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Gradient Ternary Transition based Cross Diagonal Texture Matrix for Texture Classification

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ABSTRACT

This paper derives a new local descriptor gradient ternary transition based cross diagonal texture matrix (GTCDTM) for texture classification. This paper initially divides the image into a 3x3 window in an overlapped manner. On each 3x3 window, this paper computes the gradient between center pixel and each sampling point of the window. This paper divides the gradient window into cross and diagonal matrices and computes gradient transition (GT) cross unit (GTCU) and GT diagonal unit (GTDU). The GT's are derived by computing relationship between adjacent gradient pixels of cross and diagonal matrices in a clock wise manner. This research derived GTCDTM by computing the occurrence frequencies of GTCU vs. GTDU. The gray level co-occurrence matrix (GLCM) features derived on the proposed GTCDTM descriptor derive the feature vector. The proposed descriptor is tested on the popular databases using machine learning classifiers and equated with state of art local based methods. The results indicate the efficacy of the proposed method.

Key words : gradient, 3x3 window, machine learning classifiers, ternary transitions.

1. INTRODUCTION

One of the crucial and major part in the texture analysis is the extraction of texture feature and it is one of the long standing problems. The extraction of texture features attained lot of significance due to its extensive range of applications in many applications like face detection and recognition [1-3], object recognition [4], sky extraction from fishy images [5], computer assisted diagnosis [6], pedestrian detection [7], classification of images [8-10], motion and activity analysis [11], surveillance systems [12], content based image retrieval (CBIR)[13-15] and many more. To characterize texture, which is the surface property of an object, many texture feature extraction methods have been proposed over the last decades and the significant ones are based on fractal, co-occurrence matrix, wavelet and Gabor filter approaches. Lot of literature is available on these models. In recent years local based methods have become popular tools to extract texture features. The texton based methods are also popular local based approaches [16]. The pattern based methods on local grid have become popular and widely used from the invention of local binary pattern (LBP) [17].

The LBP based approaches have become more popular and used in many research domains like medical image analysis [18], face recognition [19], CBIR[13, 14, 20]. The problem with texture feature extraction is the texture in real world presents arbitrary variations in illuminations, position, viewpoint, noise levels etc… Therefore the texture extraction methods should concentrate in deriving features that are invariant to illumination or shadows, rotation, scaling, noise etc. The texture classification can be grouped into local, region and global based methods based on the neighborhood or window size on which features are extracted. The local based methods mostly derive features on the local micro grid of size 2x2, 3x3 or 5x5. The region based methods derive features on region wise, where the image is divided into regions. The histogram methods are best examples of global based methods since histograms are derived on the entire image. Further the texture feature extraction methods are divided into probability, statistical and structure models. The statistical feature extraction methods extracts the texture features based on first, second and higher order statistics. These methods are very popular in the research and attained good results. The notable examples of this category are gray level co-occurrence matrix [21]. The best examples for probability models are Markov random fields [22], auto regressive model [23], sparse representation [24] etc.

The section two gives the proposed frame work in a detailed manner. The section 3 represents the results and discussion with a brief notes on the description of the databases. The section four describes the conclusions.

2. PROPOSED METHOD

In the literature local based methods are popular in extracting texture features than global and region based methods. Among the local based approaches LBP and its extensions are very popular and they have contributed significantly for various applications of image processing. The LBP is basically derived on a circular neighborhood of size 3x3. The LBP initially extracts the binary relationship or binary pattern by comparing the gray level value of center pixel with each sampling point. Each sampling point S_i is assigned a binary value as given in equation 1. LBP derives a unique code by using equation 2. The LBP replaces the center pixel value with the unique LBP_c.

$$b_i = \begin{cases} 0\ if\ S_i \geq S_c \\ 1\ if\ S_i < S_c \end{cases} \quad (1)$$

$$LBP_c = \sum_{i=0}^{7} b_i * 2^i \quad (2)$$

The LBP code ranges from 0 to 255 i.e. 0 to 2^P-1 where P represents the number of sampling points.

The LBP framework is shown below in Figure 1 and Figure 2.

S_0	S_1	S_2
S_7	S_c	S_3
S_6	S_5	S_4

Figure1: A 3x3 neighborhood.

