

# LOCAL TEXTURE DESCRIPTION FRAMEWORK FOR TEXTURE BASED FACE RECOGNITION

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## Abstract

*Texture descriptors have an important role in recognizing face images. However, almost all the existing local texture descriptors use nearest neighbors to encode a texture pattern around a pixel. But in face images, most of the pixels have similar characteristics with that of its nearest neighbors because the skin covers large area in a face and the skin tone at neighboring regions are same. Therefore this paper presents a general framework called Local Texture Description Framework that uses only eight pixels which are at certain distance apart either circular or elliptical from the referenced pixel. Local texture description can be done using the foundation of any existing local texture descriptors. In this paper, the performance of the proposed framework is verified with three existing local texture descriptors Local Binary Pattern (LBP), Local Texture Pattern (LTP) and Local Tetra Patterns (LTrPs) for the five issues viz. facial expression, partial occlusion, illumination variation, pose variation and general recognition. Five benchmark databases JAFFE, Essex, Indian faces, AT&T and Georgia Tech are used for the experiments. Experimental results demonstrate that even with less number of patterns, the proposed framework could achieve higher recognition accuracy than that of their base models.*

## Keywords:

*Face Recognition, Local Texture Description Framework, Nearest Neighborhood Classification, Chi-Square Distance Metric*

## 1. INTRODUCTION

Face images are one among few biometric information that can be captured from a distance without the knowledge of the subject. Moreover in some legal databases, face images are the only available biometric information. Hence face recognition systems are the widely accepted means of extracting information for visual surveillance, biometric authentication, computer-human interaction etc. There exist several techniques for face recognition. However issues like complex lighting, expression variation, partial occlusion with objects, pose variation with large rotation angles and aging remain unsolved. Therefore, to improve the effectiveness of today's recognition systems, there arises a need to enhance the systems performance.

Based on the property of the features extracted, face recognition algorithms are classified into holistic and local feature based [6]. Holistic approaches such as Principal Component Analysis (PCA) [15], Linear Discriminant Analysis (LDA) [3], variants of LDA [4, 14, 31, 33, 34, and 38], Marginal Fisher Analysis (MFA) [32], Eigen feature Regularization and Extraction (ERE) [13] were extensively studied due to their good performance and low computational complexity. Even then,

holistic information of face images is not effective under illumination variation, facial expression and partial occlusion [9]. Feature based techniques such as shape based and texture based are robust to variations in head orientation, scale and location of face in the image. But they are computationally more expensive than holistic approaches [28, 35]. Hence an effort is made in this paper to introduce a new texture description framework that produces better accuracy in face recognition with less computation burden.

## 1.1 MOTIVATION AND JUSTIFICATION FOR THE PROPOSED APPROACH

Textural feature extraction methods have an important role in recognizing objects and scenes. They can be used to determine uniformity, lightness, density, fineness, coarseness, roughness, regularity, etc., of texture patterns as a whole [2, 21]. An ample number of methods have been proposed to extract facial texture features. There exist many models that are derived from Local Binary Pattern (LBP). Ojala et al. [22] developed LBP in which a gray scale invariant texture pattern for a local neighborhood of  $3 \times 3$  is defined. A derivative of the LBP [23] was later introduced by them to describe multi-resolution rotational and gray scale invariant pattern on a circular neighborhood that could represent salient micro-patterns of face images. It is a very powerful method to analyze textures [28, 29]. Hence, several researchers have been successfully applied it for face recognition [1], facial expression analysis [37], background modeling [10] etc. Owing to its low dimensionality and efficiency in face recognition and texture classification, several variants of LBP was later introduced.

