\}$
	4	143	$\{D_4\}$
	5	124	$\{D_6\}$
	6	115	$\{D_3, D_{22}\}$
	7	24	$\{D_{21}\}$
Cf6	1	255	$\{D_1, D_2, D_5, D_7, D_8, D_9, D_{10}, D_{11}, D_{12}, D_{13}, D_{15}, D_{16}, D_{18}, D_{19}, D_{20}, D_{23}, D_{25}\}$
	2	223	$\{D_4\}$
	3	217	$\{D_6\}$
	4	206	$\{D_3, D_{24}\}$
	5	115	$\{D_{22}\}$
	6	109	$\{D_{17}\}$
	7	24	$\{D_{21}\}$
Sym8	1	255	$\{D_1, D_2, D_5, D_7, D_8, D_9, D_{10}, D_{11}, D_{12}, D_{13}, D_{15}, D_{16}, D_{18}, D_{19}, D_{20}, D_{23}, D_{25}\}$
	2	251	$\{D_4\}$
	3	217	$\{D_6\}$
	4	115	$\{D_3, D_{22}, D_{24}\}$
	5	109	$\{D_{17}\}$
	6	24	$\{D_{21}\}$

CONCLUSION

The present research have proposed a novel scheme of texture classification using skeleton primitives. The results indicate that even though the structuring element weight is same for some texture, the result may vary depending on the wavelets that are used. The common classification rate is 75% among the four wavelets for the 3×3 structuring element. The present paper has not used 2×2 square structuring element, for images because they are sensitive to stroke thickness, size and orientations. To reduce the orientation effect and sensitiveness to skeletonization, the present paper employed in the present system a 3×3 skeleton primitive. The same method can be extended to 5×5, 7×7...N×N masks also.

ACKNOWLEDGMENTS

The authors would like to express their gratitude to Sri K.V.V. Satya Narayana Raju, Chairman and K. Sashi Kiran Varma, Managing Director, Chaitanya group of Institutions for providing necessary infrastructure. Authors would like to thank anonymous reviewers for their valuable comments and Dr. G.V.S. Ananta Lakshmi for her invaluable suggestions which led to improvise the presentation quality of this study.

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