EXTRACTION OF SKELETON PRIMITIVES ON WAVELETS

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ABSTRACT

A method for dominant skeleton extraction of textures using different wavelet transforms is proposed in this paper. In the present paper 3×3 masks are used for extraction of skeleton primitives. For a 3×3 skeleton primitive there will be 2^9 skeleton primitive combinations. But the present paper considered a skeleton primitive for the skeletonization purpose if and only if its center pixel is one. By this, there will be 2^8 combinations of skeleton primitives. These skeleton primitive are used for evaluating skeleton points. The skeleton of an object has the property that it is reduced to one point when the skeleton primitive used for the skeletonization is exactly homothetic to the object. The dominant skeleton subset is evaluated by counting the skeleton points. The skeleton subset that leads to the least skeleton points will be the resultant skeleton subset. The present paper classified the textures based on two methods. In the first method textures are classified based on skeleton primitive weight, which is nothing but based on skeleton primitive combination. In the second method classification is made based on distance function of skeleton points. These two methods are applied on Brodatz textures with different wavelet transforms which resulted a good classification of textures.

Keywords: *Dominant skeleton subset, Combinations of skeleton primitives, Homothetic, Skeleton points, Classification.*

1. 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 [13,30, 8]. 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 [7,9]. Later, local linear transformations are used to compute texture features [16,22]. 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 [4]. More recently methods based on multi-resolution or multi-channel analysis such as Gabor filters and wavelet transform have received a lot of attention [3,6,23]. 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 [4]. 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 [6]. 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 [28, long linear patterns [14,27 and edge direction movements [11], Avoiding Complex Patterns [24] marble texture description [21]. Textures are also described and classified by using various wavelet transforms: one based on primitive patterns [29] and another based on statistical parameters [19].

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 [2] 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 [25,26]. 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 [15,22] and distance transform [22]. 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 [18] or Voronoi diagrams [17]. 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 [15] the improvement is still required, since the existing approximation algorithms of skeletonization often suffer from one or more of the drawbacks [5,12,15,20,31]. To overcome these problems, a novel wavelet-based method is presented in this paper.

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 [1,10]. 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, LH 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 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 wavelets (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. The present paper is organized as follows. Methodology is defined in the second section. In the third section, results and discussions were given. The last section deals with the conclusions.

2. METHODOLOGY

On a 3×3 structuring element by assuming always center pixel as one, one can have 2^8 combinations. The present study has not considered the structuring elements as shown in Fig 1. In Fig. 1'd' indicates a don't care which can be either a '0' or '1'. The Fig. 1 results 256 structuring element combinations, some of them are shown in Fig. 2. By this there will be a total of 256 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 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.

d	d	d
d	0	d
d	d	d

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

1	0	0
0	0	0
0	0	0

0	1	0
0	0	0
0	0	0

1	1	1
1	0	1
1	1	1

Fig. 2: Some of the combinations of structuring elements with central pixel as zero.

The structuring elements are represented by weight based system as shown in Fig. 3 which are called as structuring element weight (SEW). The present study has not considered the SEW of zero, which is shown in Fig.4. Some of the skeleton structuring elements with their weights are represented in the following Fig. 5.

$p\times2^0$	$p\times2^1$	$p\times2^2$
$p\times2^4$		$p\times23$
$p\times2^5$	$p\times2^6$	$p\times2^7$

Fig. 3: Structuring element weight representation.

0	0	0
0	1	0
0	0	0

Fig. 4: Structuring Element Weight of zero.

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

(e)

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

The present paper proposes in this paper a 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 paper employ 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 paper 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 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.

Skeletonization is done according to Algorithm 1. The proposed texture skeleton primitive extraction method on different wavelets is given in the form of flowchart in Fig. 6. The four wavelet transforms used in the present paper are Haar, Daubechies-6(Db6), Coiflet-6(Cf6) and Symlet-8(Sym8).