Advanced Local Binary Pattern (ALBP), which is an extension of LBP, was invented by Liao et al. [17] to capture micro information in face images. Later they introduced Dominant Local Binary Pattern (DLBP) [18] for texture classification which was extended to face recognition and detection. Suruliandi and Ramar [26] proposed a univariate texture model called Local Texture Patterns (LTP) for image classification and proved that it is robust in terms of gray scale variation and rotational variation. Heikkila et al. [11] introduced Center Symmetric Local Binary Pattern (CSLBP) that produces 16 patterns. This descriptor is robust in flat areas and has tolerance against illumination changes. Zhang et al. [36] proposed Local Derivative Patterns (LDPs) in which LBP is considered as a non-directional first-order local patterns collected from the first-order derivatives and have extended it

for  $n^{\text{th}}$  order LDPs. This operator has been successfully applied for face recognition. Guo et al. [8] proposed Local Binary Pattern Variance (LBPV) that characterizes local contrast information into a one-dimensional LBP histogram. Lei et al. [16] introduced a method that merges information obtained from image space, scale and orientation and have proved that in face recognition their method outperforms the one which considers the individual domain alone. In our early work [27], performance of LBP, Multivariate Local Binary Pattern (MLBP) [19], LBPV, DLBP, Local Texture Pattern (LTP) and LDP are evaluated for different face recognition issues, and have found that LTP and LDP outperforms other descriptors. Subrahmanyam Murala et al. [25] proposed Local Tetra Patterns (LTrPs) for content based image retrieval and have proved that their method has high discrimination power.

Except Multi-scale Local Binary Pattern Histogram (MLBPH) [5], almost all the existing local texture descriptors describe patterns by relating the closest neighbors around a pixel. When pixels at certain distance apart are considered, it may likely to acquire the features of different facial components like eyes, nose, mouth etc. This is the idea behind developing a general framework for describing a texture pattern over a local region with pixels at certain distance apart. Both the face and the components of the face can be either circular or elliptical in nature. Hence proposing a new texture description that captures features along circular or elliptical neighborhood is expected to have high discrimination power even when all the face recognition challenges are considered. Justified by these facts, a framework LTDF is proposed for either circular or elliptical neighborhood.

**1.2 OUTLINE OF THE PROPOSED APPROACH**

Overall process of face recognition is illustrated by Fig.1. At first, all the images are converted into gray-scale images. Then they are preprocessed to align into same canonical position. Subsequently certain region of interest is cropped from the images so as to prevent processing of unnecessary details. The system is then trained by extracting texture features from gallery images by the proposed LTDF, and is stored separately for every image in the database. While testing a probe image, texture features are extracted from that image, and are matched against all the images in the database using nearest neighborhood classifier with chi-square dissimilarity metric.

**1.3 ORGANIZATION OF THE PAPER**

The latter part of the paper is organized as follows. A brief review of texture descriptors LBP, LTP, and LTrPs are reported in section 2. In section 3 the proposed LTDF is presented. Section 4 gives the face recognition algorithm in detail. Section 5 is devoted to the experimental results and discussions of the proposed LTDF model for five different conditions expression variation, illumination variation, partial occlusion with spectacle, pose variation and general recognition. Finally, the conclusion is given in section 6.

**2. RELATED WORK**

**2.1 TEXTURE DESCRIPTION**

Texture is a term that characterizes the contextual property of an image. A texture descriptor can characterize an image as a whole. Texture descriptor Grey Level Co-occurrence Matrix (GLCM) [21] belongs to this category. Alternatively, it can also characterize an image locally at the micro level and by global texture description at the macro level. In local description, the relationship between a pixel and its neighborhood can be expressed in terms of local texture patterns. The occurrence frequency of such patterns ( $PTN$ ) will be collected in a histogram ( $H$ ) using (1) which describes the global feature of the image. The texture descriptors LBP, LTP, and LTrPs follow the second approach.

$$H(p) = \sum_{i=1}^N \sum_{j=1}^M f(PTN(i, j), p); \tag{1}$$

$$p \in [1, P] \tag{2}$$

$$f(x, y) = \begin{cases} 1 & \text{if } x = y \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where,  $N \times M$  represents the size of the input image and P the total number of patterns.

**2.2 LOCAL BINARY PATTERN**

Ojala et al. introduced LBP operator [23] for texture classification by which a texture pattern around a pixel in an image can be computed by comparing its gray value with its neighbors as demonstrated in Fig.2.

