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Texture Classification using Advanced Texton Texture Matrix

* K. S. R. K. Sarma[1], M. Ussenaiah[2]

[1]Research Scholar, JNTU Anantapuram, Asst. Professor, Vidya Jyothi Institute of Technology (Autonomous), Hyderabad, Telangana, India.

[2] Assistant professor, Vikram Simhapuri University, Nellore, Andhra Pradesh, India.

[1]kaipasarma@gmail.com, [2]Ussenaiah.Maligela@gmail.com

Abstract

This paper derives a new framework for texture classification by combining the features of textons with two types of patterns namely symmetric and triangular patterns and with texture features derived from gray level co-occurrence matrix (GLCM) features. The textons derived in this paper are different from the traditional textons and the derived textons are named as advanced textons. This research derived a total of ten textons shapes on a 2x2 grid with two and four identical pixels. This paper initially transforms the given texture image into an advanced texton index (ATI) image. In ATI image each location represents a local shape. This paper then derives symmetric advanced texton unit (SATU) and triangular advanced texton Unit (TATU) on the 3x3 window of the ATI image. A new matrix called advanced texton texture matrix (ATTM) is derived based on the relative frequencies of SATU and TATU codes. The GLCM features are derived on the ATTM and these features are used as a feature vector. The classification is performed using various machine learning classifiers on the popular texture databases with different types of natural images on the proposed ATTM. The results are compared with state art of existing methods and the results indicate the efficacy of the proposed method over the rest of the methods.

Keywords: *Advanced-Texton, Symmetric, Triangular-patterns, GLCM, Texture features.*

1. Introduction

For many real time applications of image processing and computer vision applications like texture classification [1,2], face recognition [3,4], age classification [5], medical diagnosis [6], scene/object recognition [7,8], image matching [9, 10], extraction of texture features serves as fundamental and most significant aspect and played a vital role in improving overall performance of the above applications [11-17]. Textures exhibits a complex and dynamic intrinsic patterns, which are very difficult to describe. And in fact there was no uniform definition of texture and it refers to the surface property of an object. The natural texture reflects large variations in rotation, deformation, brightness etc., due to different lighting conditions, backgrounds and image acquisition systems. That's why a success full classification task requires prior information of the attributes of textures. This has made texture classification as an interesting and difficult problem among researchers in the field of computer vision.

The following desirable attributes are required for texture classification

1. Invariant: The image representation should be variant to rotation, scale, illumination and view port [18-20].
2. Noise resistant [21-27].
3. Discriminative power: the extracted texture features should exhibit high discrimination among different closes of textures.
4. Dimension: the feature vector dimension should be less with all significant features, so that it can be easily integrated with other frame works such color model, gabor filters, statistical features and suitable to real time applications.
5. Efficient: The derived texture features should be efficient [18, 21, 28, 29].

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The texton based methods have exhibited significant results when dealing with the natural textures especially with significant viewport and scale changes. However texton approaches requires only costly calculations on each micro grid and extra learning phase. On the other hand local binary pattern [18] is a very popular local texture descriptor and it derives rotation invariant texture features, however LBP derives huge dimensions that’s why they are difficult to integrate with other features and further, they are sensitive to noise: a small fraction of noise may change LBP code drastically. In the literature noise resistant LBP models like binary rotation invariant and noise tolerant (BRINT) [21] is proposed to overcome the noise related problems that arises due to lightening conditions etc., however the BRINT also derives huge histogram bin size or dimension. The following methods are used in the literature to demonstrate the effectiveness in classification of textures under various image transformation and changes. The works related Gaussian framework exhibited some progress in this direction. In [20], texton based image representation is derived by employing maximum response8 [MR8] filter bank. The local energy pattern [LEP] [29] is built by using second order derivative of Gaussian filter. To extract continuous rotation invariant features in [30], the edge and bar filters are used in [31] in the literature. All the above methods [20, 29-31] extracted rotation invariant features by representing image as a texton oriented features. Recently the researchers, in the field of computer vision have shown tremendous interest in neural networks and deep neural networks [32]. The deep neural networks like DeCAF [33], the wavelet scattered networks [34] and PCANet [35] compute invariant image representation. The convolutional filters scent [34] and PCANet [35] are predefined with wavelet filters and PCA filters respectively. The convolutional neural network (CNN) is defined in several layers of convolution filters, feature pooling and non-linear rectifications. The local features of textures are extracted in the literature by using local descriptors [20, 36-38] the local derivative filters [30, 39], source image patches and random image patches [20, 40] and so on.

This paper is organized as follows: the section 2 deals with the proposed methodology, section 3 deals with results and discussions. Finally conclusions are described in section 4.

