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EVALUATION OF SHAPE FEATURES FOR EFFICIENT CLASSIFICATION BASED ON ROTATIONAL INVARIANT USING TEXTON MODEL

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Abstract: The present paper derived shape features on textons and texture orientation for rotation invariant stone texture classification of 2D images. To overcome the sensitive problems and to derive rotational invariant features on textons the present research represented textons on texture orientation matrix by reducing grey level range using a fuzzy logic. The proposed Texture orientation matrix (TOM) is formed by bitwise OR operator on Sobel and Canny edge detectors with an orientation of ten degrees at each step. The shape features are derived on the proposed "Texture Orientation Fuzzy Texton Binary Matrix (TOFTBM)".The proposed TOFTBM with TSF is computationally attractive as it computes different features with limited number of selected pixels. The proposed method is compared with various methods and the result indicates the efficacy of the proposed method over the other methods.

Keywords: Sobel operator, canny operator, Texture orientation, fuzzy, reduction of grey level range.

1. INTRODUCTION

Texture classification is one of the problems which has been paid much attention on by computer scientists since late 90s. If texture classification is done correctly and accurately, it can be used in many cases such as Pattern recognition, object tracking, and shape recognition. Various approaches are existing to investigate the textural and spatial structural characteristics of image data, including measures of texture [1], Fourier analysis [2,3], fractal dimension [4], variogram [5,6,7,8] and local variance measures [9]. Fourier analysis is found as the most useful when dealing with regular patterns within image data. It has been used to filter out speckle in radar data [10] and to remove the effects of regular agricultural patterns in image data [10]. Study of regular patterns based on fundamentals of local variance was carried out recently [11,12]. Hence, the study of patterns still plays a significant area of research in classification, recognition and characterization of textures [13].

More recently, the local-binary-pattern (LBP) operator [14,15,16] is used for texture classification. LBP operator is a statistical texture descriptor of the characteristics of the local structure. LBP provides a unified description including both statistical and structural characteristics of a texture patch, so that it is more powerful for texture analysis. The concept of LBP is also extend in applications such as face recognition and age classification [17,18,19],industrial visual inspection [20,21], segmentation of remote-sensing images [22], and classification of real outdoor images [23].Most of these algorithms make an implicit assumption that all images are captured under the same orientation. In any practical applications this assumption is not valid. Moreover, as images of the same underlying texture can vary significantly, textural features must be invariant to (large) image variations, and at the same time sensitive to intrinsic spatial structures that define textures. Therefore rotation and scale invariant texture classification becomes necessary in such applications. That is the reason the present paper carried out rotational invariant texture classification using TOM.

Many rotation invariant texture classification methods [24,25,26,27] are proposed in the literature. However, such features may fail to classify the images. Spatial structures vary with rotation while contrast does not. Ojala et al. [27] proposed using the joint histogram of the two complementary features, namely LBP/VAR, for rotation invariant texture classification. The drawback of this approach is that the value of VAR is continuous so that a quantization step is needed to calculate the histogram. The main contributions in this paper is finding rotation invariant texture shape features for texture classification and evaluating performance of the method.

This paper is organized as follows. In Section 2 methodology shape features are proposed for classification. Section3 contains experimental results and discussions. Conclusions are given in Section 4.

2. METHODOLOGY

The Fig.1 shows the proposed model of texture classification called Rotation Invariant Texture Classification based on TOFTBM with TSF, which integrates color, texture and edge features of an image. The proposed TOFTBM with TSF is used to describe the spatial correlation of textons and texture orientation for texture classification. The step wise procedure is explained in the following sub sections.