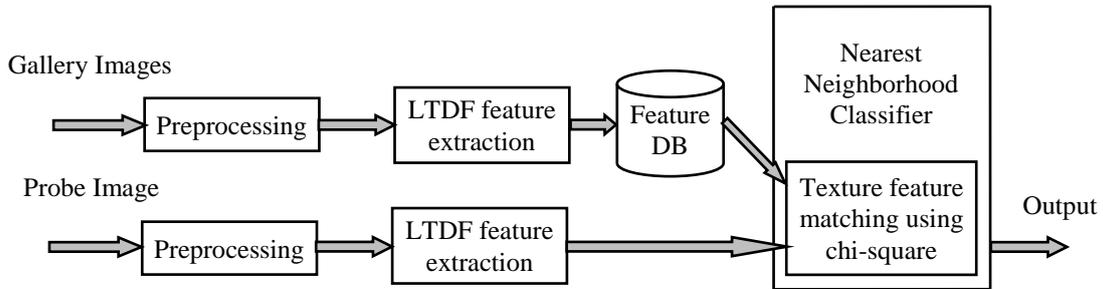


Fig.1. Face recognition process

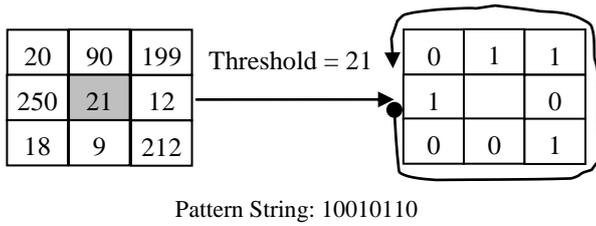


Fig.2. Pattern string computation from a sample image

LBP is deliberated as follows,

$$LBP_{P,R} = \begin{cases} \sum_{p=1}^{p-8} t(g_p, g_c) & \text{if } U \leq 2 \\ 9 & \text{otherwise} \end{cases} \quad (4)$$

where,

$$t(g_p, g_c) = \begin{cases} 0 & \text{if } g_p < g_c \\ 1 & \text{if } g_p \geq g_c \end{cases} \quad (5)$$

In the above equations  $g_c, g_p$  are the grey level of center pixel  $c$  and a vicinity pixel  $p$  respectively,  $P$  is the number of neighbors and  $R$  is the radius of the neighborhood. The pattern can be classified as either uniform or non-uniform. It is said to be uniform if in the pattern string there are at most only two transitions from 0 to 1 or vice versa. Usage of uniform patterns reduces the total number of bins required. Image analysis requires only 9 bins for uniform patterns and one extra bin for all non-uniform patterns thus requires a total of 10 bins. The uniformity measure  $U$  is computed as follows,

$$U = s(t(g_8, g_c), t(g_1, g_c)) + \sum_{i=2}^8 s(t(g_i, g_c), t(g_{i-1}, g_c)) \quad (6)$$

where,

$$s(x,y) = \begin{cases} 1 & \text{if } |x-y| > 0 \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

### 2.3 LOCAL TEXTURE PATTERN

Suruliandi and Ramar [26] have proposed LTP. In this, texture pattern around a pixel in an image is computed with the pattern units  $P$  obtained for its eight neighbors as described below.

$$P(g_i, g_c) = \begin{cases} 0 & \text{if } g_i < (g_c - \Delta g) \\ 1 & \text{if } (g_c - \Delta g) \leq g_i \leq (g_c + \Delta g), i = 1, 2, \dots, 8 \\ 9 & \text{if } g_i > (g_c + \Delta g) \end{cases} \quad (8)$$

In the above equation,  $g_c$  is the gray value of center pixel and  $g_i$  is the gray value of  $3 \times 3$  neighbors and  $\Delta g$  is a small positive integer value that plays an important role in forming the uniform patterns. A pattern string is then formed by collecting the  $P$  values of the eight neighbors starting from any position as described below.

$$LTP = \begin{cases} \sum_{i=1}^8 P(g_i, g_c) & \text{if } U \leq 3 \\ 73 & \text{otherwise} \end{cases} \quad (9)$$

$U$  is the uniformity measure and is computed as in Eq.(6). Number of uniform patterns which can be obtained by LTP scheme is 46 in total and can have values in the range 0 to 73 leaving few holes in between. Therefore patterns are relabeled to form continuous numbers from 1 to 46.

