Morphological Shape features for Classification of Textures based on Fuzzy Texture Element

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ABSTRACT
Texture is an important spatial feature useful for identifying objects or regions of interest in an image. The present paper derives a new set of texture features, which are morphological shape components derived from the fuzzy texture elements of a 3x3 mask. The proposed fuzzy texture element patterns (FTP's) extract textural information of an image with a more complete respect of texture characteristics in all the eight directions instead of only one displacement vector. The proposed FTP's retains discriminating power of texture elements. In the present paper, five simple morphological shape components are evaluated on each of the derived FTP. The experimental results on the five groups of texture images clearly show the efficacy and simplicity of the present method.

Keywords: Morphological Shape components, Textural information, Classification, Fuzzy texture element.

1. INTRODUCTION
The present paper used textural properties for classification of textures [1, 2, 3, 4, 5]. Texture is the term used to characterize the surface of a given object or phenomenon and is undoubtedly one of the main features used in image processing, pattern recognition and multispectral scanner images obtained from aircraft or satellite platforms to microscopic images of cell cultures or tissue samples. That's why the research on texture classification and analysis has received considerable attention in recent years. There are several other areas like metallography [6] and umber processing [7] that make extensive use of textural features such as grain patterns and shapes, size, and distribution for classifying and analyzing specimens.

The study of patterns on textures is recognized as an important step in characterization and recognition of texture [17, 18, 24, 25, 26]. Various approaches are in use to investigate the textural and spatial structural characteristics of image data, including measures of texture [8], Fourier analysis [9, 10], fractal dimension [11], variograms [12, 13] and local variance measures [14]. Fourier analysis is found as the most useful when dealing with regular patterns within image data. It is used to filter out speckle in radar data [15] and to remove the effects of regular agricultural patterns in image data [15]. Study of regular patterns based on fundamentals of local variance was carried out recently [16].

Texture and pattern were recognized as important attributes of image data. Patterns are used extensively in the visual interpretation of image data, in which texture is often more important than the other image attributes. Depending on the context, the word pattern has many different interpretations.

Textures are classified by pattern based approaches [11, 19, 20, 15]. This explains that the texture is characterized not only by gray value at a given pixel, but also by the gray value pattern in the surrounding pixels. The texture has both local and global meaning, in the sense that it is characterized by the invariance of certain local attributes that are distributed over a region of an image.

Based on this texture and pattern relation the present paper attempted to classify various texture images based on fuzzy texture element patterns (FTP's), which is different from the earlier studies. The proposed FTP method retains discriminating power of texture elements derived by He and Wang [21, 22] in a better way.

The present paper is organized as follows. The section 2 defines morphology and shape features, Section 3 describe the methodology, the results and discussions are presented in section 4 and conclusions are listed in section 5.

2. MORPHOLOGY & SHAPE FEATURES
Mathematical morphology is a well-founded non-linear theory of image processing [27, 28, 29, 30, 31]. Its geometry-oriented nature provides an efficient framework for analyzing object shape characteristics such as size and connectivity, which are not easily accessed by linear approaches. Morphological operations take into consideration the geometrical shape of the image objects to be analyzed. Mathematical morphology is theoretically founded on set theory. It contributes a wide range of operators to image processing, based on a few simple mathematical concepts. An image can be represented by a set of pixels. A morphological operation uses two sets of pixels, i.e., two images: the original data image to be analyzed and a structuring element (also called kernel) which is a set of pixels or a pattern constituting a specific shape such as a line, a disk, or a square. A structuring element is characterized by a well-defined shape (such as line, segment, or any pattern), size, and origin. Its shape can be regarded as a parameter to a morphological operation. In mathematical morphology, neighborhoods are, defined by the structuring element, i.e., the shape of the structuring element determines the shape of the neighborhood in the image.