(a)

70	80	40
10	90	50
25	140	120

(b)

0	0	0
0		0
0	1	1

*

(c)

2^0	2^1	2^2
2^7		2^3
2^6	2^5	2^4

(d) 48

Figure 2: The LBP framework (a) 3 x 3 neighborhoods with gray values (b) Binary pattern extraction (c) Binary weights (d) LBP code.

The Fig. 2(a) represent a sample sub image patch of 3x3 neighborhood. The binary pattern for each sampling point S_i is derived using equation 1. The Fig.2(c) represents the corresponding binary weights. The summation of the product of binary patterns and corresponding binary weights as given in equation 2 results the LBP code (LBP_c). The sample image patch of Fig.2 (a) derives LBP_c 48. The center pixel value 90 is replaced by the LBPc i.e. 48 in this case. The LBP framework repeats the same process in an overlapped manner and replaces the center pixel values with LBP_c and this finally transforms the texture image into a LBP coded image. The LBP_c holds the significant local information derived from the local image patch. The LBP_c image normalizes the image gray level ranges from 0 to 255.

To derive more significant information on the local neighborhood ternary patterns are derived using the relationship between center pixel and sampling points of the neighborhood. The ternary patterns are multiplied by the corresponding ternary weights to derive local ternary code (LTC) as given in equation 3 and 4.

$$T_i = \begin{cases} 0\ if\ S_i < S_c \\ 1\ if\ S_i = S_c \\ 2\ if\ S_i > S_c \end{cases} \quad (3)$$

$$LT = \sum_{i=0}^{7} S_i * 3^i \quad (4)$$

The LTC ranges from 0 to 3^8-1, and it derives a huge code, however the ternary patterns derive more information than binary patterns. In the literature to overcome the above disadvantages of ternary patterns, which generate a huge range of codes 0 to 3^P-1, local ternary patterns (LTP) [25] were proposed.

2.1 Local ternary pattern

The LBP was extended to ternary encoding by Tan and Trigger [25] in 2010, and this descriptor is named as local ternary pattern (LTP). The LTP extended the two conventional values of LBP {0 and 1} to three values {-1, 0, 1} named as ternary patterns codes. The LTP derives ternary patterns based on a threshold t. The gray values of sampling pixel S_i in a zone of width ±t around the center pixel gray value S_c are quantized to zero. Those below (S_c-t) are quantized to -1 and those above (S_c-t) are quantized to +1 as given in the following equation.

$$f(x) = \begin{cases} +1\ S_i > (S_c + t) \\ 0\ |S_i - S_c| \leq t \\ -1\ S_i < (S_c - t) \end{cases} \quad (5)$$

The LTP derives LTP lower (LTP_L) and LTP higher (LTP_H) based on the ternary codes derived as given in equation 5 and derives LTP_L and LTP_H codes as in the case of LBP. The framework of LTP for a image patch of 3x3 window is given in Figure 3.

3x3 sample patch

28	32	24
42	26	12
62	15	20

Ternary codes by LTP

0	1	0
1		-1
1	-1	-1

LTP_H

0	1	0
1		0
1	0	0

196 LTP_H code

LTP_L

0	0	0
0		1
0	1	1

56 LTP_L code

Figure 3: The LTP frame work.

To derive a feature vector of LTP in terms of histogram one need to concatenate the histograms of LTP_H and LTP_L as given in equation 6. The LTP generates $2x2^P$ possible different pattern where P is the number of neighboring pixels.

$$HLTP = HLTP_H\ U\ HLTP_L \quad (6)$$

This paper derives ternary patterns to extract more local information with a low dimension on a gradient image using ternary transitions derived in between gradient neighbors of a grid instead of between S_i and S_c as in the case of traditional approaches. This paper divides the 3x3 window into two sub windows of four pixels each. The proposed GTCDTM initially derives the gradient by computing absolute difference between center pixel S_c and sampling point Si as given in the following equation 7.

$$G_i = abs(S_i - S_c) \text{ for i=0,1,2..7} \quad (7)$$

Where i=0 to 7 represents the number of sampling points of 3x3 window, S_i and S_c represents the gray level value of the sampling point 'i' and center pixel S_c. The G_i represents the gradient of sampling point S_i with respect to S_c. This paper divides the gradient window G into cross and diagonal matrices as shown in Figure 4. The LBP and its variants derived binary or ternary relation by extracting a relationship between center pixel and sampling points. The proposed GTCDTM derives the ternary pattern by extracting the transitions between gradient sampling points instead of binary relation as in the case of LBP and its variants.