### 2.4 LOCAL TETRA PATTERN

Subrahmanyam et al. introduced this model in which a local texture description of a pixel can be obtained using two things: 1) the direction of the pixel with its horizontal and vertical neighbors. 2) The magnitudes of horizontal and vertical first-order derivatives. For every direction, a tetra pattern is first obtained using Eq.(14) which is further divided into three binary pattern using Eq.(16). Therefore the total number of binary pattern that an LTrPs can give is 13 including the magnitude information. The detailed explanation with example is available in [25].

Given an image  $I$ , the first-order derivatives at a pixel  $g_c$  for direction one can be calculated as,

$$I^1 0^0(g_c) = I(g_h) - I(g_c) \quad (10)$$

$$I^1 90^0(g_c) = I(g_v) - I(g_c) \quad (11)$$

where,  $g_h$  and  $g_v$  are the grey values of horizontal and vertical neighbors. The direction of the center pixel can be written as,

$$I^1 Dir(g_c) = \begin{cases} 1, & I^1 0^0(g_c) \geq 0 \text{ and } I^1 90^0(g_c) \geq 0 \\ 2, & I^1 0^0(g_c) < 0 \text{ and } I^1 90^0(g_c) \geq 0 \\ 3, & I^1 0^0(g_c) < 0 \text{ and } I^1 90^0(g_c) < 0 \\ 4, & I^1 0^0(g_c) \geq 0 \text{ and } I^1 90^0(g_c) < 0 \end{cases} \quad (12)$$

The second-order  $LTrP^2(g_c)$  is expressed as,

$$LTrP^2(g_c) = \left\{ f(I^1 Dir(g_c), I^1 Dir(g_1)), f(I^1 Dir(g_c), I^1 Dir(g_2)), \dots, f(I^1 Dir(g_c), I^1 Dir(g_P)) \right\} | P = 8 \quad (13)$$

where,

$$f(I^1 Dir(g_c), I^1 Dir(g_P)) = \begin{cases} 0, & I^1 Dir(g_c) = I^1 Dir(g_P) \\ I^1 Dir(g_P), & \text{else} \end{cases} \quad (14)$$

Above equations yield an eight bit tetra pattern for every pixel. The tetra pattern is then converted into four parts depending upon the direction of center pixel. Each tetra pattern is converted to three binary patterns.

For direction "1"  $LTrP^2$  of any pixel can be segregated into three binary patterns using,

$$LTrP^2 \Big|_{Direction=2,3,4} = \sum_{p=1}^P BP(LTrP^2(g_c)) \Big|_{Direction=2,3,4} \quad (15)$$

$$BP(LTrP^2(g_c)) \Big|_{Direction=\phi} = \begin{cases} 1, & \text{if } LTrP^2(g_c) = \phi \\ 0, & \text{else} \end{cases} \quad (16)$$

where,  $\phi = 2, 3, 4$ .

Similarly, tetra pattern for the other three directions of every pixel are converted into binary patterns. Thus the total numbers

of binary patterns are 12 ( $4 \times 3$ ). The 13<sup>th</sup> binary pattern ( $LP$ ) is obtained by using the magnitudes of horizontal and vertical first-order derivatives using,

$$M_{I^1(g_p)} = \sqrt{(I^1 0^\circ(g_p))^2 + (I^1 90^\circ(g_p))^2} \quad (17)$$

$$LP = \sum_{p=1}^P t \left( M_{I^1(g_p)} - M_{I^1(g_c)} \right) \Big|_{p=8} \quad (18)$$

### 3. PROPOSED LOCAL TEXTURE DESCRIPTION FRAMEWORK (LTDF)

Local Texture Description Framework is a framework for any texture descriptors that use nearest neighbors to describe a texture pattern around a pixel in an image. It is either circular or elliptical in shape and can have several rings that encircle a center point as illustrated in Fig.3. LTDF can be described with a single ring (LTDF<sup>s</sup>) or with combination of more number of rings (LTDF<sup>m</sup>).