Algorithm 1: To find Skeleton of an image

Begin

1. Let $k=1$ and A be the image.
2. $E(A,kB)$,Erode the image k number of times with skeleton primitive B.
3. $O(A,B)$ Open the image with structuring element B.
4. Find the k^{th} Skeleton Subset $S_k=E(A,kB)-O(E(A,kB)$.
5. $k=k+1$
6. T(A)=E(A,kB).
7. If $(T(A)\neq\varphi)$ goto 4.
8. $SK(A,B)$ is the union of all the Skeleton Subsets $S_k(A)$.

End

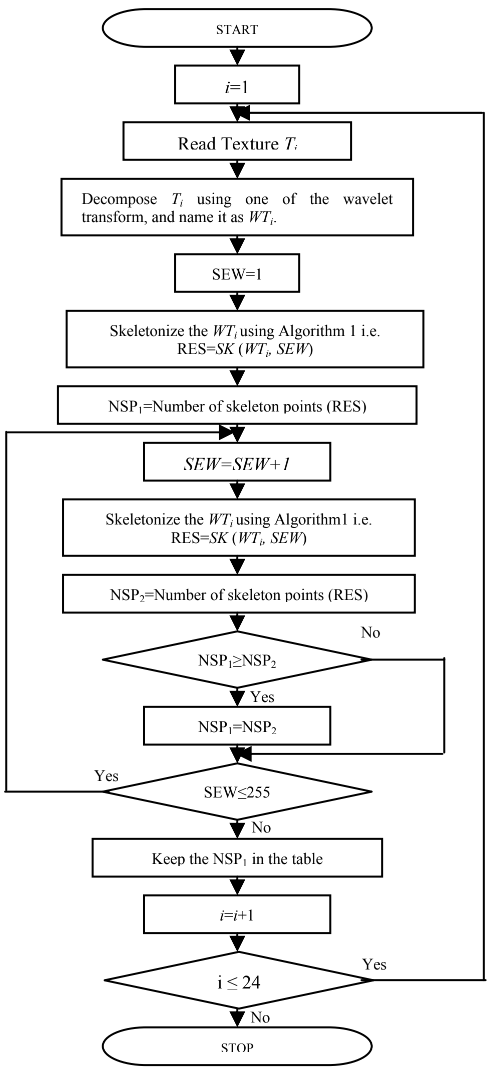

Fig. 6: Flowchart for texture skeleton primitive extraction using wavelets.

3. RESULTS AND ANALYSIS

The proposed Texture Skeleton Primitive extraction method on wavelets is applied on 24 Brodatz textures [4] shown in Fig. 7, using 255 structuring element combinations. The process of applying all structuring element combinations for skeletonization is tedious; however it gives accurate result i.e. the exact combination of skeleton subset. The Table 1, 2, 3 and 4 indicates the dominant skeleton primitive and the corresponding *SEW* for all 24 Brodatz textures using Haar, Db6, Cf6 and Sym8 wavelet transform respectively. Based on the Skeleton. Based on the skeleton primitive weight texture classification is made. Two or more textures falls into Class 'i' denote as C_i if and only if their skeleton primitive weight is same.