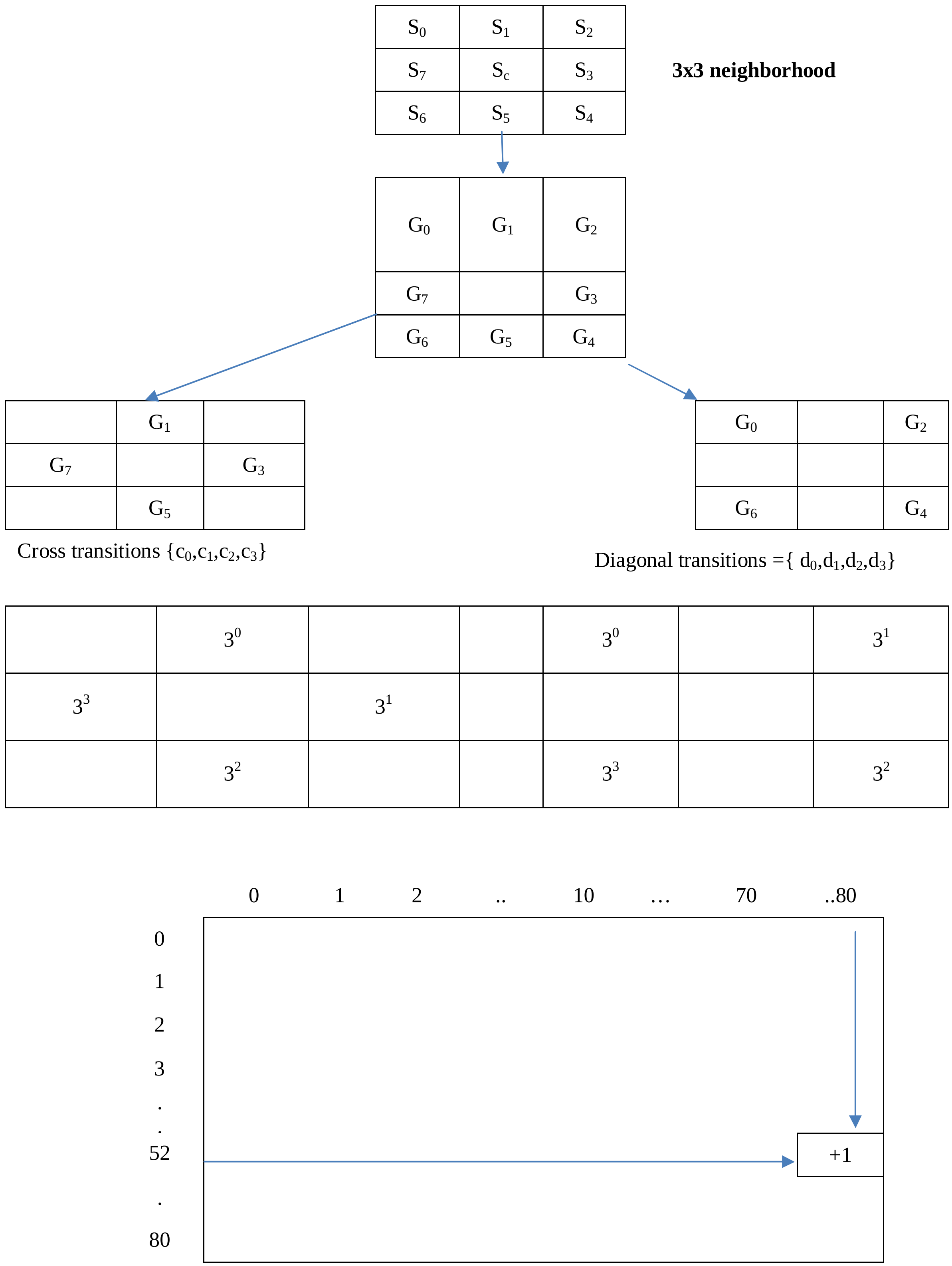

Figure 4: Proposed GTCDTM framework.