Mathematical Morphology is based on logical transformations of the image (this is no constraint when these transformations are generalized in terms of set definitions) carried out by using the set theoretical operations. This would enable us to make several measurements on the image, like trend, directional effect and holes. The basic step in morphology is to compare the objects which are to be analyzed with an object of known shape, termed structuring element (This forms one mode of definition). The result of comparison of an object under study (analogous to universe) with a structuring element (analogous to a defined set) causes an image transformation.

3. METHODOLOGY

In a square-raster digital image, each pixel is surrounded by eight neighboring pixels. The local texture information for a pixel can be extracted from a neighborhood of 3×3 pixels, which represents the smallest complete unit having eight directions surrounding the pixel. In the present paper texture features on a 3x3 mask are evaluated based on the central pixel. A neighborhood of 3×3 pixels is denoted by a set containing nine elements: P= {P0, P1 ...P8}, here P0 represents the intensity value of the central pixel and Pi {i=1, 2… 8}, is the intensity value of the neighboring pixel i as shown in Fig.1.

P_1	P_2	P_3
P_8	P_0	P_4
P_7	P_6	P_5

Fig 1: Representation of a 3x3 neighborhood

The present paper labels eight neighbors of a 3x3 mask using five possible fuzzy patterns or values {0, 1, 2, 3 and 4} derived from the fuzzy code as depicted in Equation 1 instead of ternary or binary values. In natural images, due to the presence of noise and the different processes of capture and digitations, even if the human eye perceives two neighboring pixels as equal, they rarely have exactly the same intensity value. To avoid this imprecision and be able to represent the vagueness within the processes, the present paper make use of fuzzy logic and fuzzy techniques in deriving shape elements. Therefore to deal classification effect by morphological shape components, with regions of natural images perceived as homogeneous by human beings, the present paper proposes a fuzzy texture pattern encoding. Unlike the ternary texture element, wherein each morphological shape component has one of three possible values (0, 1, or 2), in the FTP five values are assigned, each showing the degree to which the grey levels of surrounding pixels are lighter, similar, or darker than that of the seed pixel as shown in Fig 2.

$$P = \left\{ \begin{array}{l} 0 \;\; if \;\; P_i < P_0 and P_i < x \\ 1 \;\; if \;\; P_i < P_0 and P_i > P_x \\ 2 \;\; if \;\; P_i = P_0 \\ 3 \;\; if \;\; P_i > P_0 and P_i > y \\ 4 \;\; if \;\; P_i > P_0 and P_i < y \end{array} \right\} \text{for i =1,2, …,8} \qquad (1)$$

Where P is the obtained fuzzy code, Pi is the original pixel value at position i. P0 is the central pixel value, and x and y are user specified lag values. A 3x3 neighborhood that is labeled by fuzzy code is called as FTP. A pattern or a mask can be represented by a morphological structuring element. The Figs. 2(a) and 2(b) show the gray level values of a 3×3 neighborhood and the corresponding FTP.

63	28	40
88	40	35
67	40	21

(a)

4	0	2
4		1
4	2	0

(b)

Fig 2(a) : Sample Gray level Neighborhood 2(b): Fuzzy labeling of texture element.

On the FTP representation of a 3x3 mask the present study evaluated fuzzy texture features which represents the morphological shape component. The present paper derived five different morphological shape components named as Diamond Fuzzy Texture element Pattern(DFTP-I), Corner Fuzzy Texture element Pattern(CFTP-I), Left Fuzzy Texture element Pattern(LFTP-I), Right Fuzzy Texture element Pattern(RFTP-I) and Blob Fuzzy Texture element Pattern(BFTP-I), where 'I' ranges from 0 to 4. That is, DFTP-0 means the diamond shape component formed with FTP values 0. Each morphological shape components can be represented in 5-ways by using the FTP which is shown in Fig 3.

	0			1			2			3			4	
0		0	1		1	2		2	3		3	4		4
	0			1			2			3			4	
	(i)			(ii)			(iii)			(iv)			(v)	

Fig 3: (a) Representation of DFTP-I.