2. Proposed Method

The texton based methods derives textons on a 2x2 grid. A texton refers to structural pattern on a 2x2 grid. A texton is formed if and only if two or more adjacent pixels of the 2x2 grid represent exactly the same intensity or brightness values. In the literature initially the texton co-occurrence matrix (TCM)[41] is derived on a 2x2 grid and it has the following attributes / properties.

1. The TCM derived five types of textons as shown in Figure 1.
2. The textons or structural patterns in TCM are defined with three and four identical pixels.
3. The TCM derives the textons in an overlapped manner on a 2x2 grid. Therefore the TCM scans the image five times and in each time it identifies one of the texton type.
4. The TCM framework assigns a value zero to the pixel(s) which are not part of texton formation.
5. The TCM assigns a zero to all the pixels of the 2x2 grid if the particular type of texton is not found.
6. The final texton image is generated by fusing all five types of texton images, where each image represents the particular type of textons. The framework of final texton image generation for an image patch of 7x7 is shown in Figure 2.

V_1	V_2	L	L	L		L	L		L	L	L
V_3	V_4	L	L	L	L	L		L	L		L
2x2 grid		T_1		T_2		T_3		T_4		T_5	

Figure 1. The representation of textons in TCM framework

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41	52	63	48	65	65	63
85	52	52	85	96	65	58
41	96	96	32	14	85	96
88	96	96	48	48	56	48
88	88	51	48	63	98	51
96	85	48	21	23	23	63
85	48	48	65	23	85	87

(a) Raw image grey level values.

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	**96**	**96**	0	0	0	0
0	**96**	**96**	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

(b) T_1 texton identification

0	**52**	**0**	0	0	0	0
0	**52**	**52**	0	0	0	0
0	0	0	0	0	0	0
88	0	0	0	0	0	0
88	**88**	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

(c) T_2 texton identification

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	**48**	**48**	0	0
0	0	0	**48**	0	0	0
0	0	0	0	**23**	**23**	0
0	0	0	0	**23**	0	0

(d) T_3 texton identification

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	**48**	0	0	0	0
0	**48**	**48**	0	0	0	0

(e) T_4 texton identification

0	0	0	0	**65**	**65**	0
0	0	0	0	0	**65**	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

(f) T_5texton identification

0	**52**	0	0	**65**	**65**	0
0	**52**	**52**	0	0	**65**	0
0	**96**	**96**	0	0	0	0
88	**96**	**96**	**48**	**48**	0	0
88	**88**	0	48	0	0	0
0	0	**48**	0	**23**	**23**	0
0	**48**	**48**	0	**23**	0	0

(g) Final texton image

Figure 2. The transformation process of an image patch into final texton image in TCM

The disadvantages of TCM framework are

1. The fusing operation is very complex. The fusing operation with N-types of textons makes the TCM framework to scan the image N-times.
2. The TCM framework does not define a pattern or structure with two identical pixels.

To overcome the above disadvantages of TCM framework in the literature the multi texton histogram (MTH) [42] is proposed.

The MTH has the following properties

1. The MTH defined five textons with two identical pixels over a 2x2 grid as shown in Figure 3
2. The MTH assign a zero values to the entire 2x2 grid if no texton type is found.

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The MTH retains the 2x2 grid with the same intensity values, whenever a texton type is found. The formation of multi texton image with defined types of texotns of Figure 3 for an image patch of 8x8 is shown in Figure 4.

V_1	V_2
V_3	V_4

2x2 grid

S	S

T_6

	S
S	

T_7

S	
S	

T_8

S	
	S

T_9

Figure 3. The texton types of MTH

52	63	21	21	96	41	86	52
74	85	95	21	12	32	35	65
87	63	28	95	96	96	41	85
87	52	64	84	96	15	95	96
85	85	63	74	99	41	63	41
85	63	45	85	67	87	74	63
14	63	64	52	84	67	85	63
25	52	65	65	67	84	88	74

(a) Raw image grey level values.

	T6/T9		
T8		T6/T7/T8	
T6/T7/T8			T9
		T9/T7	

(b) Texton identification

0	0	**21**	**21**	0	0	0	0
0	0	**95**	**21**	0	0	0	0
87	**63**	0	0	**96**	**96**	0	0
87	**52**	0	0	**96**	**15**	0	0
85	**85**	0	0	0	0	**63**	**41**
85	**63**	0	0	0	0	**74**	**63**
0	0	0	0	**84**	**67**	0	0
0	0	0	0	**67**	**84**	0	0

(c) Final texton image.