$$c_i \; or \; d_i = \begin{cases} 0 \; if \; G_i < G_J \\ 1 \; if \; G_i = G_J \\ 2 \; if \; G_i > G_J \end{cases} \quad (8)$$

$$GTCU = \sum_{i=0}^{3} C_i * 3^i \quad (9)$$

$$GTDU = \sum_{i=0}^{3} D_i * 3^i \quad (10)$$

This paper initially divides the 3x3 gradient window into two units of 4 gradient pixels each and they are named as gradient cross (G_c) and gradient diagonal (G_d) units. This research extracted a ternary transition between adjacent sampling points of gradient cross and diagonal units as given in Eqn.8. This paper derived gradient transition cross unit (GTCU) and gradient transition diagonal unit (GTDU) using equation 9 and 10 respectively. Finally this paper derived gradient transition based cross diagonal texture matrix (GTCDTM) based on the relative frequencies of GTCU and GTDU. The size of GTCDTM will be 81x81 (0..80 x 0..80). The GTCDTM is a 2-dimensional matrix. The rows of the GTCDTM represent the GTCU and the columns represent the GTDU. GTCDTM (i,j)= V; where i and j represents the values of GTCU and GTDU respectively and V represents the number of times for GTCU 'i', the GTDU 'j' has occurred. This paper derived GLCM features on GTCDTM. The algorithm for the proposed GTCDTM is given below.

Algorithm 1:
Begin
Step 1: If the input image is a color image then convert into gray level image.
Step 2: create a matrix of size 81x81 and name it is GTCDM.
Step 3: initialize the GTCDM with zero values.
Step 4: For each 3x3 overlapped neighborhood repeat the steps from 5 to 9.
Step 5: Compute gradient of sampling points by deriving absolute difference between each sampling point and center pixel of the 3x3 window.
Step 6: divide the 3x3 gradient window in to cross and diagonal window.
Step 7: Compute GTCU let it be i.
Step 8: Compute GTDU and let it be j.
Step 9: assign GTCDTM (i,j) = GTCDTM(i,j)+1
Step 10: Shift the neighborhood in an overlapped manner (shift the column by one position until the end of column and then shift the row by one position)
Step 11: If the entire image is not convolved then go to step 5.
Step 12: Derive GLCM features on GTCDTM with different d values and with different rotations on each d value.
Step 13: place the feature vector as input to the machine learning classifiers.
Step 14: Perform the classification and note down for which d value the classification rate is high.
End of the algorithm

3. RESULTS AND DISCUSSIONS

To test the efficacy of the proposed descriptor this paper tested the existing methods and the proposed descriptor GTCDTM on five popular and widely used texture databases used in the literature namely ALOT[34], Outex [35], Brodtaz[36], UIUC[37] and KTH-TIPS [38]. The sample images of these databases are displayed in Figures 5 to 9. The brief description about these databases is summarized in table 1. The table 2 displays the number of classes, number of images per class, the size of each image considered in the experimental set up from the above affordable databases.

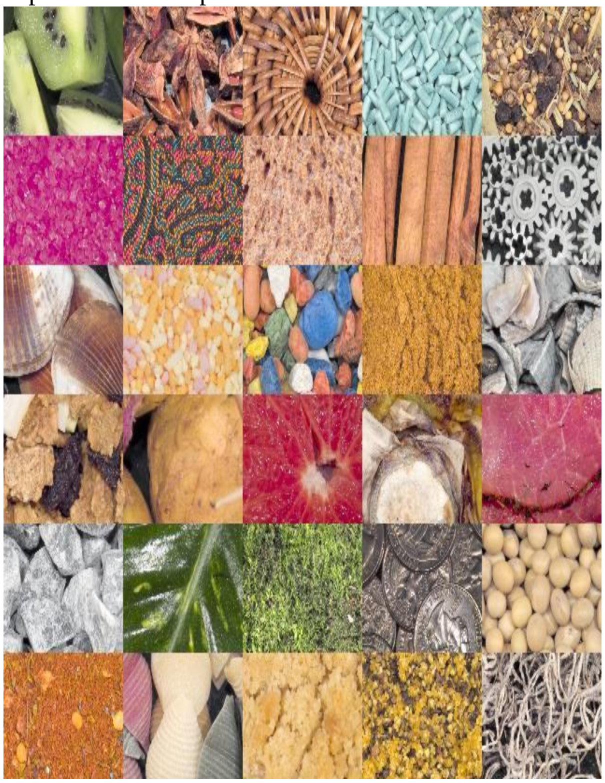

Figure 5: Sample images of ALOT database.

