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# Classification of Textures Based on Ternary Transition Motif Matrix Features

**B. Kishore, V. Vijaya Kumar**

***Abstract*: The various classification methods proposed in the literature are mostly extracted either local features or global features or color features. After an exhaustive study on various local, global and color descriptors this research found that one type of features may not yield good classification results. To address this paper, proposed new variant that integrates the color features derived from HSV color plane and transition based scan features. This paper initially converted RGB color plane image in to HSV color plane. The individual histograms of H, S and V plane are extracted as one of the features and these are named as pure color features. This paper derives a novel extension to the exiting motif frame works of the literature. The proposed ternary transition motif matrix (TTMM) is completely different from the existing motif frameworks and it is derived on the V-plane of the HSV color model. The TTTM scans the given 2x2 grid in a fixed format by visiting each pixel position exactly once. The TTMM derives a ternary transition pattern based on the relationship between grey level intensities of current pixel and its immediate pixel of scan instead of traversing on the incremental difference. The proposed TTMM derives a unique code for each 2x2 grid, ranging from 0 to 80 and replaces the 2x2 grid with this value. The co-occurrence matrix derived on this ternary transition motif (TTM) coded image is named as TTMM and it holds the spatial relationship between the TTM coded grids. The gray level co-occurrence matrix (GLCM) features derived on TTMM are integrated with the pure color features to derive final feature vector. This descriptor is applied on six popular databases using machine learning classifiers. The results are compared with existing motif based and other local based approaches. The results exhibit the high classification rate of the proposed method over the existing ones. .***

***Index Terms*: ternary transition, motif, spatial relation, machine learning.***

## I. INTRODUCTION

One of prime areas of image processing is texture analysis and it has been extensively studied in the literature due to its applications in many domains like industrial applications [1], medicine [2] face recognition [3,4], content based image retrieval (CBIR) [5, 6, 7,8,9] among others. The main goal or objective of any texture representation schemes like texture analysis, classification, CBIR , face recognition etc. is to derive important and robust features which should sustain the variation of many factors like illumination, scale, rotation, back ground intensity, pose and view port changes. Natural textures are very complex in nature due to their extrinsic nature and intrinsic structure. That's why the classification of natural textures is a complex task. Texture serves as important and crucial indication to the human visual system and sometimes we feel the type of texture by touching it. That's why the texture features carries significant information needed for interpretation and recognition of visual scene. A texture represents the surface of an object and it can be viewed as measures of surface brightness values or intensity levels. Texture represents the important attributes of image surface such as regularity, roughness, randomness, density, phase, coarseness, granularity, smoothness, uniform etc. as a whole. The classification of texture can be viewed as a two-step process. In the first step the texture features of the image are derived or the texture image is transformed into a feature vector. The second step performs the texture classification task from the derived feature vector of step one using a distance functions or machine learning classifiers. Out of these two steps the first step is most vital for texture classification. A good classifier with poor or non-significant features may yield a very low classification rate.

In the literature Local binary pattern (LBP) [10] and its variants have become popular and widely used in many image processing applications. The LBP basically derived on circular neighborhood of 3 x 3 and derivers the relationship between center pixel and sampling pixels. However the local based approaches derived on a 2 x 2 micro grid with square type of neighborhood have also become popular in the literature. The powerful local based structural approaches on a 2x2 grid are textons [11, 12, 13 ] and Peano scan motifs (PSM) [14]. These two descriptors are different from LBP. The textons and PSMs are derived on a 2 x 2 grid and they have not derived the relationship between center and sampling points. The basic textons and its variants [14, 15, 16] derives the simple patterns based on the number of pixels with similar gray levels on a 2x2 grid. The textons are the popular local based structural approaches derived on a 2x2 grid and they attained high retrieval rate in content based image retrieval (CBIR) [17, 18] and accurate classification results [19, 20]. The other popular local based approach derived on a 2x2 grid is the motifs or Peano scan motifs(PSM) proposed Jhanwar et al. [14]. Recently new variants are added to initial PSM's. In one of the recent approaches two different PSM's on a 2x2 grid are derived using two different initial scan positions [21]. A new variant to motif is derived in the literature named as LMP-CM [22].

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The initial scan position of LMP-CM can start from any pixel position of the 2 x 2 grid dynamically, that exhibits the least grey level intensity. The LMP-CM derives a total of 24 different PSM. The motif are also extended to 3x3 neighborhood [22] by dividing the sampling points into two different 2x2 grids. On each 2 x 2 grid LTCM indexes are derived. And based on the relative frequencies of these two different LMP-CM [22] a co-occurrence matrix is derived and gray level co-occurrence matrix (GLCM) features are evaluated for efficient face recognition [23, 24]. All motif frameworks proposed in the literature traverses the 2x2 grid based on the incremental differences between the pixels of the current position and the remain un-scanned position of the 2x2 grid. The proposed frame work derives a unique motif code instead of motif index. This paper derives a ternary code based on the transition from the current position of the scan to the next position of the scan. The scanning pattern is fixed in the current paper. This paper is organized as follows.

The second section discusses about related motif approaches and the third section gives a detailed explanation about the proposed method. The fourth and fifth section presents the results and conclusions..