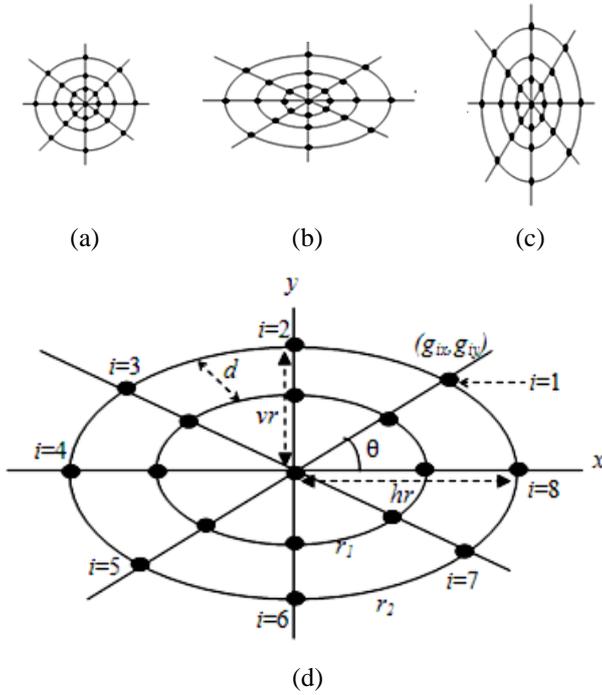


Fig.3. Position of neighborhood pixels in LTDF for shapes  
a) circular b) horizontal ellipse c) vertical ellipse and  
d) Illustration of parameters in LTDF

For a pixel in an image, LTDF<sup>s</sup> is a joint distribution of  $p(p=8)$  pixels that lie on a ring at radius  $d$  from that pixel. The shape of the ring can be either circular (LTDF<sub>c</sub><sup>s</sup>) or elliptical (LTDF<sub>e</sub><sup>s</sup>). LTDF<sub>e</sub><sup>s</sup> has two radii:  $hr$  (horizontal radius) and  $vr$  (vertical radius). All the parameters used in this model are illustrated in Fig.3(d). The pixels considered from the ring are in eight directions ( $\theta$ ) from the center pixel. Position  $(g_{ix}, g_{iy})$  of a vicinity pixel  $i$  in a ring is computed using Eq.(19) – Eq.(21). In order to determine the coordinates of the pixels, bilinear interpolation can be used. For LTDF<sub>c</sub><sup>s</sup>  $hr$  and  $vr$  are the same ( $d=hr=vr$ ).

$$g_{ix} = R_i \cdot \cos \theta_i, \quad g_{iy} = R_i \cdot \sin \theta_i \quad (19)$$

where,

$$R_i = \sqrt{\frac{hr^2 + vr^2}{hr^2 \sin^2 \theta_i + vr^2 \cos^2 \theta_i}} \quad (20)$$

and

$$\theta_i = \left[ \frac{360}{p} * (i-1) \right], \quad i = 1 \text{ to } p \quad (21)$$

In LTDF<sup>m</sup>, local pattern descriptions are made separately for each ring  $r_j$  ( $j = 1$  to  $n$ ) and are then concatenated for  $n$  rings which are several distances apart from the center pixel that represent the texture as a whole. For a circular ring  $r_j$ , which is closer to the center pixel,  $d$  is the radius of the ring from the center pixel whereas for the other rings  $r_2$  to  $r_n$ , it is the difference in radius of the ring from its predecessor. For every pixel in a ring, the corresponding pixel in the successor ring lies in the same direction as in Fig.3(d).