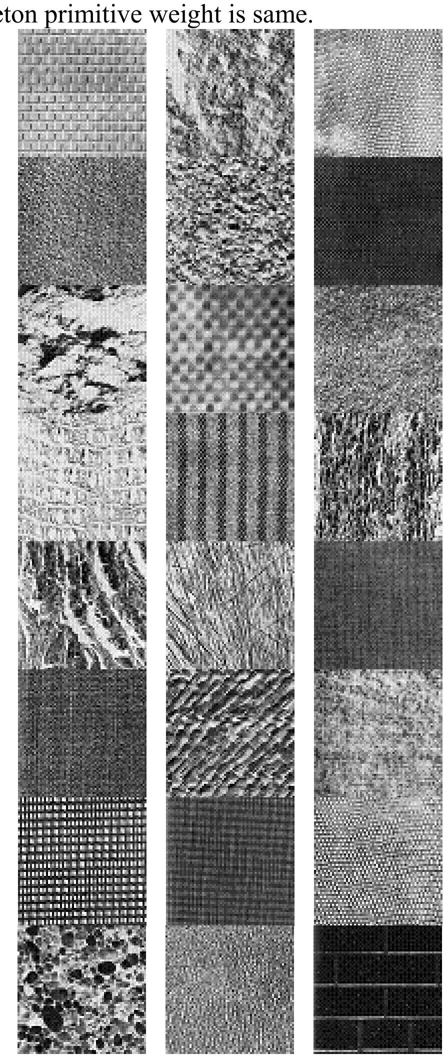

Fig. 7: Twenty four textures from Brodatz album. *Row 1*: D_1, D_2, D_3. *Row 2*: D_4, D_5, D_6. *Row 3*: D_7, D_8, D_9. *Row 4*: D_{10}, D_{11}, D_{12}. *Row 5*: D_{13}, D_{15}, D_{16}. *Row 6*:D_{17}, D_{18}, D_{19}. *Row 7*:D_{20}, D_{21}, D_{22}. *Row 8*:D_{23}, D_{24}, D_{25}.

Table 1: Textures with least skeleton points corresponding to their SEW by using Haar Wavelet Transform.

Texture	Number 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	Number 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	Number 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	Number 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

From Table 1, 2, 3 and 4, it is clearly evident that a total of 17 textures are showing a dominant skeleton primitive with a weight of 255 and 1 texture is showing a dominant skeleton primitive with weight 24 for Haar, Db6, Cf6 and Sym8 wavelet transforms respectively as shown below.

$$\text{HaarC}_1=\{D_1,D_2,D_5,D_7,D_8,D_9,D_{10},D_{11},D_{12},D_{13},D_{15},D_{16},D_{18},D_{19},D_{20},D_{23},D_{25}\}$$

$$\text{Db6C}_1=\{D_1,D_2,D_5,D_7,D_8,D_9,D_{10},D_{11},D_{12},D_{13},D_{15},D_{16},D_{18},D_{19},D_{20},D_{23},D_{25}\}$$

$$\text{HaarC}_1=\{D_1,D_2,D_5,D_7,D_8,D_9,D_{10},D_{11},D_{12},D_{13},D_{15},D_{16},D_{18},D_{19},D_{20},D_{23},D_{25}\}$$

$$\text{HaarC}_1=\{D_1,D_2,D_5,D_7,D_8,D_9,D_{10},D_{11},D_{12},D_{13},D_{15},D_{16},D_{18},D_{19},D_{20},D_{23},D_{25}\}$$

$$\text{HaarC}_2= \{D_{21}\}$$

$$\text{Db6C}_2= \{D_{21}\}$$

$$\text{Cf6C}_2= \{D_{21}\}$$

$$\text{Sym8C}_2=\{D_{21}\}$$

And no other texture is having any other skeleton primitive with common weight in all four wavelet transforms: Haar, Db6, Cf6 and Sym8. By this, the present study evaluates a common classification rate based on skeleton primitives as 75%. Further the present study classified textures based on their least number of skeleton points using distance function as follows. By distance function [29] it says that two textures are similar if and only if they contain the same number of primitive patterns or same percentage of occurrence of patterns as given in equation 1.

$$D(i)=\sum_{j=1}^{p} abs\left(F_j(x)-F_j(i)\right)=0 \text{..........(1)}$$

where 'p' stands for the total number of features used, $i=1$ to Q (Q is the number of classes in the database), $f_j(x)$, represents the j^{th} feature of unknown texture class (x) and $f_j(i)$ represents the j^{th} feature of texture belonging to i^{th} class.