## II. RELATED WORK

The related and connected pixels over a boundary are known as space filling curves and they are straight lines and pass each and every pixel of the selected neighborhood exactly once. Space filling curves are also known as connected lines over a grid. The Peano scans are treated as space filling curves and they can be defined over any neighborhood. The low level sematic can be captured easily by space filling curves or Peano scan motifs (PSM). The PSMs or motifs are defined over a 2 x 2 grid. Each Motif defines a distinctive shape of pixels starting from the initial position. A compound pattern is derived using the motifs on a 2 x 2 grid.

In the literature based on Peano scan motif (PSM) theory, Motif co-occurrence matrix (MCM) [14] is derived. The initial scan position of MCM is fixed and it always starts from top left corner of the 2 x 2 grid. The scan directions in the MCM model are based on the incremental difference of intensities among the pixels of the 2x2 grid. The MCM derives six different motifs (M0 to M5) indexes (Fig.1).

In the second step the MCM derives a Co-occurrence matrix on the Motif index image and the GLCM features are derived for CBIR.

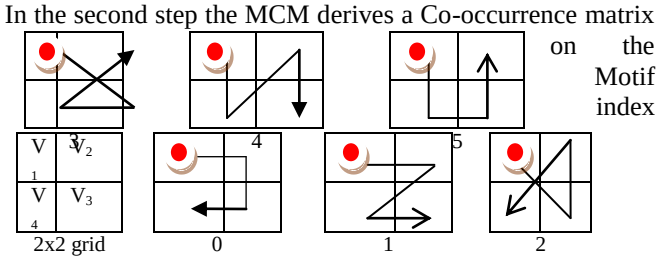


Fig.1: The MCM frame work: The PSM initiated from top left most corner pixel of a 2x2 grid.

The PSM's derives only six different patterns on a 2 x grid. Each motif or scan pattern of MCM defines a texture attribute in the form of a structure. The scan positions of MCM defines only six patterns and they fail in representing the complete texture information, since in MCM the starting scan position is fixed. To address this multi motif co-occurrence matrix (MMCM) is derived in the literature [21]. The MMCM derived two motifs on a 2x2 grid i) initiated from top most left corner named as motif indexed image initiated from top left most corner (MIITL) ii) the second motif is initiated from bottom right most corner named as motif indexed image initiated from bottom right most corner (MIIBR).The co-occurrence matrices and GLCM features are derived separately on these two different motif matrices i.e., MIITL and MIIBR. The concatenation of these two GLCM features derives the feature vector of MMCM. The authors [21, 22] also derived Local motif pattern (LMP) code co-occurrence matrix (LMP-CM) using MIITL and MIIBR [22]. In LMP-CM the authors derived a unique code ranging from 0 to 35, based on weights of 6p, where p ranges from 0 to 5 i.e., the motif indexes of MIITL and MIIBR [22]. The MMCM and LMP-CM are improved versions of MCM and however they are treated as static since the initial scan position is always fixed. Recently a dynamic PSM is proposed in the literature in which the initial scan position is not fixed. The initial scan position can be any of the pixel location of the 2x2 grid, whose gray level value is the least [21, 22]. This frame work derives a total of 24 different PSM indexes on a 2x2 grid. The following figures gives the 24 different motifs on a 2 x 2 grid initiated from different positions of the grid as shown in Figure 2.The motifs Mc ranging from 0 to 5, 6 to 11, 12 to 17 and 18 to 23 are derived by assuming the least pixel intensity value is at top left most corner, top right most corner, bottom left most corner and bottom right most corner of 2x2 grid respectively as shown in Fig. 2(a), 2(b), 2(c) and 2(d).