Figure 4. The MTH framework for an image patch of size 8x8

Recently the following disadvantages are noticed in TCM and MTH by new approach on textons known as complete texton matrix [43].

1. The TCM ignored textons of 2 identical pixels, whereas the MTH ignored the textons with four and three identical pixels. Further the MTH not defined all possible patterns with two identical pixels.
2. The CTM [43] has overcome the above disadvantage of TCM and MTH by deriving all possible textons of four, three and two identical pixels as shown in Figure 5. The CTM has defined 11 different types of textons. The CTM assigns zeros to the pixel location which are not part of texton formation.

The following process is used by CTM in detecting textons on a 2 x 2 grid:

V_1	V_2
V_3	V_4

2x2 grid

X	X
X	X

T_1

X	X
	X

T_2

X	X
X	

T_3

X	
X	X

T_4

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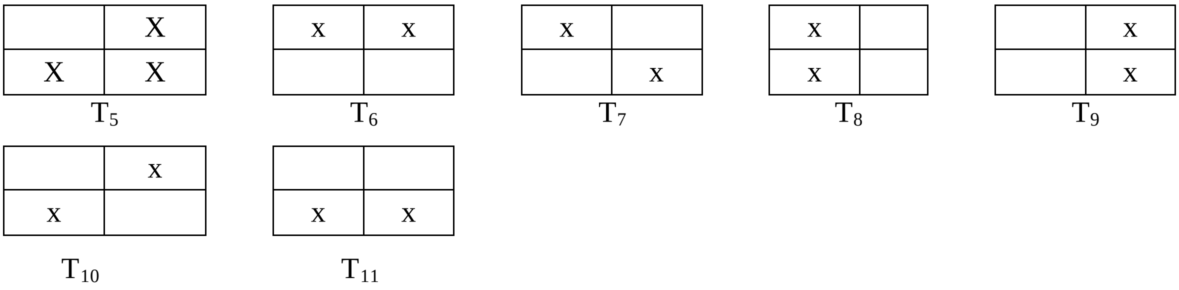


Figure 5. The complete range of textons derived by CTM

12	56	85	85	98	75	86	47
32	58	85	85	35	96	86	86
15	15	41	12	26	63	21	21
15	96	52	68	63	63	53	21
62	62	84	96	41	55	63	28
85	85	96	96	41	55	25	85
62	85	52	85	53	62	16	16
85	62	32	85	63	32	96	96

(a) Raw image grey level values.

	T_1		T_4
T_3		T_5	T_2
T_6 / T_{11}	T_5	T_8 / T_9	
T_7 / T_{10}	T_9		T_6 / T_{11}

(b) Texton identification

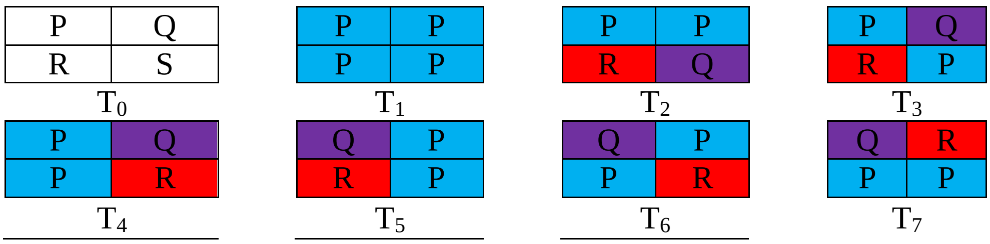
0	0	**85**	**85**	0	0	**86**	0
0	0	**85**	**85**	0	0	**86**	**86**
15	**15**	0	0	0	**63**	**21**	**21**
15	0	0	0	**63**	**63**	0	**21**
62	**62**	0	**96**	**41**	**55**	0	0
85	**85**	**96**	**96**	**41**	**55**	0	0
62	**85**	0	**85**	0	0	**16**	**16**
85	**62**	0	**85**	0	0	**96**	**96**

(c) Final texton image.

Figure 6. The CTM framework for an image patch of size 8x8

The MTH approach does not define all textons with two identical pixels. The CTM creates ambiguity in identifying textons of type T_8 and T_9; T_6 and T_{11}; T_7 and T_{10}.The proposed framework overcomes these issues.

The proposed Advanced Texton Index (ATI) model considered ten different shapes/structures on a 2x2 grid for the texton image generation (see Figure 7).The ATI framework defined all textons with two and four similar pixels on a 2x2 grid. The ATI framework replaces the 2x2 grid with ATI index. This research overcomes the ambiguity in identifying the four and two similar pixels of 2x2 grid by initializing identifying the textons with four similar pixel values. If it is not found then the proposed ATI identifies pixels with two similar values. The position of the gray values of a 2x2 grid are denoted as P,Q,R,S. This research replaces the 2x2 grid with the texton codes/indexes.