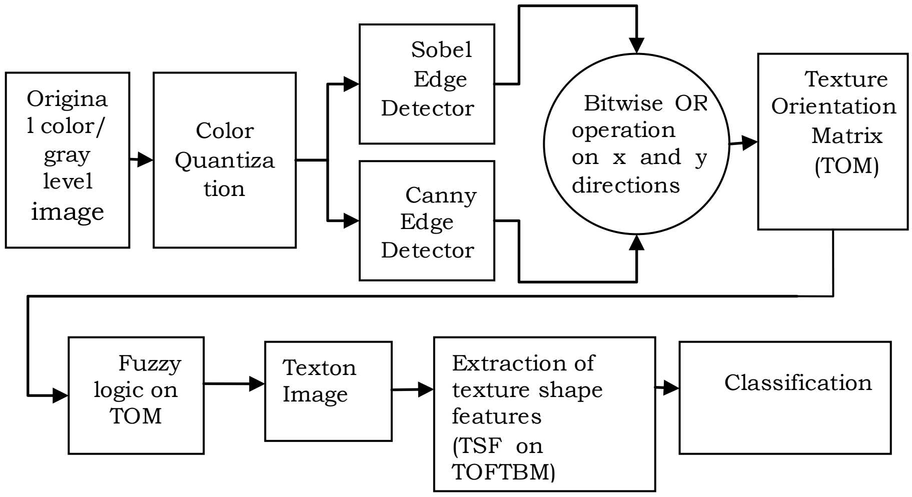

Fig.1: Rotational invariant texture classification based on TSF derived from TOFTBM.

2.1 RGB to HSV Color Model Conversion

During the course of feature extraction, the original images are quantized into 128 colors of RGB color space and the color gradient is computed from the RGB color space. In color image processing, there are various color models in use today. The RGB color space is not sensitive to human visual perception or statistical analysis especially in classification problems related to natural textures like Stones etc.. Moreover, a color is not simply formed by these three primary colors. HSV color space is a non-linear transform from RGB color space that can describe perceptual color relationship more accurately than RGB color space.

In order to extract gray level features from color information, the proposed TOFTBM with TSF utilized HSV color space. HSV is formed by hue (H), saturation (S) and value (V). Hue denotes the property of color such as blue, green, red, and so on. Saturation denotes the perceived intensity of a specific color. Value denotes brightness perception of a specific color. Thus it can be seen that HSV color space is different from RGB color space in color variations. When a color pixel-value in RGB color space is adjusted, intensities of red channel, green channel, and blue channel of this color pixel are modified. That means color, intensity, and saturation of a pixel is involved in color variations. It is difficult to observe the color variation in complex color environment or content. However, HSV color space separates the color into hue, saturation, and value which means observation of color variation can be individually discriminated. Based on the above the proposed method adopted HSV descriptor for color space because it describes colour intensity and brightness's in a significant manner. In order to transform RGB color space to HSV color space, the transformation is described as follows:

The transformation equations from RGB to HSV color model conversion is given below

$$V = \max(R, G, B) \tag{1}$$

$$\mathrm{S} = \frac{V - min(R,G,B)}{V} \tag{2}$$

$$\mathrm{H} = \frac{\mathrm{G-B}}{6S} \quad if \quad \mathrm{V = R} \tag{3}$$

$$\mathrm{H} = \frac{1}{3} + \frac{\mathrm{B-R}}{6\mathrm{S}} \quad if \quad \mathrm{V = G} \tag{4}$$

$$\mathrm{H} = \frac{1}{3} + \frac{\mathrm{R-G}}{6\mathrm{S}} \quad if \quad \mathrm{V} = \mathrm{B} \tag{5}$$

Where R, G, B are Red, Green and Blue normalized in value [0, 1]. In order to quantize the range of the H plane is normalized with value
[0, 255] for extracting features specifically.

2.2 Texture Orientation Detection

One of the powerful visual cues about the contents of an image is the orientation. Strong orientation usually indicates a definite pattern. The natural images show various contents which may have some common fundamental elements. Texture orientation analysis plays an important role in computer vision and pattern recognition. For instance, orientation is used in pre-attentive vision to characterize textons. Texture orientation can also be used to estimate the shape of the textured images. The orientation map in an image represents the object boundaries and texture structures, and provides most of the semantic information of the image.

Various low-level visual features (e.g. color, texture, shape, edges) can be extracted as a preprocessing step from the images. Out of all these image edges give good information about the image content because they allow the identification of the object structures. Edge detection is a fundamental tool used in most of the image processing applications to obtain information from the images as a precursor step to feature extraction. The image edge has a close relationship with contour and texture pattern. It can provide abundance of texture information and shape information. The edges contain the following features of the image.

1. Edge aims at identifying points in a digital image at which the image brightness changes sharply or more formally and has discontinuities.
2. Edge detection process detects and outlines the boundaries between objects and the background in the image.
3. Edge features are useful to overcome the attacks generated by noise, edge strips and acuity.
4. Edges form boundaries between the different textures.
5. Edge reveals the discontinuities in image intensity from one pixel to another.