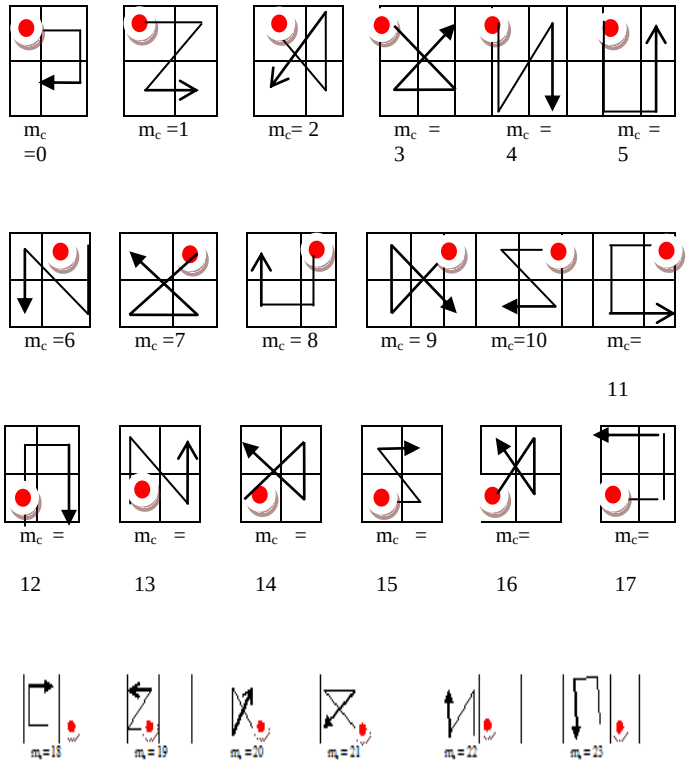


**Fig.2: The 24 motifs derived by dynamic motif.**

## III. PROPOSED METHOD

This paper develops a powerful color texture image classification model based on the capacity of transition characteristic of scanning points to capture significant information from the image content. Texture and its attributes played a significant role in most of the texture classification methods. Texture, color and other features such as shape, edge, surface, etc., plays significant role in deriving the important attributes of an image, which are essential in various image processing applications. Recently the color texture analysis methods that integrate the color components with textural features have attracted significant attention [25, 26, 27]. The researchers' pachos [28] conducted the investigation on the role of color attributes in texture classification and they have experimented on 50 images using HSV, LAB and RGB color models and found that HSV color space is the best when compared to the other. The local binary pattern (LBP) [29] and Gabor filter descriptors are used with different color spaces using both parallel and integrative approaches on Outex-13, Outex-14 and MIT-VisTex color databases. RGB is widely used color model in the literature because most of the image acquisition devices capture the image objects in RGB mode. The RGB achieved good color discrimination under controlled illumination environment. The HSV color model is treated as perceptual color space model. The HSV quantifies the subjective human color perception.

### A. Color texture features

An image texture is characterized by the texture surface and its albedo and the ambient illumination. The variation in illumination can change the perceived structures of the image and that's why the illumination variation is one of the crucial issues in color texture classification. The performance of the color texture classification will be affected by the illumination variations. The illumination invariance is achieved generally by using pertinent color space [30, 31] or by Image normalization [25]. The color and texture features can be groped in two ways: parallel methods or integrative methods [32]. The parallel methods combine the texture or gray level features with pure color features. The integrative methods extract the gray level texture features for each color component and union of these features derives the feature vector. The derivation of feature vector in integrative model is a complex task and less intuitive. The researchers' pachos [28] conducted the investigation on the role of color attributes in texture classification and they have experimented on 50 images using HSV, LAB and RGB color models and found that HSV color space is the best when compared to the other. The local binary pattern (LBP) [29] and Gabor filter descriptors are used with different color spaces using both parallel and integrative approaches on Outex-13, Outex-14 and MIT-VisTex color databases. RGB is widely used color model in the literature because most of the image acquisition devices capture the image objects in RGB mode. The RGB achieved good color discrimination under controlled illumination environment. The HSV color model is treated as perceptual color space model. The HSV quantifies the subjective human color perception. In the literature majority of texture classification methods extracted feature vector by computing texture features on gray level images [33, 34] and also by extracting texture features on each color component [35].

The extraction of color texture features can be carried out by four different perspectives: simple color features, texture features derived from grey levels, integrative color texture analysis and parallel approaches. This paper used a parallel color texture approach and the proposed frame work is shown in figure 3. The proposed framework initially transforms the RGB color model in to HSV color plane and derives individual color plane histograms of H, S and V plane. This paper derives pure color features by combining the above three color histograms. The frame work of the proposed pure color- Ternary Transition Motif matrix (PC-TTMF) is given in Fig. 3.

### B. Derivation of texture features by Ternary Transition Motif matrix (TTMF)

In the literature the PSM and its variants [21, 22 ] are very popular in deriving a structure or pattern based on the scan transversal on the 2x2 grid. The Scan traversal, in all the motif based methods proposed so far [21, 22] is based on the incremental differences of intensities among the pixels of the neighborhood. That is the scan direction is not fixed. All these methods assign an index to each motif scan which represents a structure over the neighborhood. This research derives a new variant, which is completely different from the existing motif based approaches and the proposed new variant "Ternary Transition Motif (TTM)" is derived on the V-color plane of HSV model.

The proposed TTM always traverses in the same scan direction from the initial position of the 2x2 grid. The scan traversal of TTM is initiated from the top left corner of the 2x2 grid as shown in Fig.3. The TTM after scanning the final pixel ' T3 ' traverses to the starting position ' T0 ' as shown in Fig. 4.