Once the neighborhood pixels on a ring are located, any local texture descriptors such as LBP, LTP, LTrPs etc. that encode images using eight neighbors can be used to obtain local texture description. For LTDF<sup>m</sup>, each pixel is represented by  $n$  pattern values that correspond to  $n$  number of rings considered. LTDF<sub>c</sub><sup>s</sup> using LBP is similar as MLBPH [5], and LTDF<sub>e</sub><sup>s</sup> is similar to DAISY [28] descriptor when  $d$  is 1 for all the rings. Hence these two approaches can be viewed as a subset of the proposed framework and the proposed LTDF<sub>e</sub><sup>m</sup> can also be referred as *loosely coupled DAISY*.

### 4. FACE RECOGNITION ALGORITHM

**Input:** Probe Image

**Output:** Recognized image

**Training Phase:**

For every image in the gallery, do the following,

- Rotate the images in such a way that a line connecting eye centers lies on a horizontal line.
- Crop certain region from the image to avoid computational complexity of using entire face by Eq.(22) – Eq.(25).

$$x1 = (x - p) + (p/2) \quad (22)$$

$$y1 = y - p \quad (23)$$

$$x2 = 3 * p \quad (24)$$

$$y2 = (3 * p) + p \quad (25)$$

where,  $p$  is half the distance between two eye centers.

- Compute local texture description for every pixel in the image using LTDF and store it in a feature space.
- Divide the feature space into  $n \times n$  equally sized sub regions.
- Obtain global texture description in the form of histogram as explained in section 3 for every sub region, concatenate them and store in a database. Fig.4 illustrates the feature extraction process.

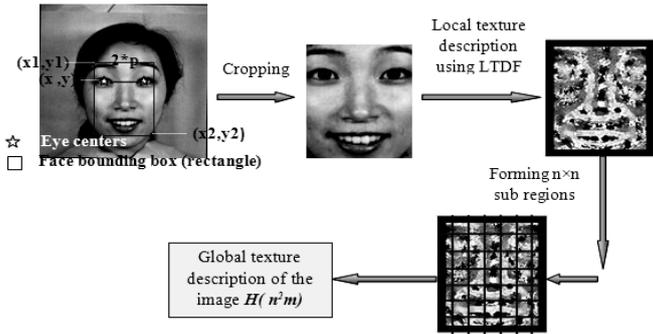


Fig.4. Illustration of the steps involved in computing texture feature of an image

**Testing Phase:**

For a probe image, do the following,

- a) Determine global texture description of the image using steps *a* to *e* in the training phase.
- b) Find out the dissimilarity between the texture feature of the probe image and texture feature of the gallery images stored in the database using Chi-square statistic as defined below,

$$\chi^2(\mathbf{H}_G, \mathbf{H}_P) = \sum_{i=1}^{n^2 m} \frac{(\mathbf{H}_G(i) - \mathbf{H}_P(i))^2}{\mathbf{H}_G(i) + \mathbf{H}_P(i)} \quad (26)$$

where,  $\mathbf{H}_G(i)$  is the  $i^{\text{th}}$  feature value of the gallery image and  $\mathbf{H}_P(i)$  is the  $i^{\text{th}}$  feature value of the probe image,  $m$  is the number of patterns and  $n^2$  is the number of sub regions.

- c) The gallery image which yields least dissimilarity measure with the probe image is considered as the recognized one.

**5. EXPERIMENTAL RESULTS AND DISCUSSIONS**

In order to determine the effectiveness and feasibility of the proposed framework in different issues including expression variation, illumination variation, general recognition, partial occlusion and pose variation, the framework is experimented with local texture descriptors such as LBP, LTP and LTrPs. Initially, an extensive experimental investigation is carried out for single ring and multiple rings in circular shape. Experimental results reveal that the single ring is sufficient in most of the cases. Hence in the elliptical shape only single ring is considered for further experimentation.