That’s why the present paper found that edges are relatively a good choice for texture orientation. Based on this assumption, the present paper derived a computationally efficient algorithm for texture orientation. To achieve this, Sobel and Canny edge detection is applied on the image to segment the enhanced borders from the background image. The Sobel edge detector applies Sobel approximation to the derivative of the image and detects edges. The canny edge detector finds edges by looking for local maximum of the gradient of unprocessed input image. In each edge detection algorithm, the gradient is calculated. A gradient map g(x,y) can be obtained with the gradient magnitude and orientation defined in equation (6).The outputs of Sobel and canny edge operators are biwise logically ORed together by horizontally and vertically to produce a new TOM image.

$|g(x,y)| = \sqrt{G_x^2 + G_y^2}$ and $\theta = \arctan(g_y/g_x)$ There are two masks associated with the Sobel and canny filters: one mask corresponds to the gradients in the X-direction and the other to the gradients in the Y-direction.

The response function for the Sobel and canny filter are given equations (7) & (8):

$$G_x = |(R_{sx}|R_{cx})| \tag{7}$$

$$G_y = |(R_{sy}|R_{cy})| \tag{8}$$

where R_{sx}, R_{sy}, R_{cx} and R_{cy} are given in equations (9) to (12):

$$R_{sx} = m_1^1 I_1 + m_2^1 I_2 + m_3^1 I_3 + \cdots + m_9^1 I_9 \tag{9}$$

$$R_{sy} = m_1^2 I_1 + m_2^2 I_2 + m_3^2 I_3 + \cdots + m_9^2 I_9 \tag{10}$$

$$R_{cx} = n_1^1 I_1 + n_2^1 I_2 + n_3^1 I_3 + \cdots + n_9^1 I_9 \tag{11}$$

$$R_{cy} = n_1^2 I_1 + n_2^2 I_2 + n_3^2 I_3 + \cdots + n_9^2 I_9 \tag{12}$$

Where m_i^1 , m_i^2 corresponds to the first and second mask of sobel operator and n_i^1, n_i^2 are canny operators.

The texture orientation is computed based on the above equations. Then texture orientation of each pixel is quantized into 18 orientations with 10^0 as the step length. From this TOM is formed. This makes the proposed TOM as rotationally invariant. The proposed TOM further can detect the saltation of color, color edge stripe and acuity problems of an image which is not possible by earlier methods like Texton co-occurrence matrix (TCM).

2.3 Formation OF Fuzzy Grey level Matrix

In natural images, due to the presence of noise, different illumination levels and various conversion factors between neighboring pixels of a window represent as equal, though they rarely have exactly the same intensity value. To avoid this imprecision and be able to represent the vagueness within the processes, the proposed study made use of fuzzy logic on the obtained grey level images of TOM. In Textons even two adjacent pixels differ with a value by one, they may not form a texton shape pattern. This leads to difficulty in analyzing homogeneity issues of varying illumination, noise based issues, scale changes and variability in measuring small surface shapes especially in natural images. To address this fuzzy logic is introduced on the proposed TOM. The proposed method labels eight neighbors of a 3×3 neighborhood using five possible fuzzy patterns or values {0, 1, 2, 3 and 4} derived from the fuzzy code as depicted in equation (13) and the fuzzy membership function is represented as shown in Fig.2. From Fig.2, the element V_i represent the intensity values of the eight neighboring pixels on a 3×3 neighborhood, V_0 represents the intensity value of central pixel, x and y are the user specified lag values.

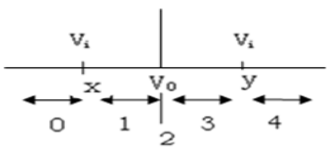

Fig.2: Fuzzy texture representation.

$$E_i = \begin{cases} 0 & \text{if} \quad V_i < V_0 \quad \text{and} \quad V_i < x \\ 1 & \text{if} \quad V_i < V_0 \quad \text{and} \quad V_i > x \\ 2 & \text{if} \quad V_i = V_0 \\ 3 & \text{if} \quad V_i > V_0 \quad \text{and} \quad V_i > y \\ 4 & \text{if} \quad V_i > V_0 \quad \text{and} \quad V_i < y \end{cases} \quad \text{for } i = 1,2,3, \ldots, 8 \qquad (13)$$

90	130	145
160	140	200
100	140	250

(a)

0	1	3
4	2	4
0	2	4

(b)

FV= {0, 1, 3, 4, 2, 4, 2, 0, 4}

(c)

Fig.3: Representation of (a) a 3×3 TOM neighborhood (b) fuzzy values (c) Fuzzy based TOM.