Equation (1) is a rare phenomenon for classification of textures based on skeleton points, because they appear in large number. To avoid this, a lag value based distance function is given in the equation 2.

$$D(i)=\sum_{j=1}^{p} abs\left(F_j(x)-F_j(i)\right)\le l_i \text{....................(2)}$$

Equation (2) is modified in the present paper as

$$D(WT_i,WT_j)=\left|NSP_i-NSP_j\right|\le l_i \text{............(3)}$$

where WT_i and WT_j are the wavelet transformed Brodatz textures , $1 \le i, j \le 24$, NSP_i and NSP_j are the number of skeleton points in the Skeletons of the two textures. This equation (3) suggests that two textures are similar if their distances or percentage of occurrence is less than or equal to lag value 'l_i'.

Table 5: Distance among the textures based on number of skeleton points using Haar Wavelet Transform.

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}	D_{13}	D_{15}	D_{16}	D_{17}	D_{18}	D_{19}	D_{20}	D_{21}	D_{22}	D_{23}	D_{24}	D_{25}
D_1	0	9	56	56	19	30	24	47	50	40	43	33	14	48	45	55	10	36	22	44	43	27	57	44
D_2	9	0	55	55	16	29	26	48	49	39	42	31	17	47	44	54	14	35	24	43	42	29	56	45
D_3	56	55	0	3	53	47	61	73	26	39	36	45	58	29	34	9	57	43	60	35	35	62	11	71
D_4	56	55	3	0	53	47	61	73	26	40	36	46	58	30	34	10	57	43	60	35	35	62	10	71
D_5	19	16	53	53	0	24	31	50	46	35	39	26	24	44	40	52	22	31	29	40	39	33	54	48
D_6	30	29	47	47	24	0	39	56	39	25	30	11	34	37	33	46	32	19	38	32	31	41	48	54
D_7	24	26	61	61	31	39	0	40	55	47	49	41	20	53	51	60	22	44	10	50	50	12	62	37
D_8	47	48	73	73	50	56	40	0	68	61	63	57	44	67	65	72	45	59	41	64	64	38	74	15
D_9	50	49	26	26	46	39	55	68	0	30	25	37	52	14	22	24	51	34	54	23	24	57	28	66
D_{10}	40	39	39	40	35	25	47	61	30	0	17	23	42	26	20	38	41	17	45	19	18	48	41	59
D_{11}	43	42	36	36	39	30	49	63	25	17	0	28	45	20	12	35	44	23	48	10	6	51	37	62
D_{12}	33	31	45	46	26	11	41	57	37	23	28	0	36	35	30	44	34	15	39	30	29	42	47	55
D_{13}	14	17	58	58	24	34	20	44	52	42	45	36	0	50	47	57	10	39	17	46	46	23	59	42
D_{15}	48	47	29	30	44	37	53	67	14	26	20	35	50	0	17	28	49	31	52	18	20	55	31	65
D_{16}	45	44	34	34	40	33	51	65	22	20	12	30	47	17	0	32	46	26	50	7	10	52	35	63
D_{17}	55	54	9	10	52	46	60	72	24	38	35	44	57	28	32	0	56	42	59	33	34	61	14	71
D_{18}	10	14	57	57	22	32	22	45	51	41	44	34	10	49	46	56	0	37	20	45	45	25	58	43
D_{19}	36	35	43	43	31	19	44	59	34	17	23	15	39	31	26	42	37	0	42	25	24	45	44	57
D_{20}	22	24	60	60	29	38	10	41	54	45	48	39	17	52	50	59	20	42	0	49	49	16	61	38
D_{21}	44	43	35	35	40	32	50	64	23	19	10	30	46	18	7	33	45	25	49	0	8	52	36	62
D_{22}	43	42	35	35	39	31	50	64	24	18	6	29	46	20	10	34	45	24	49	8	0	51	37	62
D_{23}	27	29	62	62	33	41	12	38	57	48	51	42	23	55	52	61	25	45	16	52	51	0	63	35
D_{24}	57	56	11	10	54	48	62	74	28	41	37	47	59	31	35	14	58	44	61	36	37	63	0	72
D_{25}	6	17	54	56	21	9	16	42	47	40	49	23	11	45	61	60	13	37	36	32	37	23	55	0