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P	P
Q	Q

T_8

P	Q
Q	P

T_9

P	Q
P	Q

T_{10}

Figure 7. The advanced texton Index framework

This process transforms the texture image with grey level range from 0 to ginto an advanced texton index image (ATI) with a range of grey levels /ATI from 0 to 10 (Figure 7). The ATI framework considers all possibilities or combinations of textons with two and four identical pixels. The advantage of ATI over MTH and CTM is the ATI overcomes the ambiguity issues of MTH & CTM. Further the ATI replaces the 2 x2 grid with ATI. In Figure 7 for example advanced texton index 2 and 8 appears as same, however they are different. For ATI =2 the pixel positions P=Q and R! =S whereas for ATI = 8 , P=Q and R= S and P!=R.In the similar way the proposed ATI framework differentiates T_3vs. T_9; T_4 vs.T_{10}; T_5 vs. T_{10}; T_6 vs. T_9; T_7 vs. T_8. For example from Figure 4(b) it is evident that the MTH creates an ambiguity in recognizing the texton patterns T_6 vs. T_9; T_6 vs. T_7; T_6 vs. T_8, T_7 vs. T_8; T_7 vs. T_9. In the similar way the CTM generates further ambiguity in identifying the textons with two identical pixels as discussed above (Figure 6b). The proposed ATI framework overcomes this and ATI framework for an image patch of 8 x 8 is given in Figure 8.The ATI frame work transforms the input image into ATI image with gray level ranging from 0 to 10. This paper divides the ATI image into a 3x3 neighbourhood in an overlapped manner (with step length of one). This paper derives two types of symmetric relationships on advanced texton image neighbourhood.

12	56	85	85	98	75	47	47
32	58	85	85	35	96	86	86
35	15	41	12	63	45	21	53
15	96	52	68	33	63	53	21
62	62	84	96	41	55	63	28
55	85	16	96	41	55	85	85
62	85	52	85	53	62	16	16
85	62	32	85	63	32	96	96

(a) Raw image patch grey

T_0	T_1	T_0	T_8
T_6	T_0	T_3	T_9
T_2	T_5	T_{10}	T_7
T_9	T_5	T_0	T_8

(b) Texton identification

0	1	0	8
6	0	3	9
2	5	10	7
9	5	0	8

Figure 8. The ATI framework for an image patch of size 8x8

In the literature symmetric LBP (SLBP) are derived as an extension to LBP and SLBP derives a relationship between symmetric sampling points of the 3x3 neighbourhood. A 3x3 neighbourhood is shown in Figure 9 (symmetric pixels are shown in the same color).

P_1	P_2	P_3
P_8	P_C	P_4
P_7	P_6	P_5

Figure 9. A basic 3x3 window

In the above window P_1..P_8 are the sampling points over the central pixel Pc.The main disadvantage of SLBP is it has completely ignored the central pixel in deriving the symmetric relations between sampling points. The central pixel occupies significant position on a 3x3 grid. The central pixel/ texton index will have immediate relationship with all sampling points. The 3x3 window is also represented as P=8 and R=1; where P represents the sampling points over the central pixel and

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the radius is 'R' and it is measured from the central pixel position. The 3x3 window of ATI are shown in Figure10 and T_c is the ATI of the central grid and T_1.. T_9 are the ATI of the neighbouring grids. The T_1..T_9 &T_c values ranges from 0 to 10.

T_1	T_2	T_3
T_8	T_c	T_4
T_7	T_6	T_5

Figure 10. The ATI patch of 3x3 window

This research derived two different units on the 3 x3 grid of ATI image. The first unit is named as Symmetric advanced texton unit (SATU) and the second one is named as triangular advanced texton unit (TATU).The proposed research derives Advanced Texton Texture Matrix (ATTM) by computing the relative frequencies of TATU and SATU codes (Figure 12).

The SATU derives the ternary patterns by computing relationship among symmetric ATI and centre ATI in the following way.

$$SATU = \sum_{i=1}^{4} s(T_i, T_{i+4}, T_c) * 3^{i-1} \quad (1)$$

$$where \quad S = \begin{cases} 0 & if\ T_i == T_{i+4} == T_c \\ 1 & if\ T_i == T_c \neq T_{i+4}\ or \\ & T_i == T_{i+4} \neq T_c\ or \\ & T_{i+4} == T_i \neq T_c \\ 2 & Otherwise \end{cases} \quad (2)$$

Where T_i and T_{i+4} are the symmetric ATI and Tc is the ATI of the central 2x2 grid. The SATU derives ternary patterns by evaluating a relationship between T_i and T_{i+4} and T_c as given in the above equation. Based on this the SATU values ranges from 0 to 80.