2.4 Texton Detection

Various algorithms are proposed by many researchers to extract color, texture and shape features. Color is the most distinguishing important and dominant visual feature. That's why color histogram techniques remain popular in the literature. The main drawback of this is, it lacks spatial information. To address this problem, texture patterns are introduced in the literature. The Textons [26]which represent various Patterns provide significant and abundance of texture and shape information. Textons have more powerful description ability than the pixels themselves.

The proposed Fuzzy texton approach utilized to detect micro-structures blocks from left-to-right and top-to-bottom through- out the image. The Fuzzy texton approach converts the final image into binary image. The proposed TOFTBM used for detection of shapes for classification of textures. In a 3×3 block, if one of the eight nearest neighbors has the same value as the center pixel, then it is kept unchanged and marked 1 as shown in Fig.4, otherwise set it to '0'. Incase if the centre pixel is zero and one of the eight nearest neighbors has the same value as the center pixel, then these pixel values are also set to '1'. If all the eight nearest neighboring pixels are '0', then the 3×3 block is not considered as a micro structure. The marked pixels are treated as micro-structure and this structure is set to '1'. The working mechanism of proposed method is illustrated in Fig.4.

151	143	143	143	152	153
151	143	143	143	152	153
155	142	142	138	147	153
157	143	143	135	142	151
157	143	143	135	142	151
154	146	146	140	143	148

(a)

3	2	2	1	2	3
3	2	2	1	2	3
3	0	0	0	1	3
3	1	1	0	2	3
3	1	1	0	2	3
3	2	2	1	4	4

(b)

0	2	2	1	2	0
0	2	2	1	2	0
0	0	0	0	1	0
0	1	1	0	2	0
0	1	1	0	2	0
0	0	0	1	0	0

(c)

0	1	1	1	1	0
0	1	1	1	1	0
0	1	1	1	1	0
0	1	1	1	1	0
0	1	1	1	1	0
0	0	0	1	0	0

(d)

Fig.4: Illustration of the Binary TOFTBM Matrix (a) TOM image (b) Detection of fuzzy values (c) Fuzzy texton mapping process on a 3×3 neighborhood d) Texture orientation Fuzzy Texton binary image.

2.5 Evaluation Of Texture Shape Features On TOFTBM

The present paper evaluated Texture Shape Features (TSF) on TOFTBM. The considered TSF on TOFTBM are Diamond, non connected Diagonal pixels (NCDP), Vertical Mid-Line, Horizontal Mid-Line and Blob which are donated as TSF1,TSF2,TSF3,TSF4 and TSF5 respectively as shown in Fig.5.

0	1	0
1	0	1
0	1	0

(a)

1	0	1
0	0	0
1	0	1

(b)

0	1	0
0	1	0
0	1	0

(c)

0	0	0
1	1	1
0	0	0

(d)

1	1	1
1	0	1
1	1	1

(e)

Fig.5: Representation of TSF on TOFTBM (a) TSF1 (b) TSF2 (c) TSF3 (d) TSF4 (e) TSF5.

In the TSF3 and TSF4only vertical and horizontal central lines are only considered because they are not covered under TSF1, TSF2 and TSF5 shape features. For the classification of textures the frequency occurrences of each of the TSF on TOFTBM is counted. The novelty of the present method is it uses only five different types of TSF instead of 256 on a 3 x 3 neighborhood.

3. RESULTS AND DISCUSSIONS

The proposed rotationally invariant classification method “TOFTBM using TSF” carried out the experiments on various Brick, Granite, Marble and Mosaic textures. These textures are collected from Broadtz,Vistex album, Akarmarble album , Ashishimpex album and Tradekey album databases. It becomes laborious to provide results for a large set of textures at each stage of discussion, because of which the present paper has considered eight textures from each group of stones with a resolution of 256×256. The four classes of stone textures are displayed in Fig.6. with a resolution of 128×128 to restrict the size of the paper. The names of the individual textures are given in the Tables 1, 2, 3 and 4 for Brick, Granite, Marble and Mosaic Textures respectively. For each individual texture a name is assigned with three characters followed by a digit. Now onwards the individual textures will be referred by the unique name given in the following Tables.