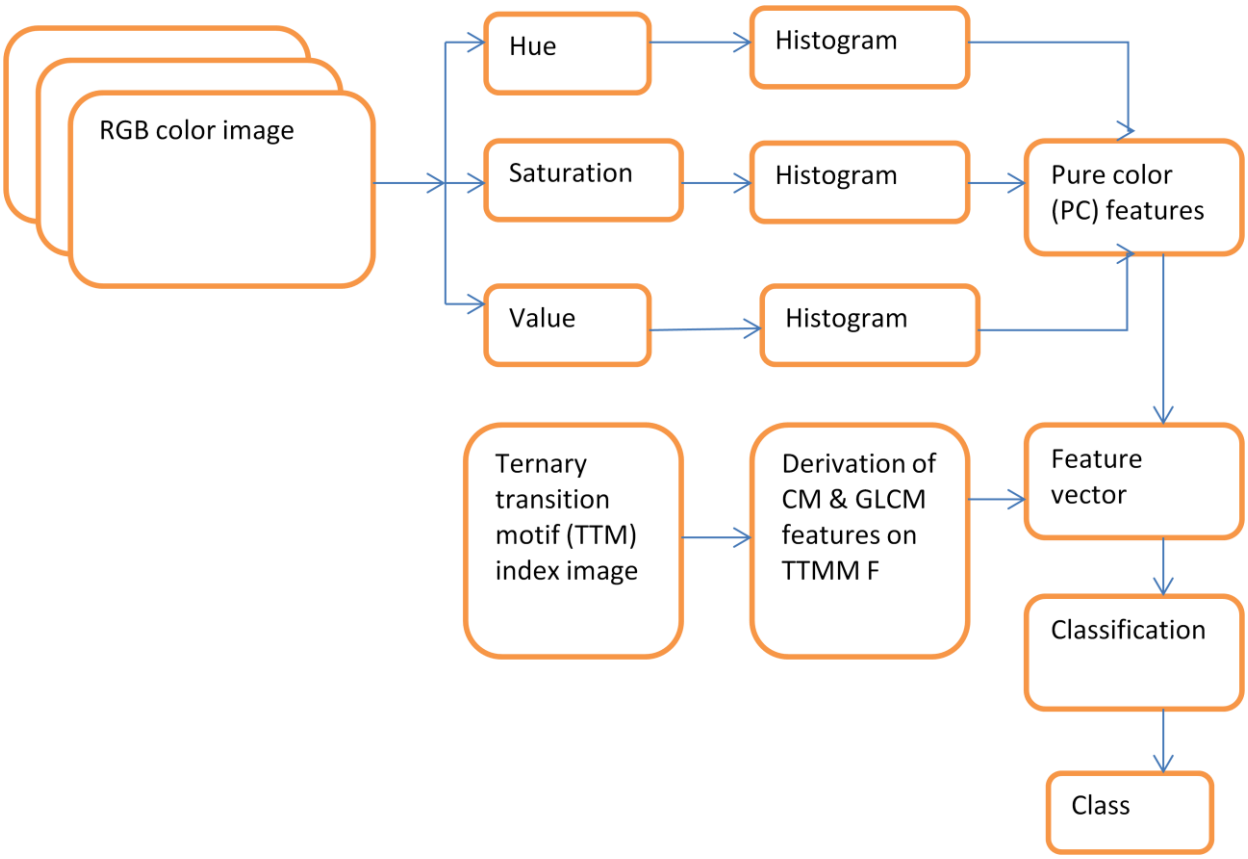


**Fig.3: Framework of the proposed PC-TTMMF.**

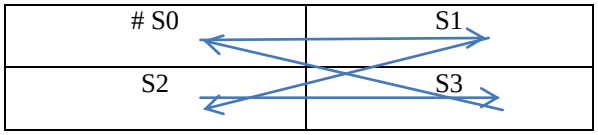


Fig.4: The scan traversal of TTM.

The initial scan position of TTM is marked with # (Fig.4). In Figure 3 {$S_0$, $S_1$, $S_2$, $S_3$ } represents the pixel positions or scan positions. A transition $T_i$ will occur by traversing from one pixel position $S_i$ to other pixel position $S_j$. The TTM assigns to each transition $T_i$ a ternary value {0,1,2} based on the magnitude difference between the current scan position ($S_i$) and its immediate next scan position's ($S_j$) gray level value as given in the equation 1 and 2. The scan directions of TTM are shown in Fig1. The proposed TTM derives a unique code based on the ternary weights assigned to each transition as given in equation 1 and 2.

$$TTM_c = \sum_{i=0}^{3} Ti * 3^i \quad (1)$$

Where

$$Ti = \begin{cases} 0 \; if \;\; g(S_i) < g\,(S_j\,) \\ 1 \; if \; g(S_i) = g(S_j) \\ 2 \; if \; g(S_i) > g(S_j) \end{cases} \quad (2)$$

The $g(S_i)$ represents the grey level intensity at pixel position $S_i$. This paper replaces each 2x2 grid with $TTM_c$. The $TTM_c$ ranges from 0 to 81. The $TTM_c$ derives ternary relationship between two neighboring pixels instead of deriving a relationship between sampling points with central pixel.

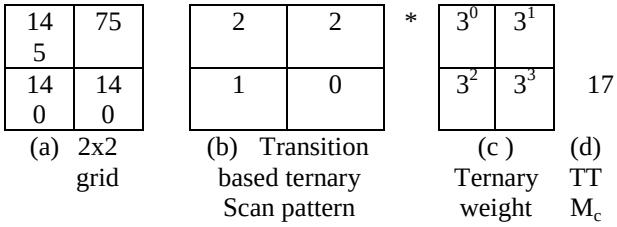


Fig. 5.Generation of $TTM_c$ on a 2 x 2 grid.

This paper proposed a completely new variant to the above existing PSM framework [4, 14, 21, 22]. The Figure 5 displays the process of generation of $TTM_c$ on a 2 x 2 grid. The proposed TTM initially divides the image into micro regions of size 2x2 (Fig. 5 (a)). The ternary transition motif is derived in Fig.5(b). The ternary transitions are multiplied by the ternary weights as shown in Fig. 5(c). The micro grid is replaced with the ternary transition motif (TTM) code as given in equation 1 and 2 instead of motif index as in the case of earlier methods as shown in Fig. 5(d). Thus the image is transformed into TTM coded image. The TTM code ranges from 0 to 80. The TTM reduces the image size into N/2 x M/2 where the actual image is NxM. This paper derives a co-occurrence matrix on TTM this derives TTMM (ternary transition motif co-occurrence matrix).

The TTMM is derived using the transformed texture image whose ($m_i$,d,$m_j$) entry characterizes the probability of finding a $TTM_c$ '$m_i$' at a distance 'd' from the $TTM_c$ '$m_j$'. The main intuition behind using the TTMM is to find out the common objects i.e. $TTM_c$ corresponding to the adjacent grids. That is the TTMM computes the co-occurrence frequencies of $TTM_c$of two grids located at a distance value'd'. The d=1 means the TTMM measures $TTM_c$ co-occurrence frequencies of adjacent grids. For each d value one can measure the frequency occurrences of two pixels or grids with a rotation angel $^0$. The size of gray level co-occurrence matrix (GLCM) depends on the range of the gray levels/ codes of the given image matrix. The size of the TTMM will 81x81, since the range of TTM index is 0 to 80.