0		0	1		1	2		2	3		3	4		4
0		0	1		1	2		2	3		3	4		4
	(i)			(ii)			(iii)			(iv)			(v)	

Fig 3: (b) Representation of CFTP-I.

0			1			2			3			4		
0			1			2			3			4		
0	0		1	1		2	2		3	3		4	4	
	(i)			(ii)			(iii)			(iv)			(v)	

Fig 3: (c) Representation of LFTP-I.

	0	0		1	1		2	2		3	3		4	4
		0			1			2			3			4
		0			1			2			3			4
	(i)			(ii)			(iii)			(iv)			(v)	

Fig 3: (d) Representation of RFTP-I.

0	0	0
0		
0	0	0

(i)

1	1	1
1		1
1	1	1

(ii)

2	2	2
2		2
2	2	2

(iii)

3	3	3
3		3
3	3	3

(iv)

4	4	4
4		4
4	4	4

(v)

Fig 3: (e) Representation of BFTP-I.

For the classification of textures the frequency of occurrence of each morphological shape component with different FTP is counted using the Algorithm 1. One can enumerate large number of morphological shape components using FTP 0, 1, 2, 3 and 4. The novelty of the present work is, it uses only five different types of morphological shape components on FTP's.

Algorithm 1: Classification of textures based on morphological shape components with different FTP.

Begin

1. Read the original texture images T_k, where k=1 to n with dimension N×M.
2. Convert each 3x3 mask of the gray level texture image into a FTP.

   The gray level texture image T_k is assigned a fuzzy value 0, 1, 2, 3 or 4 in the following way

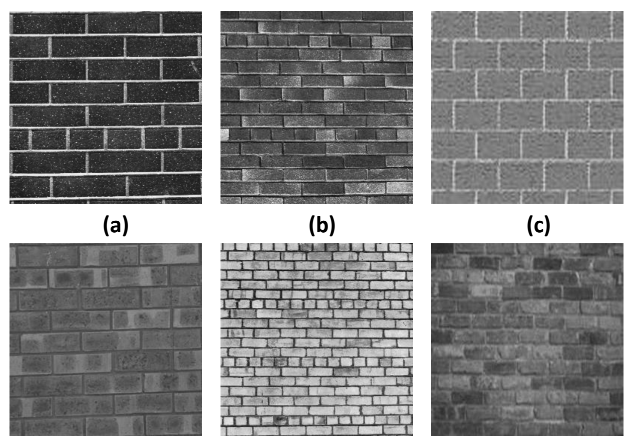
```
CP = Tk(2,2)
Y = CP + 10;
X = CP - 10;
    for u=1:3
        for v =1:3
        if Tk(u,v) < CP && Tk(u,v) < X
                    img(u,v) = 0
                    else
                    Tk(u,v) = 1
                    end
            if Tk(u,v) == CP
                    img(u,v) = 2
                    end
        if Tk(u,v) > CP && Tk(u,v) > Y
                    img(u,v) = 4
                    else
                    img(u,v) = 3
            end
        end
end
```

3. Represent the given shape patterns P_{ij} on 3×3 mask elements, where i=1 to 5 are morphological shape components and j = 1 to 5 represent FTP's 0, 1, 2, 3 and 4 .
4. Compute frequency occurrence (FO_i) of each shape pattern P_{ij} .
5. Compute the number of occurrence of each shape pattern (NSP_{ij}, i=1 to 5 and j=1 to 5) for each category of the texture T_k.