Table 1: Names of the Individual Textures of Brick.

Actual Name	Assigned Name
Brick.0000	Brk1
Brick.0002	Brk2
Brick.0003	Brk3
Brick.0004	Brk4
Brick.0005	Brk5
Brick.0006	Brk6
Brick.0007	Brk7
Brick.0008	Brk8

Table 2: Names of the Individual Textures of Granite.

Actual Name	Assigned Name
Black pearl	Grn1
Copper silk	Grn2
Golden Juprana	Grn3
Indian Mahagrony	Grn4
Kashmir White	Grn5
Royal Red	Grn6
Samantha Blue	Grn7
Tropological green	Grn8

Table 3: Names of the Individual Textures of Marble.

Actual Name	Assigned Name
Autumn Gold	Mrb1
Bidasar Brown	Mrb2
Bidasar Yellow	Mrb3
Bidasar Red	Mrb4
Black Galaxy	Mrb5
Emerald Green	Mrb6
Garnet Rush	Mrb7
Onxy White	Mrb8

Table 4: Names of the Individual Textures of Mosaic.

Actual Name	Assigned Name
Mosaic1	Msa1
Mosaic2	Msa2
Mosaic3	Msa3
Mosaic4	Msa4
Mosaic5	Msa5
Mosaic6	Msa6
Mosaic7	Msa7
Mosaic8	Msa8

To evaluate a good classification based on the TSF on the proposed TOFTBM, the present paper initially computed the frequency occurrences of each TSF. The frequency occurrences of TSF on TOFTBM on Brick, Granite, Mosaic and Marble textures are furnished in Tables 5, 6, 7 and 8 respectively. In the following tables STSF indicates sum of all TSF's considered.