This paper derives two frame works for texture classification using TTMM. The first frame work derives histograms on TTMM for a distance value 1 and with an angle of rotation of $0^o$, $45^o$, $90^o$ and $135^o$ and this frame work is name as $TTMM_H$. Thus the present research derives four $TTMM_H$. In the second framework this paper derived six GLCM features on TTMM and it is named as $TTMM_{GF}$. In the second frame work two TTMM's are derived with a distance value of 1 and 2 respectively. On each distance value five TTMM's with varying rotations $0^o$, $45^o$, $90^o$, $135^o$ and $180^0$ are computed. On each $TTMM_{GF}$ the six GLCM features are derived. The six GLCM features computed on $TTMM_{GF}$ are Entropy, Homogeneity, contrast, Correlation, Inverse Difference Moment (IDM) and Prominence feature. Thus in the second frame work $TTMM_{GF}$ 2x5x6=60 features are derived.

There are many sophisticated texture classifiers are available in the literature however the nearest neighborhood is often used for texture classification in the early days due to its simplicity and good mechanism of texture feature comparison. The objective of this paper is to compare the feature vector derived from the pure color space histograms and the features derived from TTMM, i.e. the feature vector derived by PC-TTMM and for this, this paper used the four machines learning classifiers and compared the results using the above affordable database and derived the best classifier.

**The major contribution of this paper**

1. The derivation of a new descriptor to estimate the relationship between adjacent scan pixels in the form of a ternary transition on a 2 x 2 grid.
2. The derivation of a unique ternary transition motif code (TTMc) instead of motif indexes.
3. Representation of each grid with a unique $TTM_c$ code that represents the complete structural and texture information.
4. Derivation of co-occurrence matrix on $TTM_c$ texture image and derivation of two descriptors $TTMM_H$ and $TTMM_{GF}$ respectively.
5. The proposed TTMM describes the spatial correlation of Motifs with complete set of structures with two identical pixels.
6. The integration of local ternary transition structural features with global GLCM features and pure color features to extract rich and powerful image contents with pure color features derived from H, S, V color plane for a high classification rate.

## IV. RESULTS AND DISCUSSIONS

The two proposed descriptors $TTMM_H$ and $TTMM_{GF}$ are tested using the five popular databases namely: Colored Brodatz Texture (CBT) [36], Outex [37], UIUC [38], KTH-TIPS [39] and ALOT [40]. And brief description about these databases is given below and sample images of these databases are shown from figure 6 to 10.

The Brodtaz database is one of the oldest, popular and widely used texture databases in the computer vision. Colored Brodatz Texture (CBT) database is an extension to this gray-scale Brodatz original texture database [45]. The advantage of this CBT is it holds both textural contents of the Brodtaz original database. And also it preserves the wide variety of color content. That's why the CBT has becomes relevant for the evaluation of texture and color-based approaches. The CBT database consists of 112 textures of size 640 x 640 pixels. Each one is divided into 25 non-overlapping sub images of size 128 x 128 pixels, thus creating 2800 images in total (i.e., 112 classes x 25 images/class).The sample sub set CBT database is shown in Fig.6.