The TATU computes the triangular relationship between ATI of 3x3 windows. This process divides the ATI of 3x3 window into four triangular sub windows as shown in Figure 11.

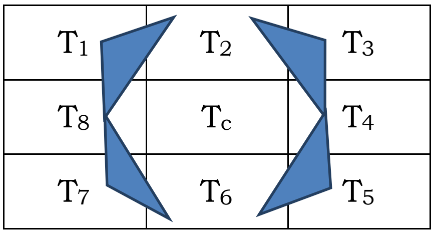

Figure 11: The subdivision of ATI window of 3 x3 into 4 triangular sub windows

Each triangular pattern consists of three ATI pixels (T_p, T_q, T_r) and this paper computed a ternary relationships among these ATI and derived TATU unit in the following way:

$$TATU = \sum_{i=1}^{4} S_i(T_p, T_q, T_r) * 3^{i-1} \quad (3)$$

$$where \quad S_i = \begin{cases} 0 & if\ T_p == T_q == T_r \\ 1 & if\ T_p == T_q \neq T_r\ or \\ & T_p == T_r \neq T_r\ or \\ & T_q == T_r \neq T_p \\ 2 & Otherwise \end{cases} \quad (4)$$

Where S_i represents triangular sub window i and i ranges from 1 to 4 (Figure11). The TATU and SATU ranges values form 0 to 80.

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The paper derives advanced texton texture matrix (ATTM) by computing the relative frequencies TATU and SATU. For this, this paper initializes the ATTM with dimensions of 0…80 x 0…80 and initializes all entries as zero. In the ATTM, the TATU unit values correspond to the row entries and SATU values corresponds to the column entries. Whenever ATTM (TATU, SATU) entry is found the position ATTM (TATU, SATU) is increased by one. The process is repeated on entire ATI image in an overlapped manner by a step/length of one. This research derives GLCM features on ATTM and these features are used as a feature vector.

