An Innovative Method for Texture Classification Based on Random Threshold and Measure of Pattern Trends

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Abstract

Study of different patterns on a local neighborhood of a texture plays an important role in characterization, and classification of the textures. The present paper proposes a method for measuring the occurrence factor of patterns on a randomly thresholded binary image. For this process eight simple patterns are chosen on a 3×3 neighborhood. The simple patterns are chosen in such a way that any complex pattern can be formed by grouping one or more of these simple patterns. The pattern occurrence factor of different binary images is also compared with the actual binary texture image. The experimental results on sixty four textures indicate good comparison of variation of occurrence in these patterns on different binary images of random threshold.

Keywords: *Simple-Patterns, Frequency of Occurrence, Complex-pattern, Characterization.*

1. Introduction

Texture classification methods used can be categorized as statistical, geometrical, model-based and signal processing methods. [1, 2, 3] Early works were based on the analysis of statistical properties of the texture which deals with the spatial distribution of gray values. Some statistical methods used are co-occurrence matrix features [4, 5] and autocorrelation function. [6] In geometrical methods textures are considered to be composed of texture primitives. [7] Several stochastic models have been proposed for texture modeling and classification such as Gaussian Markov random fields [8, 9, 10] and spatial autocorrelation function model. [11] The signal processing techniques are mainly based on texture filtering for analyzing the frequency contents either in spatial domain [12, 13] or in frequency domain. [14] Hence, for some applications, more powerful texture feature extraction method should be found to measure the characteristics of the images.

Several sets of points will be obtained if the thresholding of the image is done for several thresholds. The gathering of these thresholds will generate the random thresholds to be used for texture classification. Study of patterns on textures is recognized as an important step in characterization and classification of texture. It has been used to filter out speckle in radar data [13] and to remove the effects of regular agricultural patterns in image data. [13] Study of regular patterns based on fundamentals of local variance was carried out recently. [14] Hence, the study of patterns still plays a significant area of research in classification and characterization of textures. That's why the present paper investigates how the frequency of occurrences of patterns varies after applying different random thresholds for binary image of the original textured image. The present paper assumes that a texture is characterized not only by the gray value at a given pixel, but also by the gray value pattern in a neighborhood surrounding the pixel. The ability to efficiently analyze and describe textured patterns is thus of fundamental importance. A simple or complex pattern of a neighborhood can be considered as one of the texture primitive feature. [15] The organization of the paper is as follows. The methodology of texture classification by random thresholds and measure of frequencies is provided in section 2, the results and discussions are presented in section 3 and the conclusions are accomdated in the last section.

2. Methodology

A binary image is obtained from a grey level image based on some threshold. That is N number of different binary images can be obtained from a grey level image. Where 'N' is the number of different grey levels of the image. The thresholded binary image of a grey level image I at threshold (th) is defined by the Equation (1).

$$I(x,y) = \begin{Bmatrix} 1 & if & I(x,y) \geq th \\ 0 & if & I(x,y) < th \end{Bmatrix} \tag{1}$$

Therefore a binary image is considered as a realization or outcome of a random closed set. A grey scale image is reduced to several binary images and, from a stochastic point of view, is a realization of a multivariate random closed set. In the present method, binary images are obtained on the random threshold of a grey level image as stated in equation (2) where μ and σ^2 be the grey level mean and variance of an image I respectively and for some integers of k and i.