end

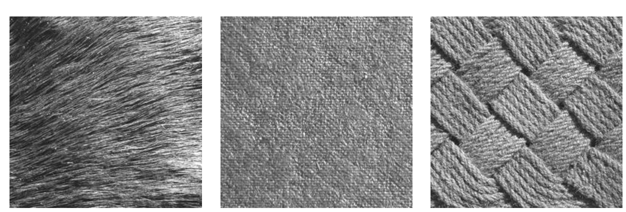
4. RESULTS AND DISCUSSIONS

To evaluate a good classification and recognition based on the morphological shape components of FTP, the present paper initially computed the frequency occurrences of each morphological shape component with each FTP. The novelty of the present scheme is, it classifies the given set of textures without any distance function, and that, it reduces the time complexity. For the classification purpose the present paper considers 5 groups of textures namely Brick, Fabric, Granite Marble and Mosaic each with six textures of 256 x 256 resolutions as shown in Fig. 4, 5, 6, 7 and 8 respectively. These texture image groups are collected mainly from the VisTex album and other standard albums. Based on Algorithm 1 the frequency of occurrence of each morphological shape component using different FTP for each group of textures is evaluated and represented in Tables 1, 2, 3, 4 and 5 for Brick, Fabric, Granite, Marble and Mosaic textures respectively.

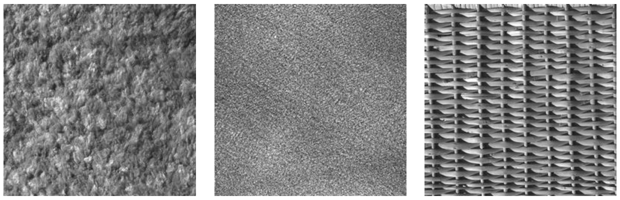


(a) (b) (c)
(d) (e) (f)

Fig 4: Original images of six Brick textures from (a)-(f).

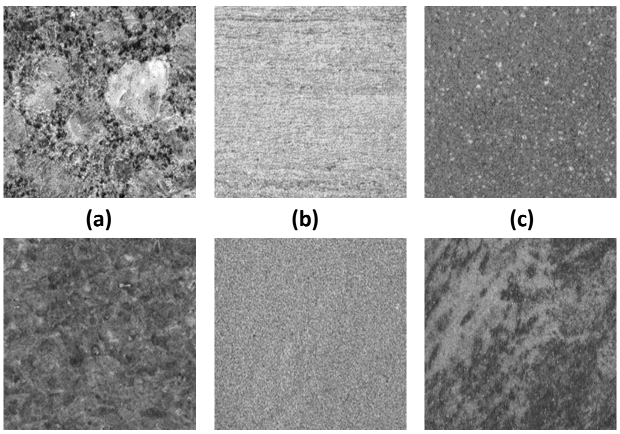


(a) (b) (c)



(d) (e) (f)

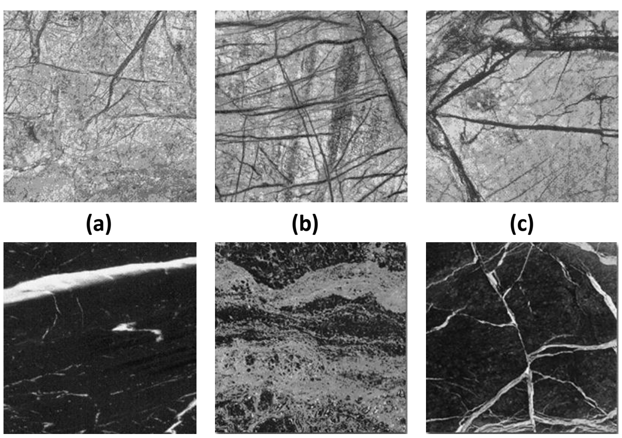
Fig 5: Original images of six Fabric textures from (a)-(f).



(a) (b) (c)

(d) (e) (f)

Fig 6: Original images of six Granite textures from (a)-(f).



(a) (b) (c)

(d) (e) (f)

Fig 7: Original images of six Marble textures from (a)-(f).

(a) (b) (c)

(d) (e) (f)

Fig 8: Original images of six Mosaic textures from (a)-(f).

The present study utilized one dimensional (1D) and two dimensional (2D) analysis or plots based on the frequency count of morphological shape components using FTP's for the classification purpose.