The following experimental setup and parameter settings are used. If any part of a ring falls outside the boundary then the ring is neglected. For LTP,  $\Delta g$  is assigned to have value 5. In original LTrPs, positional weights ( $2^P$ ) are used but in this paper it is not used in order to reduce the total number of patterns. Further, for LTrPs the direction “1” alone is considered. The input image is cropped and divided into  $7 \times 7$  sub regions on applying the algorithm in section 4. For all the experiments, the recognition rate obtained for the best LTDF is tabulated and the radius is given inside parenthesis. Owing to the usage of very less number of patterns by LBP, experiments are carried out for

LTDF<sup>m</sup> using LBP alone. Fig.5 shows the LTDF coded faces of a sample subject from AT&T database for the local texture descriptors LBP, LTP and LTrPs. Sample images used from different databases are displayed in Fig.6.

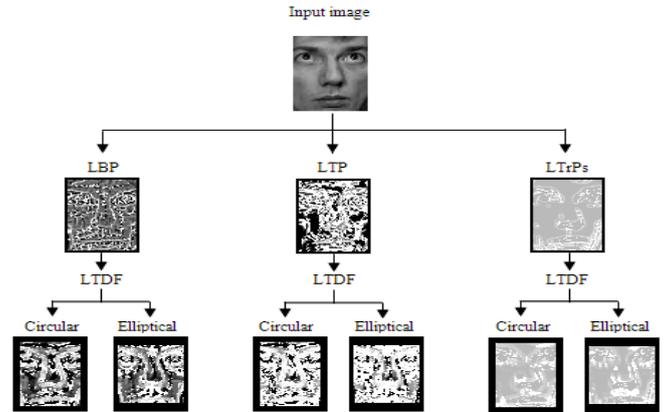
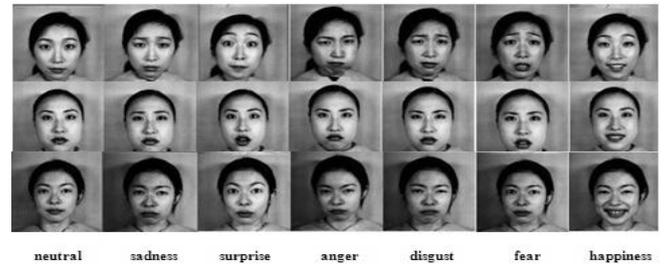


Fig.5. Feature maps obtained for an image from AT&T database



(a) Sample images used for expression variation experiment from JAFFE database



(b) Sample images used for illumination variation and partial occlusion from ESSEX database



(c) Sample images used for pose variation experiment from Indian Faces database



(d) Sample images used for general recognition experiment from AT&T database

Fig.6. Images used for different experiments from various databases

### 5.1 RESULTS ON EXPRESSION VARIATION

Robustness in face recognition under different facial expression is the most challenging issue. Facial expressions result in temporally deformed facial features that lead to false recognition. In order to test the effectiveness of the proposed model, experiment is conducted for expression variation images by JAFFE database [20]. The database contains 213 frontal face images of 10 Japanese female models with seven different expressions. Two types of experiments are conducted on this database: one to recognize faces with varying expression and another to understand facial expression.

Initially the performance of the proposed  $LTDF_c$  is experimented for the standard LBP, by varying the number of rings and the difference in radius between the rings. Experiment is conducted by setting one neutral expression image per subject in the gallery set and the rest of the images in the probe set. The results are tabulated in Table.1(a). From the results it is evident that the  $LTDF_c^s$  is capable of achieving a recognition accuracy of 94.08% which is greater than that of  $LTDF_c^m$  with three rings which yields an accuracy of 93.59% when  $d$  is 3. Higher the number of rings, greater being the total number of patterns represented by the model. This shows the effectiveness of  $LTDF_c^s$  model.

Table.1(a). Performance evaluation of  $LTDF_c^m$  (loosely coupled DAISY) using LBP on JAFFE database

Recognition rate (%)							
No: Rings		1 ( $LTDF_c^s$ )	2	3	4	5	6
Bins		10	20	30	40	50	60
Distance between rings (d)	1 (DAISY)	35.46	41.87	47.78	56.15	63.14	72.90
	2	46.79	65.02	86.69	92.11	93.10	90.64
	3	71.92	90.64	93.59	90.64	91.13	90.64
	4	87.19	93.10	90.14	91.62	90.14	90.14
	5	92.61	91.62	91.13	91.62	90.64	88.17
	6	<b>94.08</b>	90.64	91.62	91.13	90.14	86.69
	7	91.13	89.16	91.13	89.16	85.71	83.74