$$th = \mu + (i/n)k\sigma \tag{2}$$

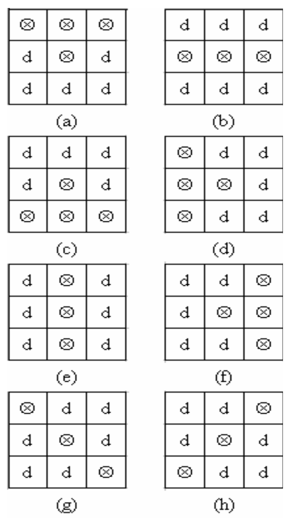
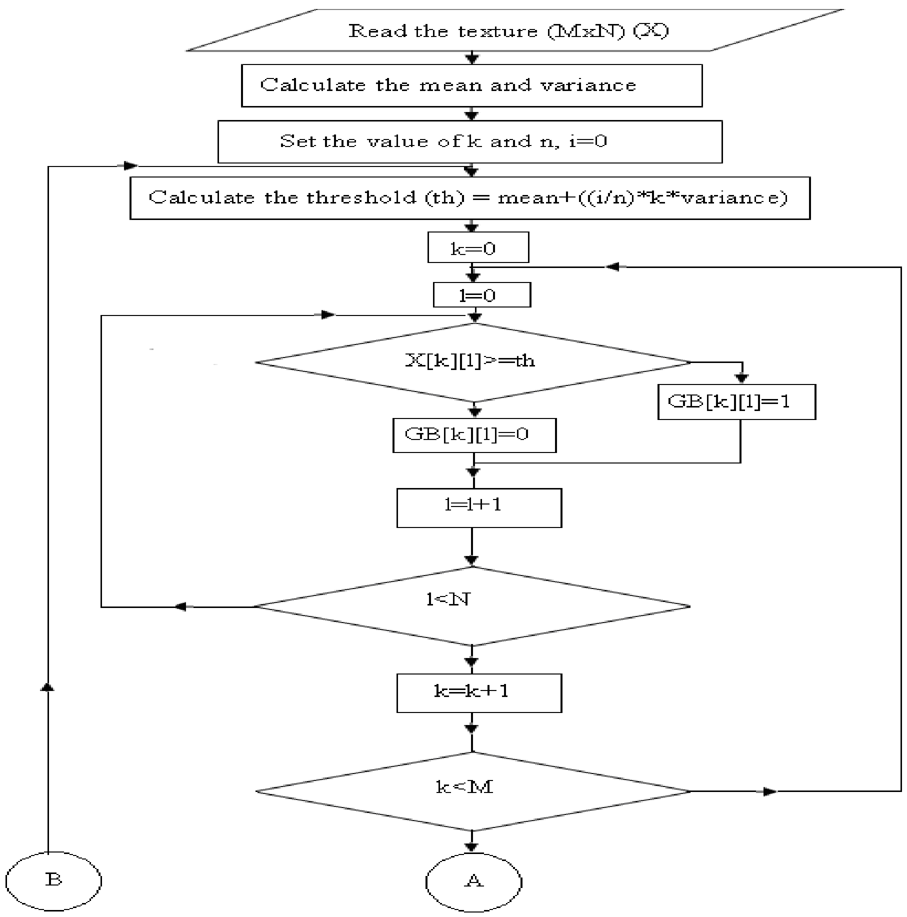


Figure 1. Representation of Primitive Patterns (a) Top Horizontal Line Patterns (b) Middle Horizontal Line Patterns (c) Bottom Horizontal Line Patterns (d) Left vertical Line Patterns (e) Middle Vertical Line Patterns (f) Right Vertical Line Patterns (g) Left Diagonal Line Patterns (h) Right Diagonal Line Patterns.

Depending on the context the word pattern has many different interpretations. The biology community seems to use the word pattern without defining it. The implicit meaning generally brings to mind some kind of repeated arrangement (regular or not) and the term is often defined by examples. The word texture certainly has many interpretations in the graphics community. Using a 3 × 3 grid one can generate 512 patterns. However, if we specify the center point of a 3 × 3 grid should be a grain component then the number of spatial patterns will be reduced to 256. The present study uses this concept. It is possible to enumerate all the 256 patterns using a 3 × 3 grid. But such an exhaustive enumeration is removed in the present paper by considering only 8 simple patterns. The present paper considers a pattern when the central pixel is necessarily a grain component. On these binary images the occurrence of simple patterns like Top Horizontal Line (THL), Middle Horizontal Line (MHL), Bottom Horizontal Line (BHL), Left Vertical Line (LVL), Middle Vertical Line (MVL), Right Vertical Line (RVL), Left Diagonal (LD), and Right Diagonal (RD) are studied. The Figure 1 specifies the particular kind of arrangement of the above simple patterns. In the Figure 1 the '⊗' specifies a grain or 1 and the symbol d specifies don't care symbol that is either zero or 1. The entire scheme is explained in the Figure 2.