This indicates that lag value plays crucial role and by increasing lag value the percentage of correct classification (PCC) increases. The distances among all 24 textures based on number of skeleton points using Haar, Db6, Cf6 and Sym8 wavelet transform are listed in Table 5, 6, 7 and 8 respectively. Based on the lag value a classification is resulted in the following way. That is two or more textures belong to the same class C_i if they differ with the lag value less than or equal to l_i. When lag value is 30 the classes resulted based on least number of skeleton primitive points for the four wavelets are shown in Table 9 In the same way, when the lag value is 50 the resultant classes are shown in Table 10.

Table 6: Distance among the textures based on number of skeleton points using Db6 Wavelet Transform.

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}	D_{13}	D_{15}	D_{16}	D_{17}	D_{18}	D_{19}	D_{20}	D_{21}	D_{22}	D_{23}	D_{24}	D_{25}
D_1	0	12	55	54	12	40	32	50	47	35	41	29	18	43	41	47	20	32	26	39	40	30	53	44
D_2	12	0	57	55	17	42	30	48	49	37	42	31	13	45	43	49	17	34	23	41	42	28	54	42
D_3	55	57	0	13	54	38	64	74	29	43	38	47	58	34	37	29	59	45	61	39	38	63	17	71
D_4	54	55	13	0	52	36	63	73	26	40	35	45	57	32	34	25	57	43	60	36	36	62	10	69
D_5	12	17	54	52	0	38	34	51	45	33	39	26	22	42	39	46	24	30	28	37	38	33	51	46
D_6	40	42	38	36	38	0	51	64	25	19	6	28	44	17	10	25	45	24	48	7	4	50	34	60
D_7	32	30	64	63	34	51	0	38	57	48	52	43	27	54	52	57	25	45	19	51	51	11	62	30
D_8	50	48	74	73	51	64	38	0	68	61	64	57	46	66	65	69	45	59	42	63	64	39	72	23
D_9	47	49	29	26	45	25	57	68	0	31	24	37	50	18	23	6	51	35	54	26	25	56	24	64
D_{10}	35	37	43	40	33	19	48	61	31	0	20	21	40	25	21	31	41	15	44	17	18	47	39	56
D_{11}	41	42	38	35	39	6	52	64	24	20	0	29	44	15	7	24	45	25	48	10	7	51	34	60
D_{12}	29	31	47	45	26	28	43	57	37	21	29	0	34	33	30	38	35	14	38	27	28	42	44	52
D_{13}	18	13	58	57	22	44	27	46	50	40	44	34	0	47	45	51	10	37	19	43	44	24	56	40
D_{15}	43	45	34	32	42	17	54	66	18	25	15	33	47	0	14	19	48	29	50	18	17	53	30	62
D_{16}	41	43	37	34	39	10	52	65	23	21	7	30	45	14	0	23	46	26	49	12	11	51	33	60
D_{17}	47	49	29	25	46	25	57	69	6	31	24	38	51	19	23	0	52	35	54	26	26	56	23	65
D_{18}	20	17	59	57	24	45	25	45	51	41	45	35	10	48	46	52	0	38	16	44	45	22	57	39
D_{19}	32	34	45	43	30	24	45	59	35	15	25	14	37	29	26	35	38	0	41	23	24	44	42	54
D_{20}	26	23	61	60	28	48	19	42	54	44	48	38	19	50	49	54	16	41	0	47	47	16	59	36
D_{21}	39	41	39	36	37	7	51	63	26	17	10	27	43	18	12	26	44	23	47	0	6	50	35	59
D_{22}	40	42	38	36	38	4	51	64	25	18	7	28	44	17	11	26	45	24	47	6	0	50	34	59
D_{23}	30	28	63	62	33	50	11	39	56	47	51	42	24	53	51	56	22	44	16	50	50	0	61	32
D_{24}	53	54	17	10	51	34	62	72	24	39	34	44	56	30	33	23	57	42	59	35	34	61	0	69
D_{25}	44	42	71	69	46	60	30	23	64	56	60	52	40	62	60	65	39	54	36	59	59	32	69	0