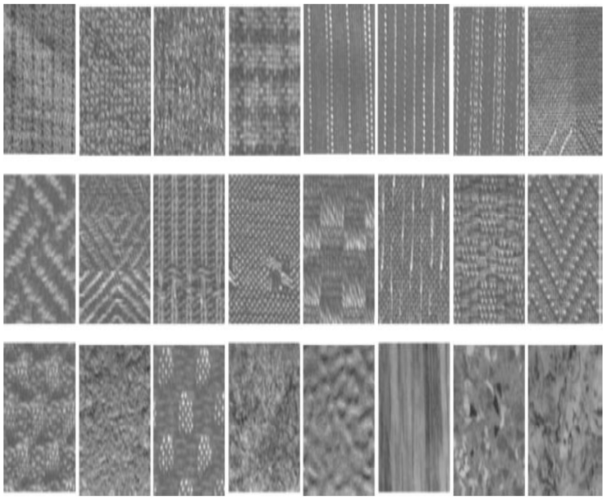

Figure 6: sample images of Outex database.

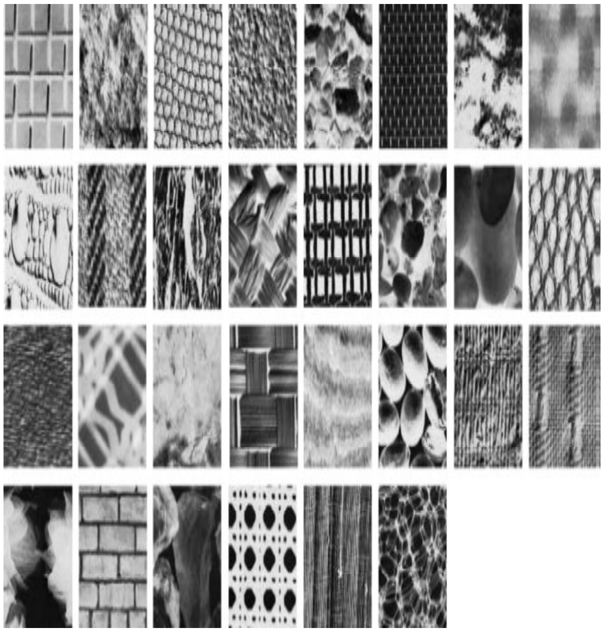

Figure 7: Sample images of Brodatz database.

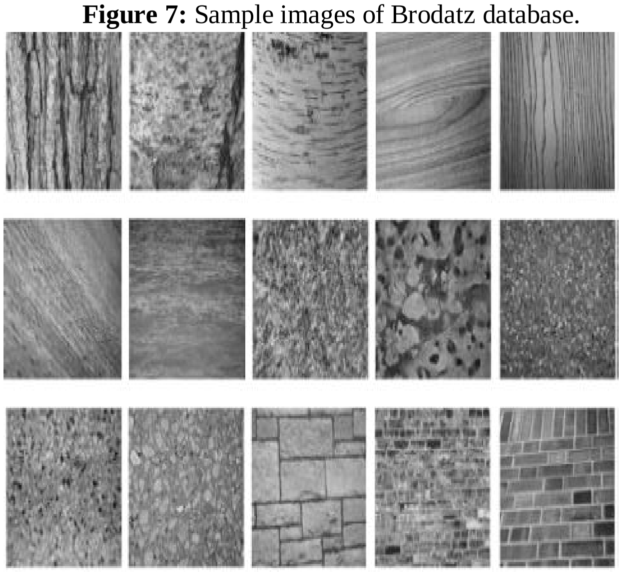

Figure 8: Sample images of UIUC database.

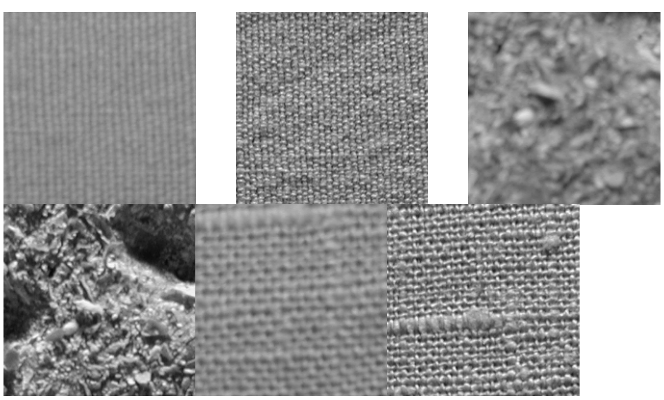

Figure 9: Sample images of KTU-TIPS texture database.