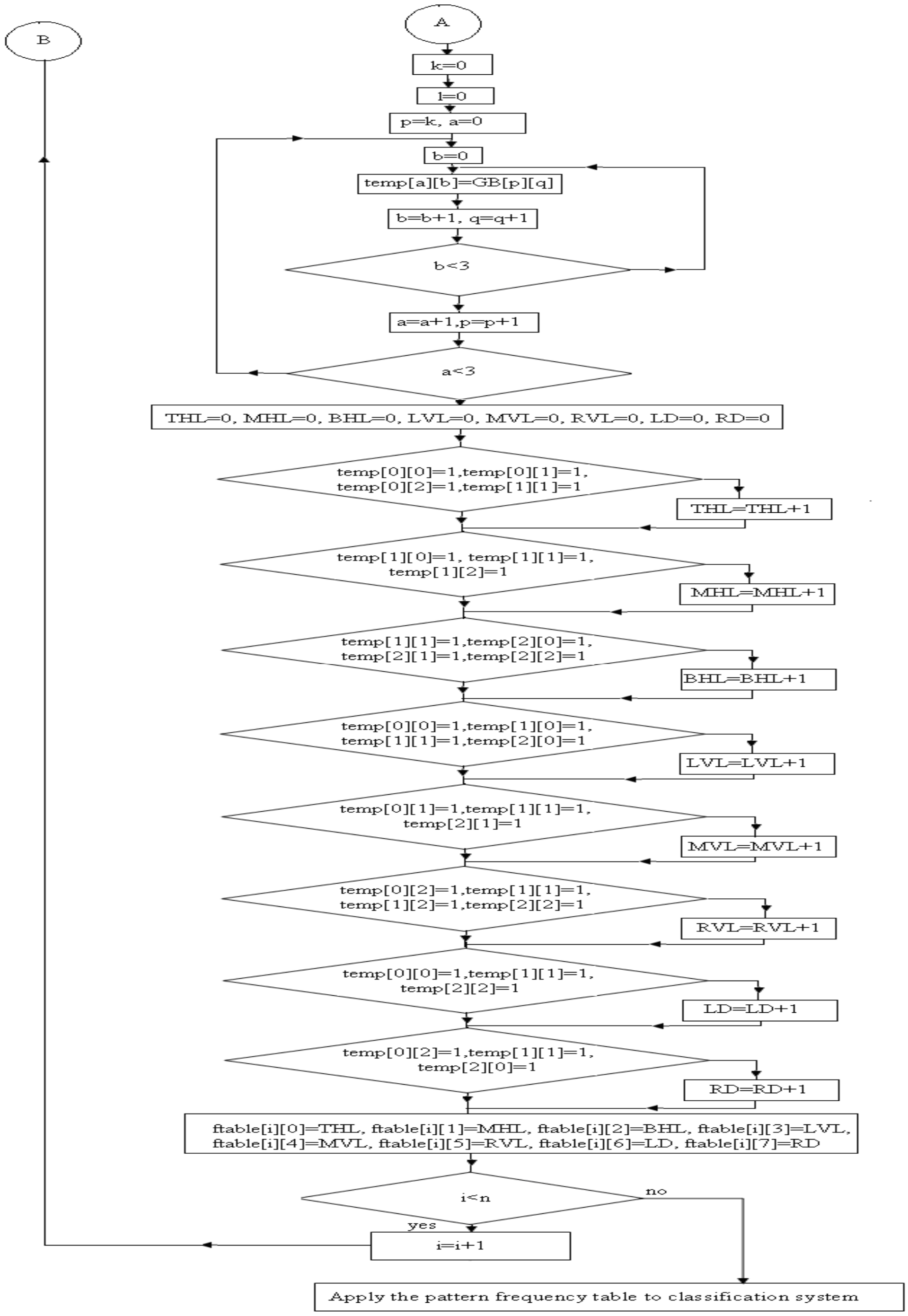


Figure 2. Flowchart for generation of patterns based on random thresholds.