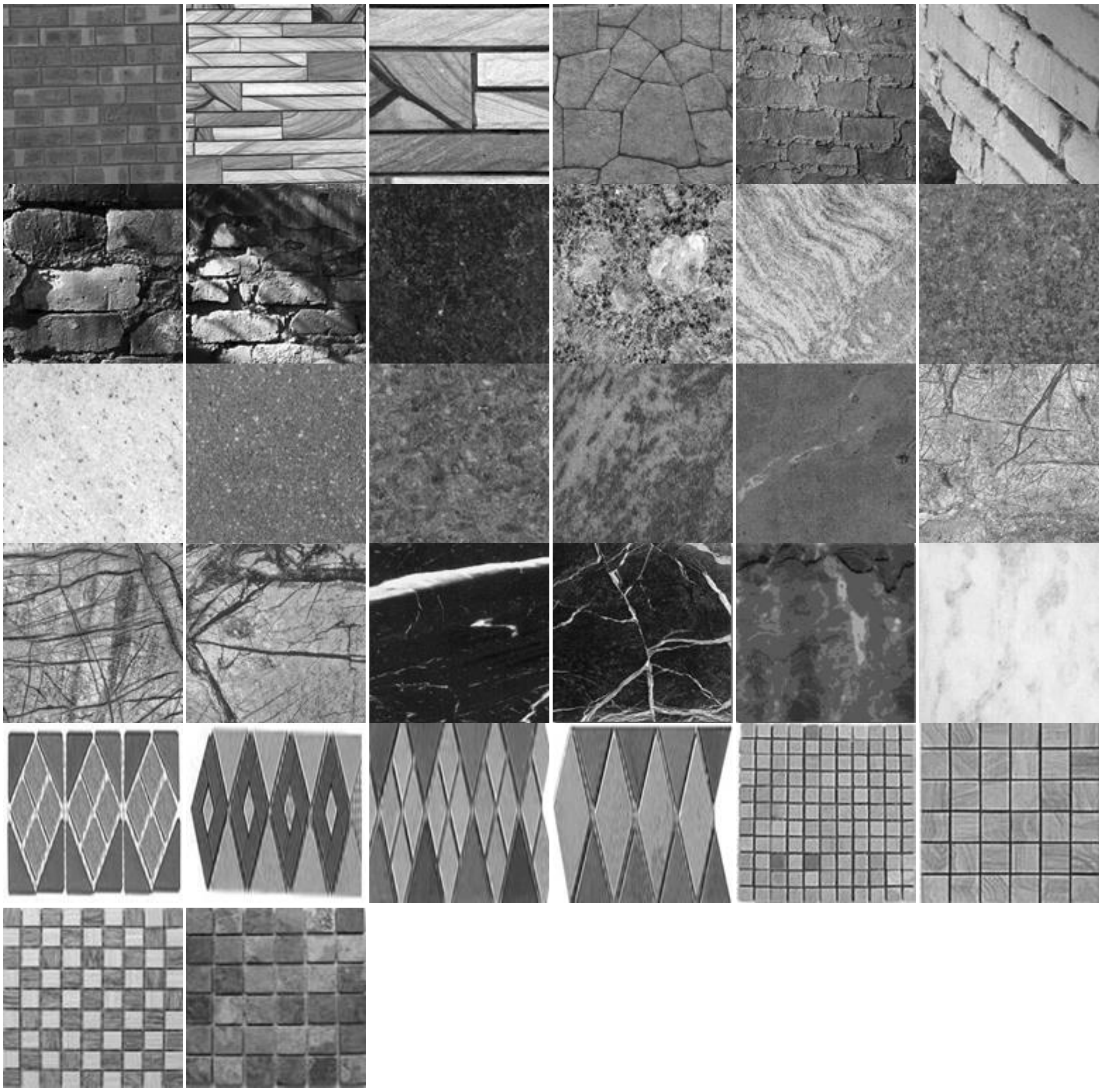

Fig.6: Brick, Granite, Marble and Mosaic Textures

Table 5: Frequency occurrences of TSF on brick using TOFTBM.

Stone texture	TSF1	TSF2	TSF3	TSF4	TSF5	STSF
Brk1	213	375	413	312	183	1496
Brk2	321	473	507	476	173	1950
Brk3	197	316	482	297	281	1573
Brk4	261	348	467	393	212	1681
Brk5	281	344	395	379	153	1552
Brk6	297	413	452	484	232	1878
Brk7	394	452	469	471	141	1927
Brk8	343	397	501	363	159	1763

Table 6: Frequency occurrences of TSF on granite using TOFTBM.

Stone texture	TSF1	TSF2	TSF3	TSF4	TSF5	STSF
Grn1	263	328	321	213	148	1273
Grn2	272	356	294	337	106	1365
Grn3	185	243	283	265	93	1069
Grn4	197	241	317	293	123	1171
Grn5	133	184	216	205	153	891
Grn6	137	207	275	183	115	917
Grn7	180	187	192	153	185	897
Grn8	135	198	278	192	142	945

Table 7: Frequency occurrences of TSF on mosaic using TOFTBM.

Stone texture	TSF1	TSF2	TSF3	TSF4	TSF5	STSF
Msa1	643	637	821	753	266	3120
Msa2	543	690	723	715	292	2963
Msa3	417	412	626	425	195	2075
Msa4	650	546	665	697	313	2871
Msa5	497	573	541	688	379	2678
Msa6	463	497	585	484	327	2356
Msa7	624	613	613	704	317	2871
Msa8	479	577	515	659	326	2556

Table 8: Frequency occurrences of TSF on marble using TOFTBM.

Stone texture	TSF1	TSF2	TSF3	TSF4	TSF5	STSF
Mrb1	37	106	113	85	74	415
Mrb2	93	115	123	136	46	513
Mrb3	95	117	237	273	152	874
Mrb4	79	158	127	165	57	586
Mrb5	67	81	99	77	67	391
Mrb6	63	107	121	88	83	462
Mrb7	84	292	203	113	92	784
Mrb8	105	185	263	129	131	813

Algorithm one: ALGORITHM FOR TEXTURE CLASSIFICATION USING SUM OF TSF'S (STSF)

Begin

```
if (STSF > 400 )&&(STSF < 875)
        print "THE TEXTURE IS MARBLE"
else if (STSF >=875 )&& (STSF <1400)
        print "THE TEXTURE IS GRANITE"
else if (STSF >= 1400 )&& (STSF < 2000)
        print "THE TEXTURE IS BRICK"
else if (STSF >= 2000) && (STSF <= 3500)
        print "THE TEXTURE IS MOSAIC"
```

End

Based on the above algorithm, the present paper carried out percentage of classification rate using STSF on the proposed TOFTBM for different group of stone databases and listed in Table 9 and also graphical representation is shown in Fig.7.