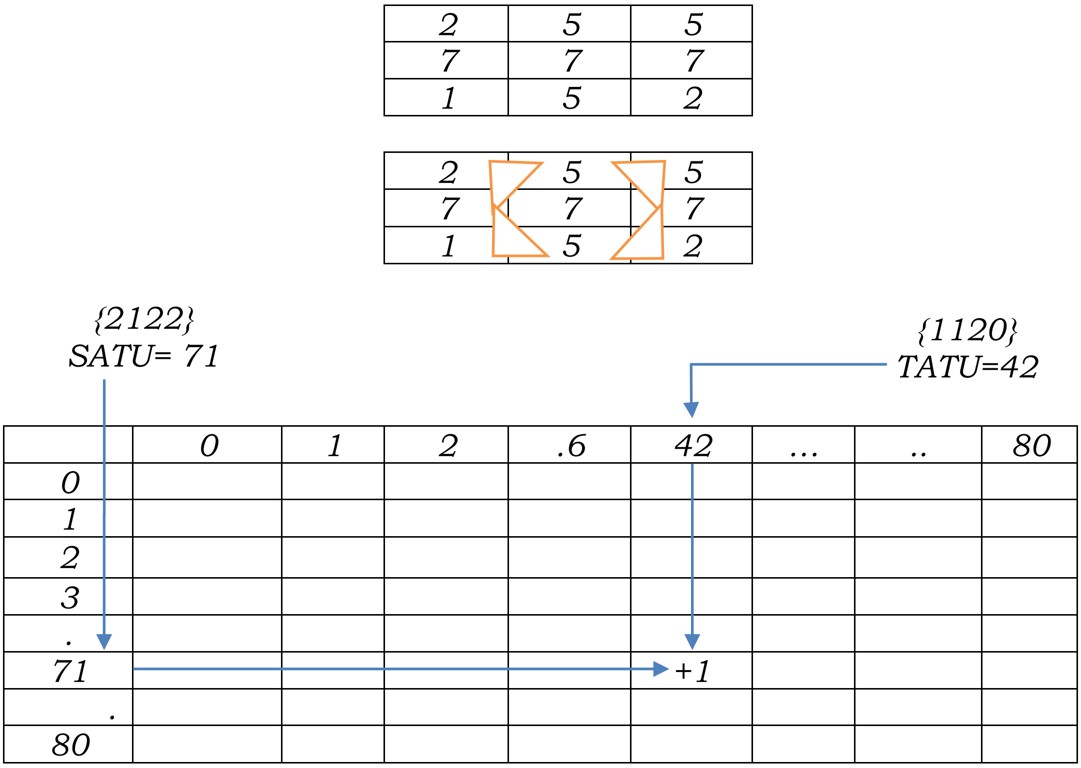

Figure 12: The frame work of ATTM

3. Results and Discussions

This paper computed six GLCM features namely: Contrast, correlation, Entropy, Homogeneity, Inverse Difference Moment (IDM) and Prominence feature, on each rotation angle on the proposed ATTM. This paper derived ATTM for two distance values d = 1 and 2 and with six degrees of rotations i.e. $\alpha = 0^o, 45^o, 90^o, 135^o, 180^o$ and 225^o on each d value. This results a total of 6x6 = 36 features i.e. the feature vector size is 36 on each d value. To analyze the performance of the proposed method in terms of classification accuracy, this paper carried out investigation on most popular and most widely used texture databases namely: MIT Vision Texture database (Vistex) [44], Salzburg Texture database (Stex) [45], Colored Brodatz Texture database (CBT) [46], the USPtex [47], the Outex TC-00013 [48]. The classification accuracies of the proposed method on the above affordable databases are compared with recent state of art local based approaches. The sample images are displayed in the following figures (Figure13 to Figure 17) and for the sake of clarity a brief description about the number of classes and images considered per each class is given in table 1.

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Figure 13. The sample images of Vistex-640

Figure 14. Stex-7616 database sample images

Figure 15. The sample images of USPtex-2292

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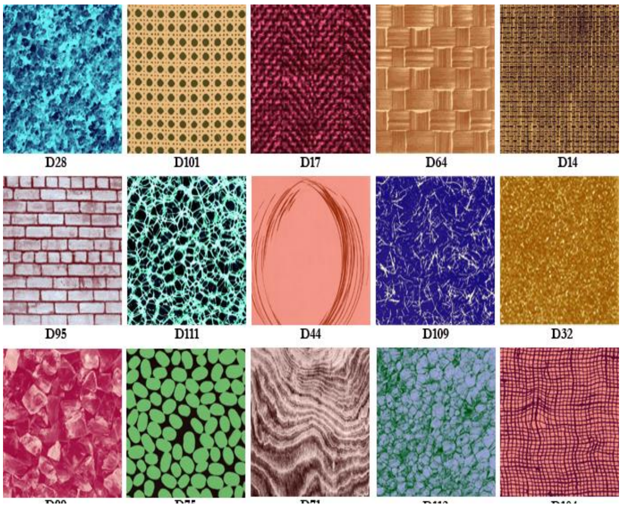

Figure 16. The sample images of CBT-2800

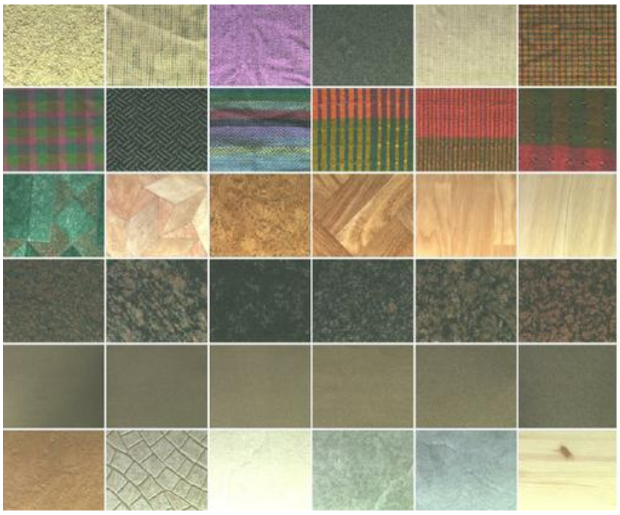

Figure 17. The sample images of Outex-1360

Table 1: Summary of image databases consideration

S.No.	Image database name	Actual image Dimension (AD)	Considered image Dimension (CD) [non-overlapped]	No. of non-overlapped images obtained per each image (AD/CD)	Total number of classes considered	Images per each class	Total number of images considered
1	MIT-VisTex	512X512	128X128	4	40	16	640
2	Stex	512X512	128X128	4	476	16	7616
3	CBT	640X640	128X128	5	112	25	2800
4	USPTex	191X191	128X128	1	191	12	2292
5	Outex	128X128	128X128	1	68	20	1360

The feature vector of the proposed descriptor ATTM is given as input to the multilayer perceptron, naïvebayes, Ibk and J48 classifiers and they have achieved a good classification rate on the above affordable databases and the classification rates are given in Table 2 for ‘d’ value =2. In fact classification accuracies are computed for ‘d’ value =1 and 2 and high classification is resulted for ‘d’ value 2.Out of these four classifiers, multilayer perceptron achieved high classification rate followed

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by Ibk, naïvebayes and J48. The final row of the Table 2 displays the average classification rate on all databases considered for for 'd' value 2. This paper used the classification rate of multilayer perceptron in the remaining part of the paper. The classification rates of the proposed method are compared with other existing methods and classification rates are displayed in table 3 and also shown in Figure 10.