3. Results and Discussions

The present paper has considered 48 textures from visitex album and 8 granite textures and 8 marble textures from the website.[16] This results a total of 64 textures with a resolution of 256×256. The textures are displayed in Figure 3 with a resolution of 50×50 to restrict the size of the paper. The experiments are carried out on all these 64 textures, but it becomes laborious to provide results for this large set of textures at each stage of discussion. The present paper investigated the variation of above simple patterns on different binary images generated by different random thresholds. On these binary images percentage of frequency of occurrences of simple patterns are evaluated for 64 textures. The percentage of correct classification based on the frequency measure of all the eight patterns is calculated. The tables from 1 to 8 shows the classification rate based on different patterns between the Brick and Fabric and Brick and Granite textures. The Table 9 shows the frequency measure of all patterns on the Brick.0000 texture by Random Thresholds generated by the Equation (2). From this table, it is evident that the frequency of occurrence of all the simple patterns show a decreasing order on the binary images obtained from the random thresholds. The Figure 4 and Figure 5 clearly show the classification between water and fabric texture databases by the MHL pattern in the interval1 and interval2.

Table 1. Percentage of correct classification based on frequency measure of THL pattern

Interval	**Brick Vs Fabric**		**Brick Vs Granite**	
	Brick	***Fabric***	***Brick***	***Granite***
1	50.00	50.00	37.50	62.50
2	87.50	62.50	37.50	87.50
3	75.00	75.00	75.00	87.50
4	75.00	75.00	75.00	87.50
5	75.00	75.00	75.00	75.00
6	62.50	87.50	62.50	75.00
7	50.00	50.00	62.50	62.50
8	75.00	37.50	50.00	50.00
9	50.00	50.00	75.00	75.00
10	50.00	62.50	62.50	50.00
11	50.00	62.50	50.00	37.50

Table 2. Percentage of correct classification based on frequency measure of MHL pattern

Interval	**Brick Vs Fabric**		**Brick Vs Granite**	
	Brick	***Fabric***	***Brick***	***Granite***
1	75.00	75.00	75.00	62.50
2	50.00	75.00	50.00	87.50
3	75.00	75.00	75.00	75.00
4	75.00	75.00	75.00	87.50
5	75.00	87.50	75.00	75.00
6	62.50	75.00	62.50	87.50
7	62.50	75.00	62.50	62.50
8	62.50	50.00	62.50	62.50
9	62.50	50.00	62.50	75.00
10	50.00	75.00	50.00	87.50
11	50.00	62.50	50.00	50.00