4.1 Classification Based on 1D Survey of Morphological Shape Components Using FTP's

From the frequency of occurrences of morphological shape components on FTP's of Tables 1 to 5, it is clearly evident that the Fabric and Granite textures can be classified easily based on the frequency of occurrences of DFTP-2 which results a zero count for these two groups of textures as shown in Table 2 and Table 5. It is also clearly evident that Mosaic textures can be classified as another group based on the frequency of occurrences of DFTP-4 which results a zero count for this group of texture. The classification using 1D survey based on DFTP-2 is shown in the form of flowchart in Fig.9. That is from the 1D survey of morphological shape components based on FTP's the following three classes are found from the considered five groups of textures.

Class-1: {Fabric, Granite}

Class-2: {Mosaic}

Class-3: {Brick, Marble}

Further classification that is individual classification of Class-1 and Class-3 textures is not possible by the proposed 1D survey of morphological shape components using FTP's. From the above 1D survey it is clearly evident that only diamond shape components on FTP of a 3x3 mask results a good classification and all other four morphological shape components failed in classification of textures. The same morphological shape components on texture elements without fuzzy logic has resulted only two classification groups [23].

Table 1. Frequency of occurrence of each morphological shape component of Brick textures using FTP.

Image	Diamond					Corners					Left - L					Right - L					Blob				
	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
Brick1	473	114	7	84	52	661	81	2	88	219	556	122	1	111	128	565	126	0	99	135	333	6	0	1	17
Brick2	421	64	9	71	141	785	56	1	41	422	554	71	1	47	224	513	63	1	46	212	249	3	0	2	50
Brick3	0	101	12	84	40	14	170	6	143	7	32	330	23	303	41	63	361	12	278	52	0	30	3	38	0
Brick4	6	227	8	171	16	91	227	2	230	80	40	345	11	355	53	43	324	16	334	59	6	44	0	53	14
Brick5	97	88	6	75	121	232	77	1	46	542	287	116	1	69	312	261	99	3	89	283	48	8	0	9	74
Brick6	0	143	32	119	32	12	205	22	181	11	11	339	45	304	9	15	394	45	328	9	0	46	5	31	0
Average	166	123	12	101	67	299	136	6	122	214	247	221	14	198	128	243	228	13	196	125	106	23	1	22	26

Table 2. Frequency of occurrence of each morphological shape component of Fabric textures using FTP.

Image	Diamond					Corners					Left - L					Right - L					Blob				
	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
Fabric1	395	12	0	12	257	835	7	0	7	737	655	15	0	12	460	592	12	0	8	480	220	2	0	1	119
Fabric2	380	5	0	6	181	739	1	0	0	554	775	8	0	0	525	785	2	0	3	540	285	0	0	0	110
Fabric3	469	9	0	7	370	598	3	0	2	549	732	6	0	8	596	668	12	0	2	613	218	0	0	0	206
Fabric4	134	8	0	11	87	318	15	0	5	174	501	28	0	30	394	540	50	0	22	407	71	0	0	0	28
Fabric5	575	2	0	2	517	791	3	0	1	651	849	4	0	0	719	808	7	0	0	742	340	0	0	0	270
Fabric6	222	11	0	8	84	1698	56	0	8	1398	808	115	0	16	475	545	76	0	6	686	79	4	0	2	41
Average	363	8	0	8	249	830	14	0	4	677	720	29	0	11	528	656	27	0	7	578	202	1	0	1	129

Table 3. Frequency of occurrence of each morphological shape component of Marble textures using FTP.