Table 1: Description about the databases.

S.No	Name of the database	Number of different classes	Number of images per class	Size of the image
1	A LOT	250	100	250x100
2A	Outex-TC-10	6	20	128x128
2B	Outex-TC-12	6	20	128x128
3	Brodtaz	30	-	512x512
4	UIUC	25	40	640x480
5	KTH-TIPS	10	81	128x128

Table 2: Number of classes and images considered for the experimental purpose.

S. No	Name of the database	Considered set by the present research				
		Number of different classes	Number of non-overlapped portions	Size of the each image	No. of images per class	Total images of database
1	A LOT	250	3	64x64	10	2500
2A	Outex-TC-10	6	-	128x128	20	120
2B	Outex-TC-12	6	-	128x128	20	120
3	Brodtaz	30	16	128x128	16	480
4	UIUC	25	151	128x128	100	2500
5	KTH-TIPS	10	81	128x128	81	810

This paper derived GTCDTM with three distance values d = 1, 2 and 3 and on each distance value this research considered six different rotations $\alpha = 0^o, 45^o, 90^o, 135^o, 180^o$ and 225^o. This paper derived six GLCM features namely: Contrast, correlation, Entropy, Homogeneity, Inverse Difference Moment (IDM) and Prominence feature on each rotation angle. This raises the feature vector of six $\alpha^o*f= 6*6=36$ features on each distance value. In the literature most of the work on classification used distance functions as a classifiers. This research used machine learning classifiers for classification purpose. The proposed GTCDTM descriptor carried out the classification task by using multiplayer perceptron, naivebayes, IBK and J48 classifiers on the above databases. The feature vector is given as input to the four machine learning classifiers. This paper initially compared the performance of the proposed descriptor GTCDTM on these four machine learning classifiers on different databases with different d values i.e. d=1,2 and 3 and found that for the d value =2, all the four classifiers has given more significant classification rate. The table 3 gives the classification rate of the proposed descriptor for the d value 2.

Table 3: The classification rates of GTCDTM with different classifiers on d=2.

S.No	Database	Ibk	Naivebayes	J48	Multilayer perceptron
1	A LOT	92.36	82.36	82.68	93.26
2	Outex-TC-10	94.65	83.62	84.32	97.29
2A	Outex-TC-12	92.36	84.26	85.63	99.29
3	Brodtaz	93.62	83.85	84.69	96.45
4	UIUC	94.99	84.89	85.63	97.21
5	KTH-TIPS	96.32	85.21	86.36	98.29
	Average classification rate	94.05	84.03	84.89	96.97

The last row of the table 3 gives the average classification rate of the proposed GTCDTM and it shows that the multilayer perceptron exhibited high classification rate when compared to the rest of the classifiers. This paper used multilayer perceptron classification rates of GTCDTM when compared to other existing methods.

Table 4: Classification rate (%) of proposed method and existing classifiers.

Database	LBP[17]	LTP[25]	CLBP-SMC [31]	CS-LBP [32]	MCM [33]	MMCM [13]	LMP-CM [14]	CDCETM [34]	Proposed GTCDTM
Brodatz	54.28	67.50	85.23	74.56	86.32	87.68	88.56	95.81	96.23
Outex-Tc-10	56.11	74.56	89.88	74.11	89.92	90.21	91.25	91.42	92.32
Outex-Tc-12	56.19	75.88	90.30	74.64	91.25	92.35	93.36	97.52	98.21
UIUC	62.86	67.16	87.64	74.24	88.63	89.88	90.24	96.92	96.52
KTH-TIPS	64.16	66.18	89.14	72.14	90.21	91.23	92.31	96.72	97.21
ALOT	52.26	56.24	80.46	70.14	81.52	82.68	83.54	98.02	98.11