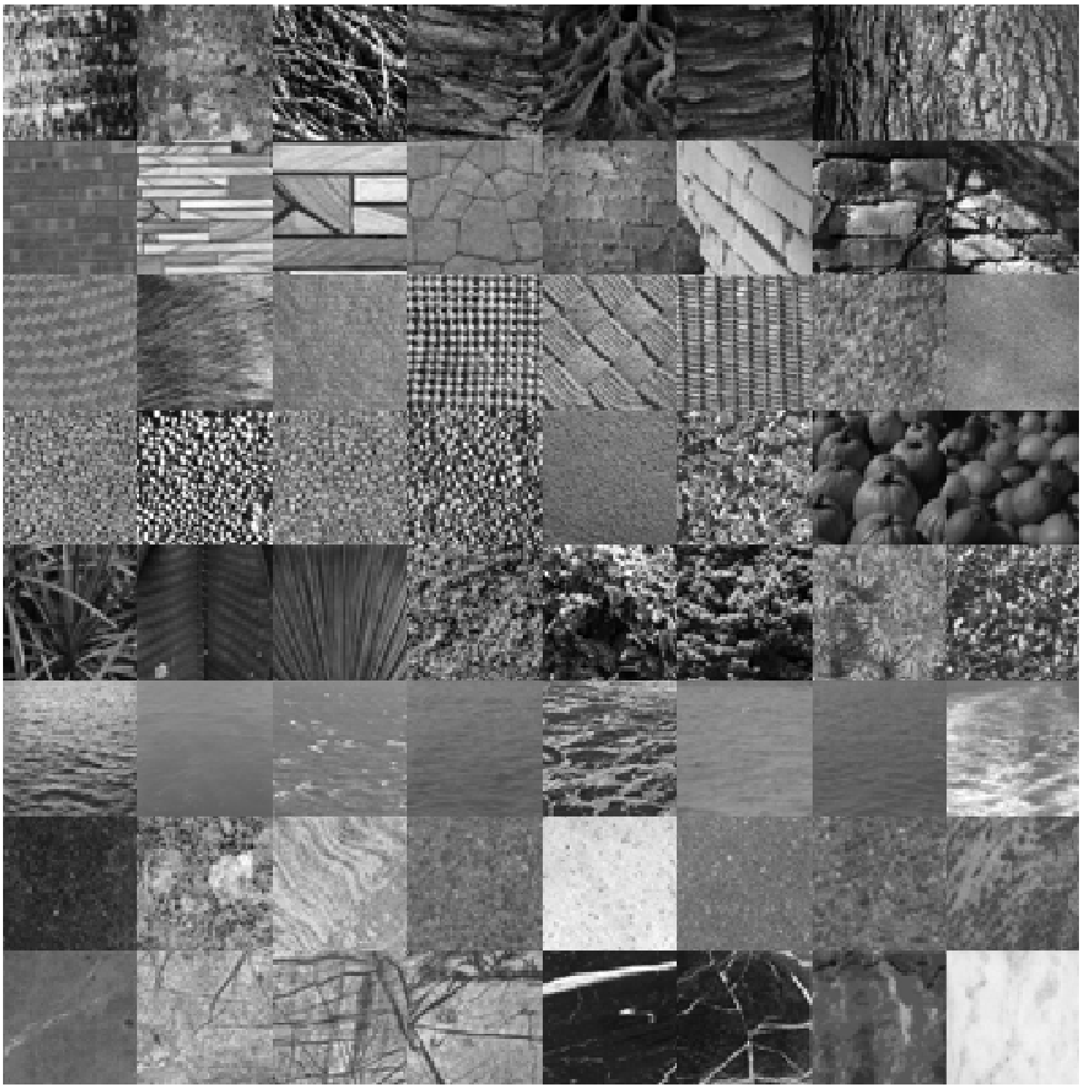


Figure 3. Texture images from left-right and top - bottom: Bark.0000, Bark.0001 Bark.0003, Bark.0004, Bark.0005, Bark.0006, Bark.0007, Bark.0009, Brick.0000, Brick.0002, Brick.0003, Brick.0004, Brick.0005, Brick.0006, Brick.0007, Brick.0008, Fabric.0000, Fabric.0004, Fabric.0007, Fabric.0008, Fabric.0011, Fabric.0013, Fabric.0015, Fabric.0018, Food.0000, Food.0001, Food.0002, Food.0003, Food.0005, Food.0006, Food.0010, Food.0011, Leaves.0000, Leaves.0001, Leaves.0002, Leaves.0003, Leaves.0005, Leaves.0006, Leaves.0010, Leaves.0011, Water.0000, Water.0001, Water.0002, Water.0003, Water.0004, Water.0005, Water.0006, Water.0007, Granite.0000, Granite.0001, Granite.0002, Granite.0003, Granite.0004, Granite.0005, Granite.0006, Granite.0007, Marble.0000, Marble.0001, Marble.0002, Marble.0003, Marble.0004, Marble.0005, Marble.0006, Marble.0007.