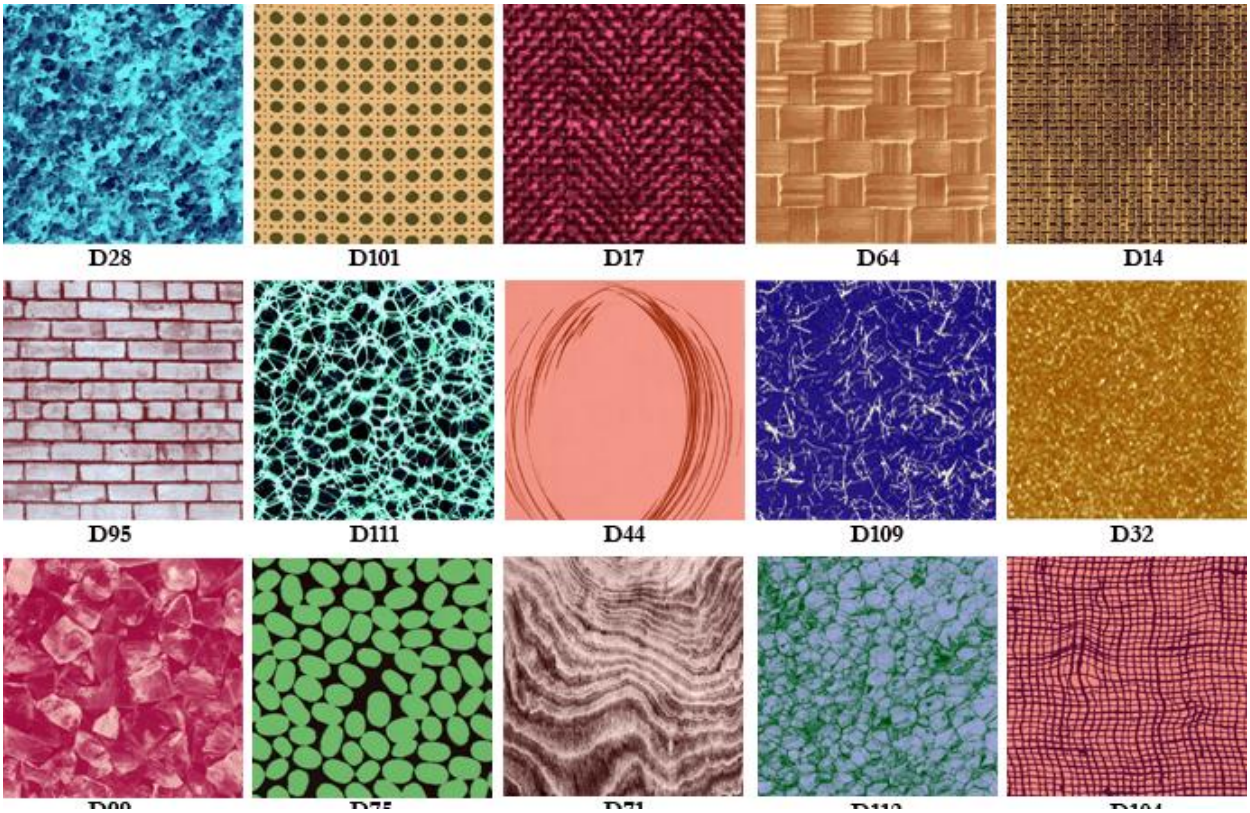


**Fig.6: sample images from CBT.**

There are two different sets of texture image in Outex-TC database i.e. Outex-TC-10 and Outex-TC-12 (Fig.7). The images of Outex are captured under different conditions with nine rotation angle 0 to 90$^o$ (0$^o$, 5$^o$, 10$^o$, 15$^o$, 30$^o$, 45$^o$, 60$^o$, 75$^o$, 90$^o$). The texture image sizes are 128 x128. And there will be 20 different images under each rotation.

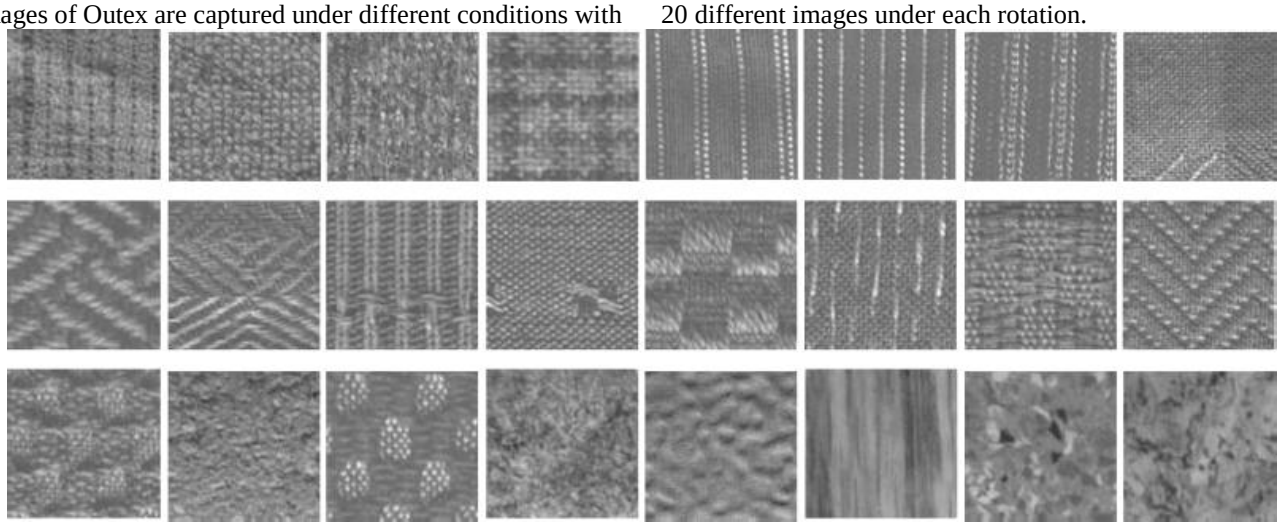

**Fig.7. sample images of Outex database.**

The UIUC texture database image consists of 1000 images with 25 categories and there will be 40 texture images under each category and the size of each image is 640 x 480. This paper divided each image into 70 non-overlapped images of size 64x64. This process has made a total of 1750 images under each category with a size of 64x64. The sample images of UIUC are shown in Fig.8.