Image	Diamond					Corners					Left - L					Right - L					Blob				
	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
Marble1	155	93	5	73	123	336	46	1	40	340	494	102	1	75	478	487	97	3	89	459	87	6	0	8	103
Marble2	120	107	4	91	87	278	16	1	14	353	427	59	1	43	389	399	43	4	46	409	75	1	0	0	81
Marble3	97	76	5	97	92	233	37	3	32	251	352	82	7	69	350	361	106	6	91	347	58	2	2	5	60
Marble4	20	300	4	323	5	75	326	1	294	17	82	491	1	387	33	94	437	3	429	30	14	80	0	67	3
Marble5	150	89	3	75	111	314	33	0	18	289	459	63	0	50	419	453	62	0	46	416	99	9	0	3	79
Marble6	51	159	7	172	16	139	178	1	153	66	194	303	2	261	109	179	328	7	257	99	30	48	0	43	5
Average	99	137	5	139	72	229	106	1	92	219	335	183	2	148	296	329	179	4	160	293	61	24	0	21	55

Table 4. Frequency of occurrence of each morphological shape component of Mosaic textures using FTP.

Image	Diamond					Corners					Left - L					Right - L					Blob				
	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
Mosaic1	0	6	38	2	0	175	423	31	427	165	48	515	84	417	91	86	425	96	480	35	0	3	24	1	0
Mosaic2	2	40	2	53	0	132	112	0	123	206	89	244	3	293	79	109	298	2	268	61	2	20	0	25	0
Mosaic3	0	60	4	64	0	120	182	1	192	91	38	350	13	381	38	40	422	9	363	17	0	30	0	39	0
Mosaic4	0	55	2	45	0	8	192	2	150	60	26	307	11	315	25	37	338	6	260	18	0	26	0	24	0
Mosaic5	0	51	6	32	0	3	184	3	116	34	5	518	14	436	13	8	485	12	395	12	0	29	2	17	0
Mosaic6	0	23	10	23	0	0	165	5	96	0	0	429	33	564	0	0	625	22	394	0	0	18	3	20	0
Average	0	39	10	37	0	73	210	7	184	93	34	394	26	401	41	47	432	25	360	24	0	21	5	21	0

Table 5. Frequency of occurrence of each morphological shape component of Granite textures using FTP.

Image	Diamond					Corners					Left - L					Right - L					Blob				
	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
Granite1	210	19	0	25	181	411	20	0	15	392	563	36	0	32	569	577	41	0	33	615	129	2	0	3	99
Granite2	161	15	0	34	139	399	13	0	11	402	473	22	0	18	484	464	29	0	22	456	100	1	0	2	98
Granite3	102	40	0	22	149	274	29	1	16	409	388	78	1	48	470	341	76	2	54	446	55	0	0	0	85
Granite4	46	45	0	46	135	170	51	0	27	122	240	107	1	85	177	247	126	0	67	212	30	6	0	4	22
Granite5	181	24	0	11	154	470	17	0	14	468	526	25	0	17	493	529	27	0	18	482	125	0	0	0	102
Granite6	73	46	0	44	157	280	32	0	20	270	354	104	0	68	314	366	101	0	66	301	52	2	0	1	40
Average	129	32	0	30	153	334	27	0	17	344	424	62	0	45	418	421	67	0	43	419	82	2	0	2	74