Table 3. Percentage of correct classification based on frequency measure of BHL pattern

Interval	Brick Vs Fabric		Brick Vs Granite	
	Brick	*Fabric*	*Brick*	*Granite*
1	50.00	62.50	37.50	62.50
2	87.50	62.50	50.00	87.50
3	87.50	62.50	87.50	87.50
4	62.50	75.00	75.00	87.50
5	75.00	75.00	75.00	75.00
6	62.50	75.00	62.50	87.50
7	75.00	50.00	62.50	75.00
8	75.00	50.00	75.00	25.00
9	50.00	75.00	50.00	75.00
10	50.00	62.50	62.50	75.00
11	75.00	75.00	50.00	37.50

Table 4. Percentage of correct classification based on frequency measure of LVL pattern

Interval	Brick Vs Fabric		Brick Vs Granite	
	Brick	*Fabric*	*Brick*	*Granite*
1	62.50	62.50	50.00	62.50
2	87.50	87.50	87.50	87.50
3	75.00	87.50	75.00	87.50
4	75.00	50.00	75.00	75.00
5	75.00	50.00	75.00	75.00
6	62.50	62.50	50.00	87.50
7	75.00	62.50	75.00	50.00
8	62.50	62.50	75.00	50.00
9	50.00	75.00	50.00	62.50
10	50.00	87.50	50.00	75.00
11	75.00	87.50	50.00	37.50

Table 5. Percentage of correct classification based on frequency measure of MVL pattern

Interval	Brick Vs Fabric		Brick Vs Granite	
	Brick	*Fabric*	*Brick*	*Granite*
1	62.50	87.50	50.00	62.50
2	87.50	62.50	62.50	75.00
3	87.50	75.00	75.00	50.00
4	75.00	75.00	62.50	50.00
5	87.50	50.00	75.00	75.00
6	62.50	50.00	62.50	50.00
7	75.00	62.50	62.50	62.50
8	62.50	62.50	50.00	50.00
9	50.00	62.50	50.00	62.50
10	50.00	87.50	50.00	87.50
11	50.00	75.00	50.00	75.00

Table 6. Percentage of correct classification based on frequency measure of RVL pattern

Interval	Brick Vs Fabric		Brick Vs Granite	
	Brick	***Fabric***	***Brick***	***Granite***
1	50.00	87.50	50.00	62.50
2	75.00	87.50	75.00	87.50
3	87.50	62.50	75.00	87.50
4	75.00	87.50	75.00	87.50
5	75.00	87.50	75.00	75.00
6	62.50	62.50	62.50	75.00
7	50.00	50.00	62.50	62.50
8	62.50	62.50	62.50	50.00
9	50.00	75.00	50.00	75.00
10	50.00	87.50	50.00	75.00
11	50.00	75.00	50.00	62.50

Table 7. Percentage of correct classification based on frequency measure of LD pattern

Interval	Brick Vs Fabric		Brick Vs Granite	
	Brick	***Fabric***	***Brick***	***Granite***
1	50.00	87.50	50.00	75.00
2	87.50	62.50	62.50	75.00
3	87.50	75.00	75.00	50.00
4	50.00	87.50	75.00	62.50
5	75.00	87.50	75.00	75.00
6	75.00	62.50	62.50	87.50
7	75.00	62.50	75.00	50.00
8	62.50	62.50	62.50	50.00
9	50.00	75.00	50.00	75.00
10	62.50	62.50	50.00	62.50
11	50.00	75.00	50.00	62.50

Table 8. Percentage of correct classification based on frequency measure of RD pattern

Interval	Brick Vs Fabric		Brick Vs Granite	
	Brick	***Fabric***	***Brick***	***Granite***
1	62.50	87.50	75.00	62.50
2	87.50	87.50	87.50	87.50
3	87.50	62.50	75.00	62.50
4	75.00	87.50	75.00	87.50
5	87.50	87.50	87.50	75.00
6	75.00	62.50	62.50	75.00
7	75.00	37.50	62.50	50.00
8	75.00	50.00	75.00	50.00
9	50.00	87.50	50.00	75.00
10	50.00	75.00	50.00	75.00
11	50.00	87.50	50.00	50.00

Table 9. The Frequency Measure of All Patterns on the Brick.0000 Texture by Random Thresholds