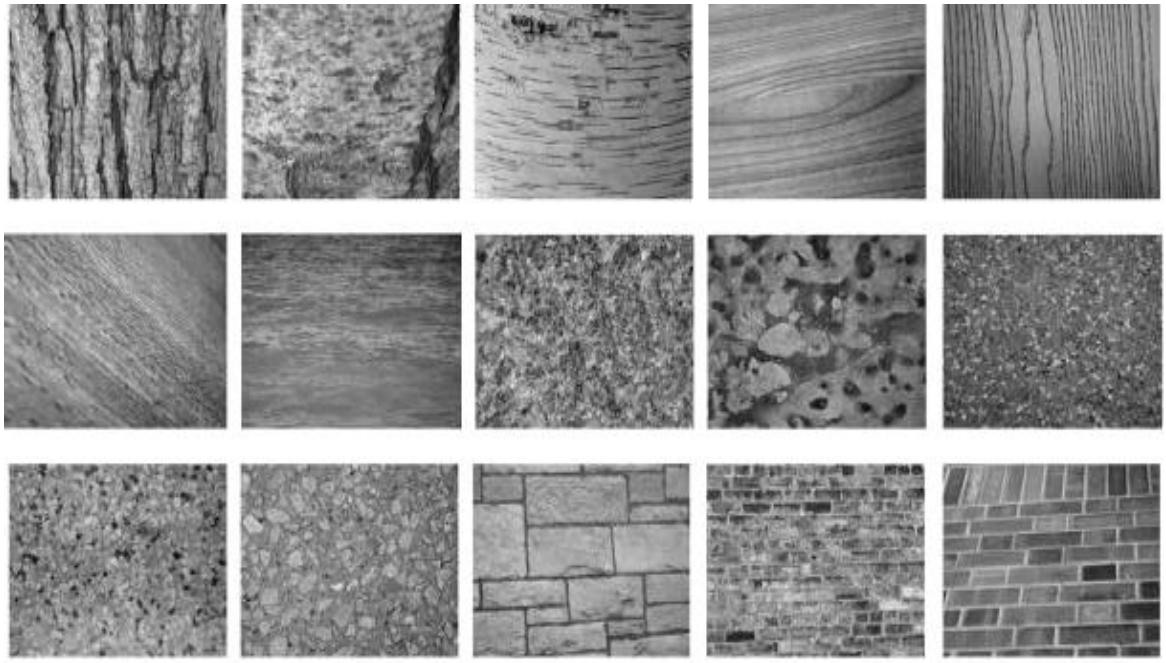

**Fig. 8: Sample images of UIUC database.**

The KTH-TIPS textures under varying illumination, pose and scale database was an extension to CURET database. The KTH-TIPS considered as extensions into two directions and provides variation in scale as well as pose and illumination. There are only 10 categories of texture image and 81 images under each category. The sample images of this database are shown in Fig.9.

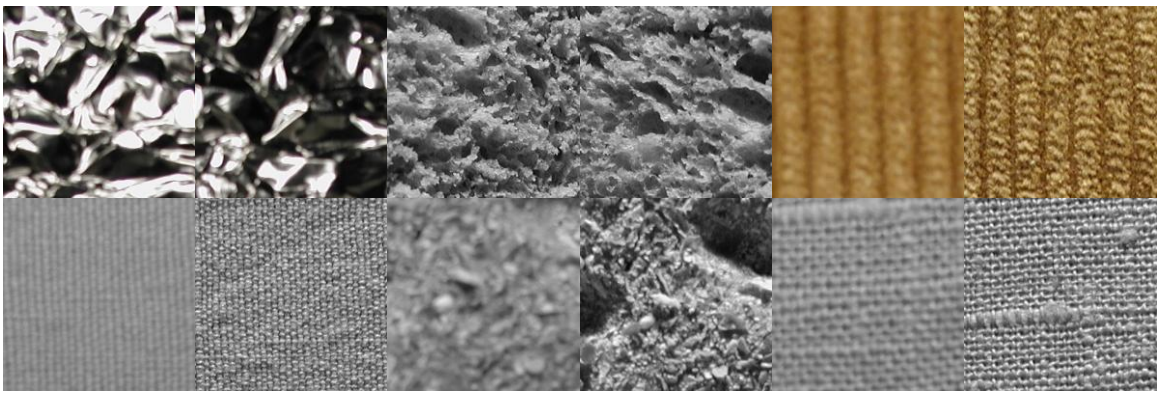

**Fig.9: Sample images of KTU-TIPS texture database.**

The ALOT dataset images [10] are obtained under different illumination conditions like variation in illumination color, camera view point and illumination direction. This dataset consists of huge number of texture categories i.e. 250 and each category consist of 100 texture images. This leads to a total of 250x100 =2500 images and each image is of size 384x256 pixels. This paper divided each image in to non-overlapped images of resolution 128 x 128. This facilitates 4 non-overlapped images and this leads to 400 texture images per category.

**Fig.10. Sample images of ALOT database.**

The average classification rate of the proposed descriptors $TTMM_H$ and $TTMM_{GF}$ using multilayer perceptron (MLP), Naivebayes, Ibk and J48 classifiers are computed and classification rates of the above affordable databases are listed in Table 1 and Table 2.

The last row of the Table 1 and Table 2 gives the average classification rate of the proposed descriptor on all databases using four different machine leaning classifiers. The multilayer perceptron has resulted on average 4 to 5% of high classification rate when compared to the rest of the classifiers. The multilayer perceptron has exhibited high classification rate on the proposed two $TTMM_H$ and $TTMM_{GF}$ descriptors. In the remainder of this paper, we have used multilayer perceptron classification results on the proposed descriptors when compared with the other existing methods. Out of these two descriptors $TTMM_{GF}$ attained a better classification rate.