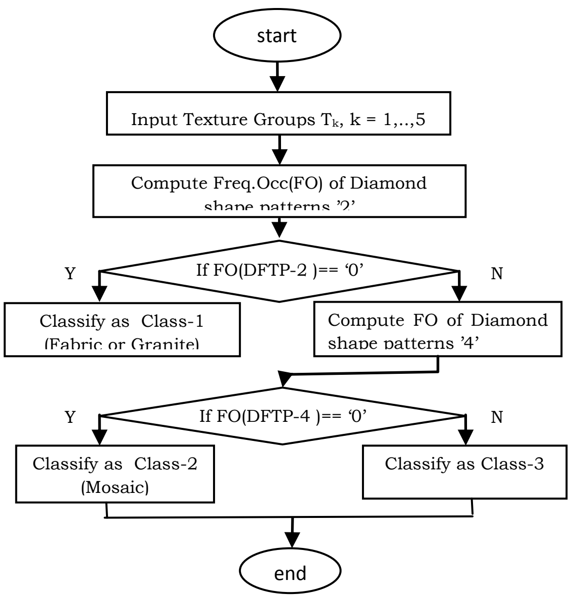


Figure 9. DFTP-2

4.2 Classification of Textures Based on 2D Plots of Morphological Shape Components Using FTP's

The present paper also classified the texture groups based on the 2D analysis on the morphological shape components using FTP's which are represented in the form of graphs. By this mechanism one can have one morphological shape component frequency count on X-axis and the other on Y-axis. There can be a total of 24 classification graphs that represent DFTP-0 on X-axis and other morphological shape components or same morphological shape component with different FTP on Y-axis. By removing duplication the total number of such graphs for classification of textures based on the 2D analysis on the proposed five morphological shape components with FTP's 0, 1, 2, 3 and 4 is given by the Equation-2.

$$T_g = n(n+1)/2 \tag{2}$$

Where T_g is total number of different graphs, n is ((S x P) – 1), where S represents the total number of morphological shape components and P is the number of FTP's. This leads to an exhaustive study. To overcome this present approach plotted the following graphs as shown in Figures 10, 11, 12, 13 and 14 respectively. The graphs reveal the same factor that Fabric, Granite and Mosaic textures are plotted as different groups or in a region and other texture groups (Marble and Brick) are scattered entirely on the graphs. Thus a good classification system is built based on the 2D plots of morphological shape components using FTP for Mosaic, Fabric and Granite textures. From the 2D survey of morphological shape components based on FTP's the following four classes are found from the considered five groups of textures.

Class-1 :{Mosaic}

Class-2 :{Fabric}

Class-3 :{Granite}

Class-4 :{Brick and Marble}

The above grouping clearly indicates the efficacy of the 2D graphs. However the present study suggests that it is not necessary to plot all graphs to classify textures. One can plot the frequency occurrence of DFTP-1 on X-axis and DFTP-4 on Y-axis, for a clear classification of Mosaic, Fabric and Granite textures as shown in Fig.10. The same classification of textures is also resulted in Fig.11, by plotting frequency occurrence of DFTP-3 on X-axis and DFTP-4 on Y-axis. Thus it reveals that a good classification can be resulted by diamond shape component feature based on FTP's on a 3x3 mask and one need not necessarily count the other four morphological shape components for classification of textures. Further classification that is individual classification of Brick and Marble textures is not possible by the proposed 2D surveys of morphological shape components using FTP's. Also it is to be noted that there is little bit of overlapping for Fabric and Granite textures using 2D graphs. However the similar 2D graphs without fuzzy coding using the same morphological shape components [23] resulted only two classification groups on the same texture groups.

Table 6. Percentage of occurrence of each morphological shape components with all patterns.

Texture	Percentage's of				
	DFTP	CFTP	LFTP	RFTP	BFTP
Brick	15.36	25.60	26.62	26.55	5.88
Fabric	12.50	30.28	25.51	25.10	6.60
Marble	12.68	20.65	30.74	30.77	5.15
Mosaic	3.48	22.80	36.09	35.72	1.90
Granite	10.84	23.15	30.42	30.45	5.12
Average	10.97	24.50	29.88	29.72	4.93

The present study also analyzed the percentage of occurrence factor of each morphological shape component with all patterns and it is represented in the Table 6. The Table 6 reveals that CFTP, LFTP and RFTP morphological shape components have dominant grouping in all considered groups of texture images but fail in classification. The DFTP which is having moderate percentage, resulted as a good texture feature for classification. The BFTP shows the least percentage of morphological shape component and fails in classification.