Interval	THL	MHL	BHL	LVL	MVL	RVL	LD	RD
1	32.638	33.945	32.615	34.652	38.203	34.652	32.941	31.994
2	27.940	29.207	27.900	29.841	33.330	29.852	28.190	27.277
3	23.126	24.329	22.957	24.874	28.272	24.909	23.326	22.353
4	19.011	20.111	18.815	20.545	23.786	20.640	19.187	18.301
5	14.824	15.864	14.696	16.213	19.150	16.252	15.054	14.037
6	10.986	11.947	10.898	12.177	14.773	12.183	11.234	10.298
7	7.927	8.708	7.859	8.866	11.110	8.928	8.107	7.339
8	5.039	5.627	4.943	5.625	7.318	5.720	5.165	4.531
9	2.847	3.280	2.792	3.154	4.263	3.202	2.937	2.449
10	1.203	1.457	1.167	1.364	2.012	1.384	1.229	0.973
11	0.194	0.279	0.184	0.205	0.392	0.222	0.198	0.122

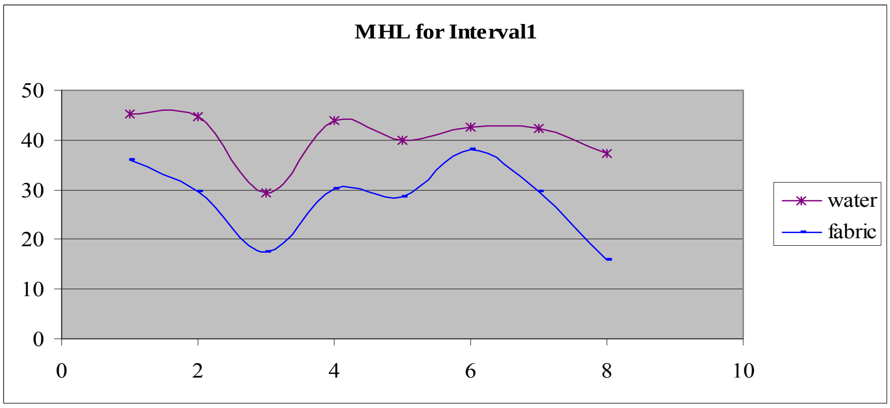


Figure 4. Classification Graph for Water and Brick by MHL Pattern in Interval1

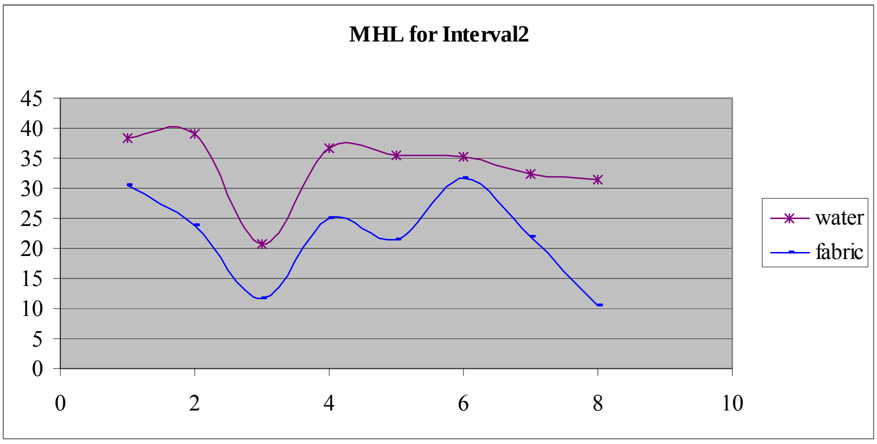


Figure 5. Classification Graph for Water and Brick by MHL Pattern in Interval2

4. Conclusions

The present paper proposed a novel scheme of texture classification using various simple patterns. The results indicate that there is a decreasing order of the frequency measure of all simple patterns on the binary images obtained from random thresholds. Even though the thresholds are varying, there is a constant percentage of correct classification based on frequency measure of all simple patterns. Finally a precise classification is achieved by random thresholds between various textures.

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