Table 1: Classification rates of the proposed $TTMM_H$ descriptor.

| Database | Multilayer Perceptron | Naivebayes | IBK | J48 |
|---|---|---|---|---|
| Brodatz | 93.41 | 85.88 | 87.15 | 87.11 |
| ALOT | 88.82 | 82.91 | 85.12 | 82.03 |
| KTH-TIPS | 94.91 | 88.07 | 88.93 | 85.93 |
| UIUC | 93.57 | 86.89 | 88.24 | 84.84 |
| Outex-TC-10 | 94.17 | 86.77 | 87.25 | 87.49 |
| Outex-TC-12 | 95.67 | 87.11 | 88.94 | 82.93 |
| Average | 93.43 | 86.27 | 87.61 | 85.06 |

Table 2: Classification rates of the proposed $TTMM_{GF}$ descriptor.

| Database | Multilayer Perceptron | Naivebayes | IBK | J48 |
|---|---|---|---|---|
| Brodatz | 95.76 | 88.23 | 89.46 | 89.42 |
| ALOT | 91.17 | 85.26 | 87.43 | 84.34 |
| KTH-TIPS | 97.26 | 90.42 | 91.24 | 88.24 |
| UIUC | 95.92 | 89.24 | 90.55 | 87.15 |
| Outex-TC-10 | 96.52 | 89.12 | 89.56 | 89.80 |
| Outex-TC-12 | 98.02 | 89.46 | 91.25 | 85.24 |
| Average | 95.78 | 88.62 | 89.92 | 87.37 |

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

| Database | LBP[10] | LTP[41] | CLBP-SMC [42] | CS-LBP [43] | MCM [14] | MMCM [21] | LMP-CM [22] | Proposed $TTMM_H$ | Proposed $TTMM_{GF}$ |
|---|---|---|---|---|---|---|---|---|---|
| Brodatz | 54.28 | 67.50 | 85.23 | 74.56 | 86.32 | 87.68 | 88.56 | 93.41 | 95.76 |
| Outex-Tc-10 | 56.11 | 74.56 | 89.88 | 74.11 | 89.92 | 90.21 | 91.25 | 88.82 | 91.17 |
| Outex-Tc-12 | 56.19 | 75.88 | 90.30 | 74.64 | 91.25 | 92.35 | 93.36 | 94.91 | 97.26 |
| UIUC | 62.86 | 67.16 | 87.64 | 74.24 | 88.63 | 89.88 | 90.24 | 93.57 | 95.92 |
| KTH-TIPS | 64.16 | 66.18 | 89.14 | 72.14 | 90.21 | 91.23 | 92.31 | 94.17 | 96.52 |
| ALOT | 52.26 | 56.24 | 80.46 | 70.14 | 81.52 | 82.68 | 83.54 | 95.67 | 98.02 |

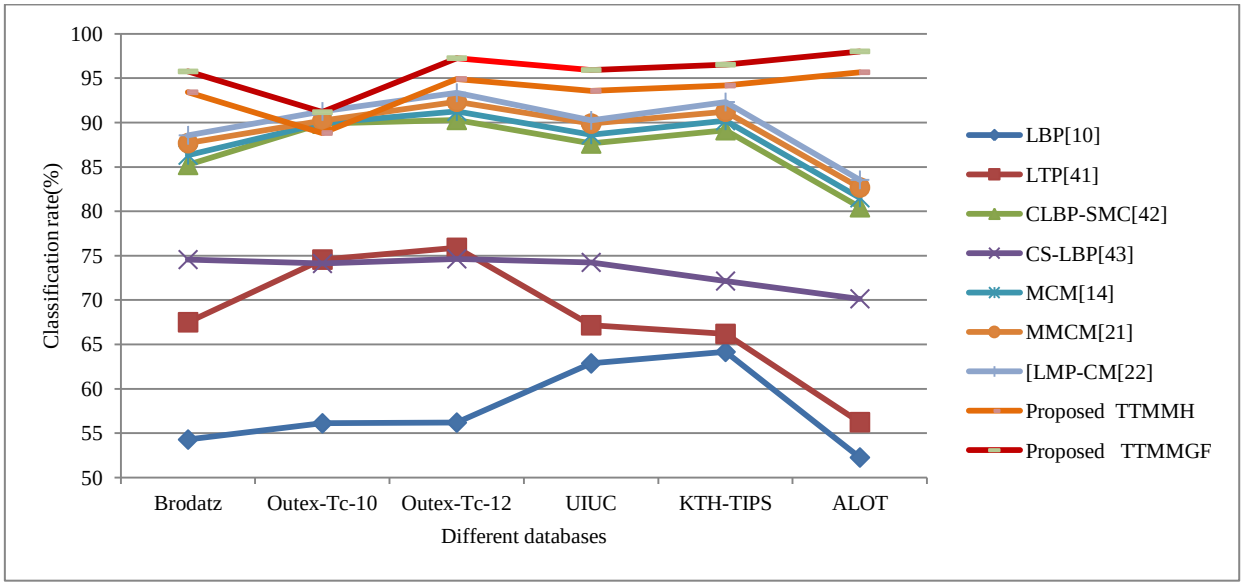


**Fig.11 : Comparison graph of Proposed vs. state-of-art methods.**

## V. CONCLUSIONS

This paper presented completely a different version of the existing motif based approaches for texture classification. The proposed TTMM extracted more powerful and discriminative texture information by deriving ternary relationship among the two neighboring pixels of the Peano scan. The derived TTM code is more robust in nature. This paper derived two frame works namely $TTMM_H$ and $TTMM_{GF}$ for texture classification and out of these two the $TTMM_{GF}$ obtained high classification rate due to the computation of six GLCM features with different degrees of rotation ($0^o$,$45^o$,$90^o$, and $135^o$) and with two different d values. This makes the second frame work i.e. $TTMM_{GF}$ is rotational invariant and robust and holds the rich texture information.

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