Table 2. classification rates of the proposed ATSTM descriptor with different classifiers for d value 2

Database	Multilayer Perceptron	Naivebayes	IBK	J48
MIT-VisTex	94.98	85.36	86.11	86.04
Stex	92.39	82.39	84.08	80.96
USPTex	96.48	87.55	87.89	84.86
CBT	95.14	86.37	87.20	83.77
Outex-13	95.74	86.25	86.21	86.42
Average	94.94	85.58	86.30	84.41

Table 3. Classification rate (%) of proposed and state-of-art-methods on various databases

Database	LBP [18]	LTP [49]	CLBP-SMC [50]	CS-LBP [51]	TCM [41]	MTH [42]	CTM [43]	Proposed method ATTM
MIT-VisTex	56.49	59.74	87.33	76.89	88.62	89.63	90.52	94.98
Stex	58.32	76.8	91.98	76.44	91.87	92.21	93.21	92.39
USPTex	58.4	78.12	92.4	76.97	92.73	93.21	94.51	96.48
CBT	65.07	69.4	89.74	76.57	89.89	91.35	93.54	95.14
Outex-13	66.37	68.42	91.24	74.47	91.58	92.54	93.65	95.74

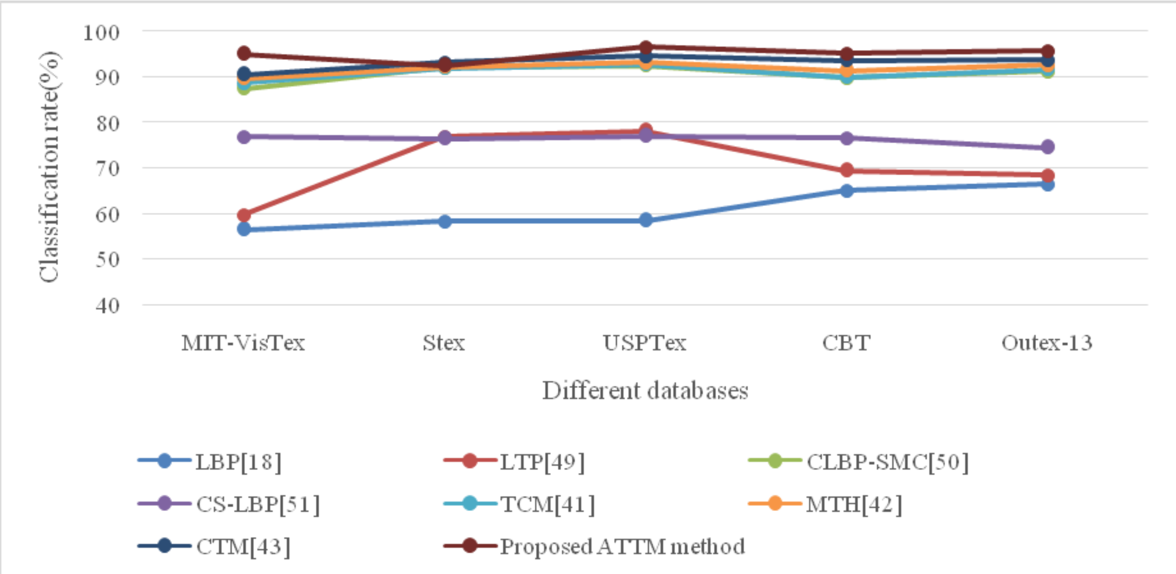

Figure 10. Comparison of proposed method performance with existing methods on different database

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This paper initially compared the classification results among the two existing popular local neighborhood descriptors based on 3x3 neighborhoods. The LBP and its variants LTP, CSLBP-SMC, CS-LBP are derived on 3x3 windows. The local patterns in LBP and LTP are derived by comparing center pixel value with sampling pixels gray level value. The LBP derived binary patterns and LTP derived ternary patterns. The CS-LBP derived binary patterns by comparing the grey level intensity relationships among symmetric sampling pixels over the center pixel. The CS-LBP produces relatively less number of bins when compared to LBP and LTP. The CS-LBP has attained high classification rate when compared to LBP and LTP. The texton based methods derived structural patterns on a 2 x 2 grid based on similar intensity levels of adjacent pixels. This paper compared the proposed descriptor with the popular texton based methods namely; TCM, MTH and CTM. The TCM and MTH derived different micro patterns on a micro grid. The TCM and TMH has its own advantages and disadvantages. The CTM has overcome these demerits of TCM and MTH. The CTM further improves the classification rate. The texton based descriptors attained high classification rate than LBP, LTP and CS-LBP descriptors due to its compactness. Out of existing texton descriptors the new variants of texton namely CTM, exhibited relatively improved classification rate than basic texton descriptors TCM and MTH on all affordable databases.