Table 7: Distance among the textures based on number of skeleton points using Cf6 Wavelet Transform.

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}	D_{13}	D_{15}	D_{16}	D_{17}	D_{18}	D_{19}	D_{20}	D_{21}	D_{22}	D_{23}	D_{24}	D_{25}
D_1	0	17	58	56	23	42	26	47	51	40	43	33	6	47	45	52	8	35	21	40	42	26	56	42
D_2	17	0	56	53	15	39	31	50	48	36	40	28	18	44	42	49	19	31	27	37	38	31	53	45
D_3	58	56	0	17	54	40	64	75	28	43	39	48	59	34	37	27	59	46	62	42	40	64	17	72
D_4	56	53	17	0	51	36	61	73	23	39	35	45	56	29	33	21	56	43	59	38	37	61	1	70
D_5	23	15	54	51	0	36	34	52	46	32	37	24	23	42	39	46	24	27	31	33	35	34	51	48
D_6	42	39	40	36	36	0	49	63	28	15	10	27	43	21	16	30	43	23	47	13	5	49	36	60
D_7	26	31	64	61	34	49	0	39	57	47	50	42	25	54	52	58	24	44	15	48	49	1	61	33
D_8	47	50	75	73	52	63	39	0	69	61	64	57	47	67	65	70	46	59	42	62	63	39	73	21
D_9	51	48	28	23	46	28	57	69	0	32	27	39	51	19	23	9	51	37	55	31	29	57	23	66
D_{10}	40	36	43	39	32	15	47	61	32	0	18	22	40	26	22	33	40	18	45	8	14	47	39	58
D_{11}	43	40	39	35	37	10	50	64	27	18	0	29	44	19	13	28	44	25	48	16	11	50	35	60
D_{12}	33	28	48	45	24	27	42	57	39	22	29	0	33	34	31	40	34	13	39	24	26	42	45	53
D_{13}	6	18	59	56	23	43	25	47	51	40	44	33	0	48	46	52	4	36	19	41	42	25	56	42
D_{15}	47	44	34	29	42	21	54	67	19	26	19	34	48	0	14	21	48	31	52	25	22	54	29	63
D_{16}	45	42	37	33	39	16	52	65	23	22	13	31	46	14	0	25	46	28	50	20	17	52	33	62
D_{17}	52	49	27	21	46	30	58	70	9	33	28	40	52	21	25	0	52	38	56	32	30	58	21	67
D_{18}	8	19	59	56	24	43	24	46	51	40	44	34	4	48	46	52	0	36	19	41	43	25	56	41
D_{19}	35	31	46	43	27	23	44	59	37	18	25	13	36	31	28	38	36	0	41	19	23	44	43	55
D_{20}	21	27	62	59	31	47	15	42	55	45	48	39	19	52	50	56	19	41	0	45	47	15	59	37
D_{21}	40	37	42	38	33	13	48	62	31	8	16	24	41	25	20	32	41	19	45	0	12	48	38	58
D_{22}	42	38	40	37	35	5	49	63	29	14	11	26	42	22	17	30	43	23	47	12	0	49	37	59
D_{23}	26	31	64	61	34	49	1	39	57	47	50	42	25	54	52	58	25	44	15	48	49	0	61	33
D_{24}	56	53	17	1	51	36	61	73	23	39	35	45	56	29	33	21	56	43	59	38	37	61	0	70
D_{25}	42	45	72	70	48	60	33	21	66	58	60	53	42	63	62	67	41	55	37	58	59	33	70	0

Table 8: Distance among the textures based on number of skeleton points using Sym86 Wavelet Transform.