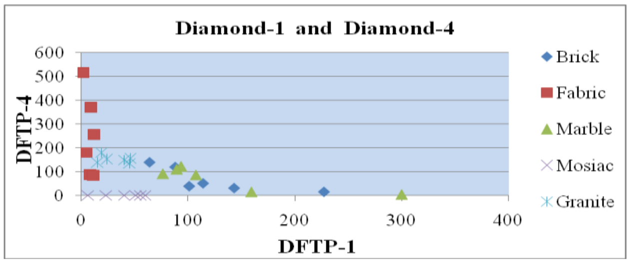


Fig 10: Graph between DFTP-1 and DFTP-4

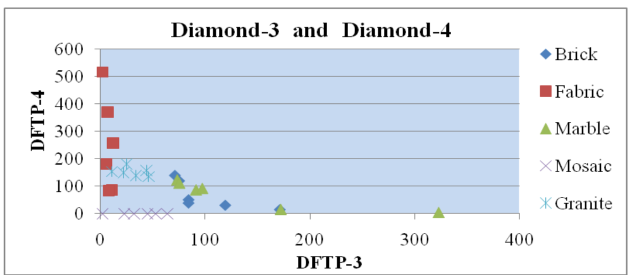


Fig 11: Graph between DFTP-3 and DFTP-4

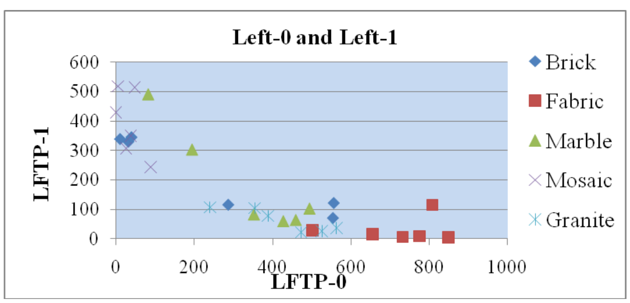


Fig 12: Graph between LFTP-0 and LFTP-1

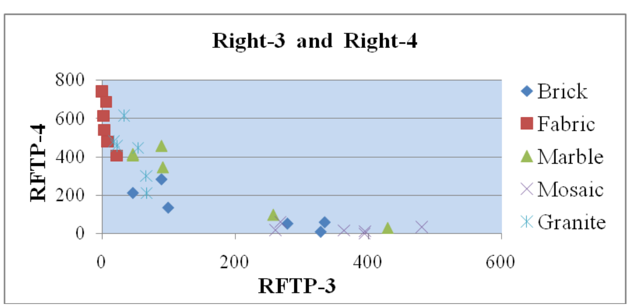


Fig 13: Graph between RFTP-3 and RFTP-4

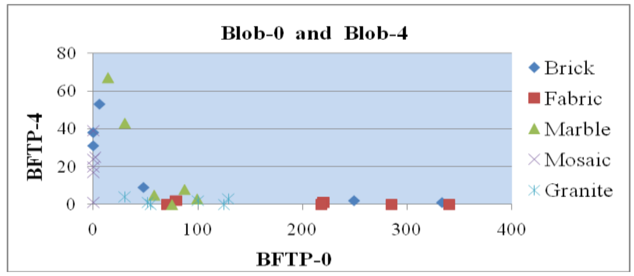


Fig 14: Graph between BFTP-0 and BFTP-4

5. CONCLUSIONS

The present study created a new direction for classification of textures based on morphological shape components derived from FTP of a 3x3 mask. By investigating texture classification using different morphological shape components the present paper concludes that diamond shape component contains more textural information for classification purpose than other morphological shape components. Based on the experimental results of 1D and 2D analysis the present paper concludes that one need not consider the other texture features CFTP, LFTP, RFTP and BFTP for classification purpose, since these morphological shape components contains least textural features. The FTP concept increased classification rate when compared to texture element patterns without fuzzy logic which classified the considered five groups of textures into only two groups of textures[23], resulting a poor classification. The present method proved as efficient tool when compared to previous one. The present paper also investigated that any stone texture contains more than 84% of occurrences of CFTP, LFTP and RFTP morphological shape components compared to DFTP with 11% and BFTP with 5% of occurrence.

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