The proposed ATTM attained high classification rate when compared to local descriptors derived on a 3x3 neighborhood i.e. LBP, LTP, CS-LBP and CS-LBP. The proposed ATTM has exhibited relatively high classification rate than TCM, MTH and CTM. The proposed descriptor attained a 4% of high classification rate than these. Out of the five databases the proposed descriptors attained high classification rate on USPTex, Outex-13 and CBT databases followed by MIT-VisTex and Stex. The proposed descriptors ATTM attained a high classification rate due to the following integrated operations: derivation of advanced texton indexes that over comes the ambiguity and this derives a path for replaced the 2x2 grids with ATI indexes.

The main contribution of this research

1. Derivation of advanced texton indexes that significantly contributes to derive more local information.
2. Derivation of two different units on the advanced texton index image on a 3x3 window.
3. Derivation of ATTM using the relative frequencies of the above two different units on 3 x3 window of ATI image.
4. Derivation of all possible textons with two identical pixels and thus overcoming the ambiguity issues of MTH and CTM.
5. Replacing the 2 x2 grid with ATI thus reducing the overall histogram bin size and thus capable to integrate with other frameworks.
6. Integration of textons with all possible combinations of two and four identical pixels (without any ambiguity) with symmetric and triangular units of ATI and GLCM features made the proposed frame work more efficient and precise.

The extensive experimental analysis on five natural databases and systematic and comprehensive comparison of classification rates between the proposed and the existing descriptors is the other significance by the proposed framework.

4. Conclusions

This paper derived a new framework for texture classification by extracting a new set of texton patterns from the two and four identical pixels of the 2x2 grid. The proposed advanced texton pattern overcomes the ambiguity issue of MTH and CTM. The significant achievement of this paper is the derivation of all possible texton patterns with two identical pixels by addressing the ambiguity issues or formation of multiple textons with two identical pixels. The other major contribution of this paper is the replacement of the 2x2 grid with ATI ranging from 0 to 9. The third significant achievement of this paper is the derivation of two different units on the 3x3 window of ATI image and formation of ATTM by relative frequencies of these two units namely TATU and SATU, finally extraction of

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GLCM features as feature vector. The derivation of GLCM features on the ATTM holds the significant local information of the texture. The experimentation results of the proposed descriptor on various databases using various machine learning classifiers reveals the high performance of the present descriptor due to the above factors. The proposed descriptor is also compared with various other local descriptors especially with texture based methods to test the efficacy of the proposed descriptor. The results indicate the superiority of the proposed descriptor. The proposed ATTM approach initially divides the input texture image into micro grids of the size 2x2 in a non-overlapped manner. This overcomes the complex fusing operations as in the case of TCM. This research overcomes the ambiguity in identifying the four and two similar pixels of 2x2 grid. The integration of advanced texton structures on 2 x 2 grids with triangular and symmetric patterns on the 3x3 window of ATI image and derivation of texture features in the form of GLCM features extracted significant and precise features and thus the proposed method of texture classification is more effective, precise and suitable to real time texture applications.

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Authors

Mr. K.S.R.K.Sarma, is pursuing his Ph.D. from Jawaharlal Nehru Technological University Anantapuram, Andhra Pradesh, India with the roll no. 13PH0521, under the guidance of Dr. M. Ussenaiah, Assistant Professor, Vikrama Simhapuri University, Nellore. Presently he is working as Assistant Professor in CSE Department at Vidya Jyothi Institute of Technology (Autonomous), Hyderabad, Telangana, India. He is having more than ten years of teaching experience. He has published more than ten research articles in various conferences and journals.

Dr. M.Ussenaiah is working as assistant professor in the department of computer science at VikramSimhapuri University, Nellore, Andhra Pradesh, India. He is having a total of nine years of teaching experience. He has obtained Ph.D in Computer science in 2008 from Sri Krishnadevaraya University, Anantapur. At present he is guiding five Ph.D. students in various fields of computer science.

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