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}	D_{13}	D_{15}	D_{16}	D_{17}	D_{18}	D_{19}	D_{20}	D_{21}	D_{22}	D_{23}	D_{24}	D_{25}
D_1	0	9	54	54	15	37	30	49	48	38	43	30	16	45	41	48	17	35	24	41	39	29	53	44
D_2	9	0	55	54	18	38	28	48	49	39	44	31	13	46	42	49	14	36	22	42	40	28	54	43
D_3	54	55	0	10	52	40	62	73	25	39	33	45	57	30	36	26	57	42	60	36	38	62	10	70
D_4	54	54	10	0	51	39	61	73	23	38	32	44	56	28	34	24	56	41	59	34	37	61	3	69
D_5	15	18	52	51	0	34	34	52	46	35	40	26	22	43	38	45	23	31	29	38	36	33	51	47
D_6	37	38	40	39	34	0	47	61	31	8	22	22	40	26	18	31	41	12	44	18	12	47	39	58
D_7	30	28	62	61	34	47	0	39	57	48	52	42	25	54	51	56	25	46	17	51	49	5	61	32
D_8	49	48	73	73	52	61	39	0	69	62	65	58	47	67	64	69	46	60	43	64	63	39	73	22
D_9	48	49	25	23	46	31	57	69	0	30	22	38	51	17	25	7	51	34	54	26	29	57	23	66
D_{10}	38	39	39	38	35	8	48	62	30	0	20	23	41	25	17	30	41	14	45	16	9	48	38	58
D_{11}	43	44	33	32	40	22	52	65	22	20	0	31	46	15	12	21	46	25	49	13	18	52	32	62
D_{12}	30	31	45	44	26	22	42	58	38	23	31	0	34	34	28	37	34	18	39	28	25	42	44	53
D_{13}	16	13	57	56	22	40	25	47	51	41	46	34	0	48	44	51	5	38	18	44	42	25	56	41
D_{15}	45	46	30	28	43	26	54	67	17	25	15	34	48	0	19	15	48	29	52	20	24	54	28	63
D_{16}	41	42	36	34	38	18	51	64	25	17	12	28	44	19	0	24	45	22	48	5	14	51	34	60
D_{17}	48	49	26	24	45	31	56	69	7	30	21	37	51	15	24	0	51	33	54	25	28	56	24	65
D_{18}	17	14	57	56	23	41	25	46	51	41	46	34	5	48	45	51	0	39	18	44	42	24	56	41
D_{19}	35	36	42	41	31	12	46	60	34	14	25	18	38	29	22	33	39	0	43	21	17	46	41	56
D_{20}	24	22	60	59	29	44	17	43	54	45	49	39	18	52	48	54	18	43	0	48	46	16	59	37
D_{21}	41	42	36	34	38	18	51	64	26	16	13	28	44	20	5	25	44	21	48	0	13	50	34	60
D_{22}	39	40	38	37	36	12	49	63	29	9	18	25	42	24	14	28	42	17	46	13	0	49	37	59
D_{23}	29	28	62	61	33	47	5	39	57	48	52	42	25	54	51	56	24	46	16	50	49	0	61	33
D_{24}	53	54	10	3	51	39	61	73	23	38	32	44	56	28	34	24	56	41	59	34	37	61	0	69
D_{25}	44	43	70	69	47	58	32	22	66	58	62	53	41	63	60	65	41	56	37	60	59	33	69	0

Table 9 Classes of textures for the four wavelets when the lag value is 30.