Table 9: Mean % classification rate of the proposed method.

Image Dataset	Brick	Granite	Mosaic	Marble
Akarmarble	95.13	94.05	95.7	92.6
VisTex	94.17	93.9	94.17	93.13
Ashishimpex	93.85	93.7	92.27	92.05
Broadtz	94.01	91.7	90.38	91.07

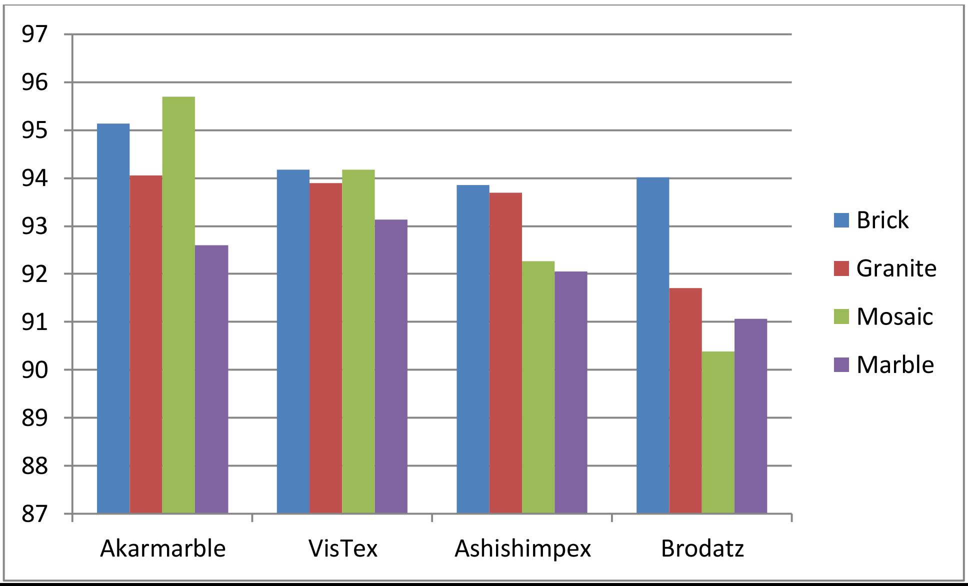

Fig.7: Mean % classification rate graph of proposed method.

3.1 Comparison with the other methods

The proposed TOFTBM method is compared with Syntactic Pattern on 3D method [27] Primitive Pattern Unit approach [28] and texton feature evolution method [29]. The above two methods [27,28] classified stone textures into two groups only. This indicates that the existing methods [27,28] failed in classifying all stone textures. The percentage of classification rates of the proposed method and other existing methods [27,28,29] are listed in Table 10. The Table 10 clearly indicates that the proposed TOFTBM method outperforms the two existing methods [27,28]. However it shows little bit low classification rate when compared to texton feature evolution method [29]. This is due to the rotational invariant property of the proposed method.

Table 10: Mean % classification rate of the proposed and existing methods.

Image Dataset	Syntactic Pattern on 3D method	Primitive Pattern Unit approach	Texton Feature Detection	Proposed TOFTB method
Akarmarble	93.29	92.19	95.56	94.37
VisTex	92.53	92.56	94.15	93.84
Ashishimpex	93.30	91.29	95.27	92.96
Broadtz	93.59	92.16	94.97	91.79

4. CONCLUSION

The proposed TOFTBM with TSF can capture the spatial distribution of edges, and it is an efficient texture descriptor for images with heavy textural presence. The present paper created a new direction for classification of textures based on texture features derived from shape components on a 3×3 neighborhood. The proposed TOFTBM investigated texture classification using different Texture Shape Features TSF1, TSF2, TSF3, TSF4, TSF5 and STSF. The proposed method is computationally effective. Experimental results and comparison with other methods clearly indicates that proposed TOFTBM with STSF shows superior performance than existing methods.

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