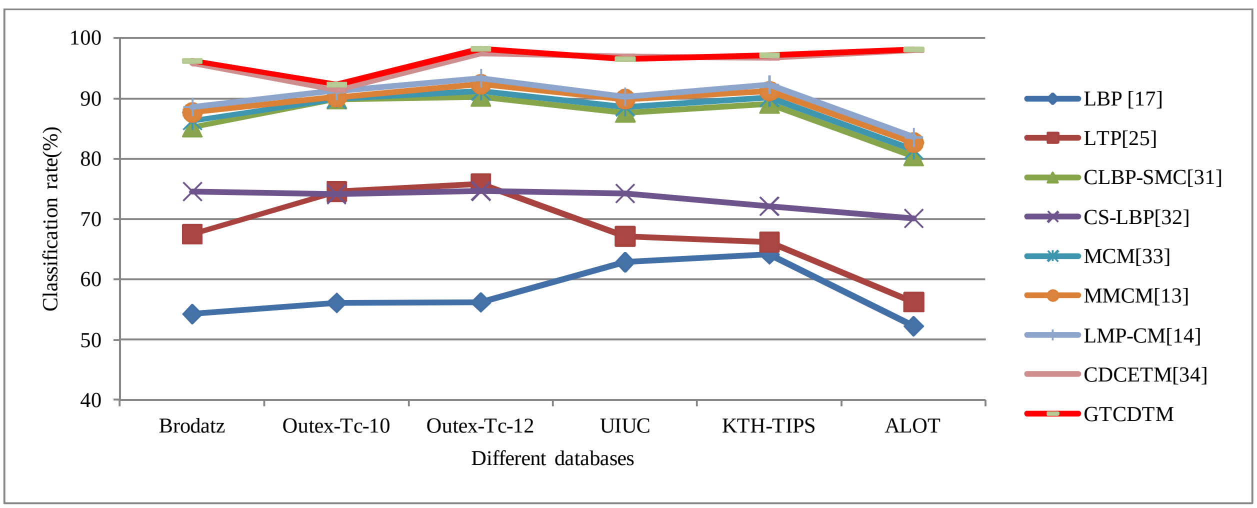

Figure 11: Comparison of proposed method and state-of-art methods.

The proposed descriptor compared the classification accuracies with the existing and popular classification frame works: LBP[17], LTP[25], CLBP-SMC [31], CS-LBP [32], MCM[33], MMCM [13], LMP-CM[14] and CDCETM [34]. The classification accuracies are listed in Table 4.

Major contribution of this work:

1. Derivation of gradient based cross and diagonal units by partitioning the 3x3 neighborhood.
2. Derivation of transition functions in between adjacent sampling points of cross and diagonal matrices, instead of center pixel and sampling points.
3. Derivation of GTCDTM based on occurrence frequency of GTCU vs GTDU
4. Derivation of GLCM features on proposed GTCDTM for efficient texture classification.

Form the experimental results it is evident that among LBP, LTP and CS-LBP: the CS-LBP attained high classification rate mainly due to the extraction of center symmetric relations among the 3x3 neighborhood. Among LBP and LTP, the LTP attained good classification rate due to the derivation of ternary patterns. This paper also considered three motif methods namely MCM, MMCM, LMP-CM and these methods are derived on a 2 x 2 grid in contrast with above LBP based methods which are derived on 3 x 3 neighborhood. In the literature the motif based methods are mainly derived for CBIR, however due to their extraction of texture features on a micro grid of size 2x2, they are also experimented in this paper for texture classification. And these methods attained high classification rate than LBP based methods considered in this paper. The three motif based methods almost achieved the similar classification rate however a slight high classification rate is achieved for LMP-CM due to derivation of rich local information. The dimension of LMP-CM is 36x36 and it does not depend on the gray level or intensity level range of the raw texture image. The MMCM results are slightly better than MCM due to its high tendency in capturing more discriminative texture information, than MCM, by deriving Peano scan motifs in two different directions. Finally the proposed GTCDTM attained high classification rate when compared to the rest of the methods.

4. CONCLUSION

This paper derived a new descriptor called GTCDTM that is based on gradient and ternary transitions concept. The gradient approach derives the significant information between center pixel and sampling points. The divisions of 3x3 windows into cross and a diagonal matrix reduces the overall dimensionality. The ternary transitions between sampling points resembles the scanning pattern of a motif. The scanning pattern is in clockwise direction i.e. fixed direction this overcomes the ambiguity issues. The proposed descriptor derives relationship between center pixel and sampling points in the form of a gradient and ternary relationship between adjacent gradient pixels using a transition function and thus it derives more significant information than other descriptors. The GLCM features derived on the GTCDTM makes the present descriptor to integrate with statistical features also. The proposed descriptor is tested on popular databases, the experimental results indicates high classification rate and also a better classification rate than the existing state art of methods. The main reasons for this is due to the gradient approach derivation of ternary transition in a fixed scan direction and integration of GLCM features on GTCDTM.

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