Wavelet	**Class**	**Textures**
Haar	C_1	$\{D_1,D_2,D_5,D_6\}$
	C_2	$\{D_3,D_4,D_9,D_{15},D_{17}\}$
	C_3	$\{D_7,D_{13},D_{18},D_{20},D_{23}\}$
	C_4	$\{D_8,D_{25}\}$
	C_5	$\{D_{10},D_{11},D_{12},D_{16},D_{19},D_{21},D_{22}\}$
	C_6	$\{D_{24}\}$
Db6	C_1	$\{D_1,D_2,D_5,D_{13},D_{18},D_{20}\}$
	C_2	$\{D_3,D_4,D_9,D_{17},D_{24}\}$
	C_3	$\{D_6,D_{10},D_{11},D_{12},D_{16},D_{19},D_{21},D_{22}\}$
	C_4	$\{D_7,D_{23}\}$
	C_5	$\{D_8,D_{25}\}$
	C_6	$\{D_{15}\}$
Cf6	C_1	$\{D_1,D_2,D_5,D_{13},D_{18}\}$
	C_2	$\{D_3,D_4,D_9,D_{17},D_{24}\}$
	C_3	$\{D_6,D_{10},D_{11},D_{12},D_{19},D_{21},D_{22}\}$
	C_4	$\{D_7,D_{20},D_{23}\}$
	C_5	$\{D_8,D_{25}\}$
	C_6	$\{D_{15},D_{16}\}$
Sym8	C_1	$\{D_1,D_2,D_5,D_{13},D_{18},D_{20}\}$
	C_2	$\{D_3,D_4,D_9,D_{15},D_{17},D_{24}\}$
	C_3	$\{D_6,D_{10},D_{11},D_{16},D_{19},D_{21},D_{22}\}$
	C_4	$\{D_7,D_{23}\}$
	C_5	$\{D_8,D_{25}\}$
	C_6	$\{D_{12}\}$

Table 10. Classes of textures for the four wavelets when the lag value is 50.

Wavelet	**Class**	**Textures**
Haar	C_1	$\{D_1,D_2,D_5,D_6,D_7,D_{10},D_{11},D_{12},D_{13},D_{18},D_{20},D_{21},D_{22}\}$
	C_2	$\{D_3,D_4,D_9,D_{15},D_{16},D_{17},D_{24}\}$
	C_3	$\{D_8,D_{23},D_{25}\}$
Db6	C_1	$\{D_1,D_2,D_5,D_6,D_9,D_{10},D_{11},D_{12},D_{13},D_{15},D_{16},D_{19},D_{21},D_{22}\}$
	C_2	$\{D_3,D_4,D_{17},D_{24}\}$
	C_3	$\{D_7,D_8,D_{18},D_{20},D_{23},D_{25}\}$
Cf6	C_1	$\{D_1,D_2,D_5,D_6,D_7,D_{10},D_{11},D_{12},D_{13},D_{18},D_{19},D_{20},D_{21},D_{22},D_{23}\}$
	C_2	$\{D_3,D_4,D_9,D_{15},D_{16},D_{17},D_{24}\}$
	C_3	$\{D_8,D_{25}\}$
Sym8	C_1	$\{D_1,D_2,D_5,D_6,D_7,D_{10},D_{12},D_{13},D_{18},D_{19},D_{20},D_{22},D_{23}\}$
	C_2	$\{D_3,D_4,D_9,D_{11},D_{15},D_{16},D_{17},D_{21},D_{24}\}$
	C_3	$\{D_8,D_{25}\}$

4. CONCLUSIONS

The present paper investigated extraction of skeleton primitives by using skeleton subset. Though it is a tedious process of applying 2^8 possibilities, it is applied and it has given a clear and accurate dominant skeleton subset. If one wants classification mainly based on skeleton subset combination, then first method of classification is more appropriate. Since all textures considered have the same dimension second method of classification is also adopted based on least skeleton points. This classification may be appropriate for shape primitive classification. By increasing lag value, number of classes will be decreased and more number of textures will be added into each class. The same method can be extended to 5×5, 7×7…N×N masks also.

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