To further evaluate the generalization performance of  $LTDF^s$  on novel subjects, a 10-fold cross-validation experiment scheme is adopted. The dataset is randomly partitioned into ten groups. Roughly equal number of subjects is kept in each group. Nine groups are used as gallery set and the remaining group is used as probe set. This process is repeated for each group to have 10 runs in total. The recognition rate for the best  $LTDF^s$  in

comparison with the tested base models are reported in Table.1(b) in terms of mean and standard deviation error. In 6-class face recognition, neutral expression images are not included whereas in 7-class face recognition, all the expressions are considered.

The results are evident for the effectiveness of the proposed framework in recognizing faces with different expressions. The performance of the base models are enhanced when the proposed framework is applied on them. The reason behind this might be that the expression variations affect local regions and so when pixels lie at certain region apart are used to form a texture pattern, it has high discrimination power.

To analyze the ability of  $LTDF^s$  on recognizing different expressions, the confusion matrices are obtained for the base models,  $LTDF_c^s$  and  $LTDF_e^s$  and are given in Table.1(c), Table.1(d) & Table.1(e) respectively.

It is observed from the table results that both  $LTDF_c^s$  and  $LTDF_e^s$  outperform their base models to identify facial expression. Moreover  $LTDF_e^s$  performs better in distinguishing different expressions especially fear, happiness and surprise.

Table.1(b). Recognition rate (%) on the JAFFE database for several methods

Methods	6-Class	7-Class
LBP	89.82±9.21	89.73±11.17
LTP	96.91±4.28	97.68±4.44
LTrPs	96.16±5.69	97.63±3.35
$LTDF_c^s$ _LBP <sub>(6)</sub>	100	100
$LTDF_c^s$ _LTP <sub>(6)</sub>	100	100
$LTDF_c^s$ _LTrPs <sub>(5)</sub>	100	100
$LTDF_e^s$ _LBP <sub>(5,7)</sub>	100	100
$LTDF_e^s$ _LTP <sub>(5,8)</sub>	100	100
$LTDF_e^s$ _LTrPs <sub>(2,4)</sub>	100	100

### 5.2 RESULTS ON ILLUMINATION VARIATION

Recognition under different lighting condition is a challenging problem in computer vision. This variation in illumination affects the classification greatly. The performance of the proposed  $LTDF$  is evaluated by conducting an experiment on images with different lighting condition. Frontal images of 27 persons with controlled illumination variation are taken from Essex database [7] and in this paper the set is named as Essex-illu. One exemplar per subject is kept in the gallery and 9 images per individual are kept in the probe set. Experimental results are given in Table.2.

Table.1(c). Confusion Matrix of 7-Class Facial Expression Recognition using LBP, LTP and LTrPs on JAFFE database

(%)		Anger	Disgust	Fear	Happiness	Sadness	Surprise	Neutral
Anger	LBP	56.66	6.66	6.66	0	20	0	10
	LTP	60	10	13.33	0	6.66	0	10
	LTrPs	73.33	6.66	6.66	0	10	3.33	0

<b>Disgust</b>	<b>LBP</b>	10.34	51.72	24.13	3.44	6.89	0	3.44
	<b>LTP</b>	20.68	65.51	10.34	0	0	0	3.44
	<b>LTrPs</b>	0	89.65	10.34	0	0	0	0
<b>Fear</b>	<b>LBP</b>	6.25	9.37	43.75	3.12	18.75	18.75	0
	<b>LTP</b>	3.12	9.37	75	0	0	6.25	6.25
	<b>LTrPs</b>	0	6.25	78.12	0	0	9.37	6.25
<b>Happiness</b>	<b>LBP</b>	0	0	0	80.64	6.45	3.22	9.67
	<b>LTP</b>	0	0	3.22	74.19	6.45	16.12	0
	<b>LTrPs</b>	0	3.22	0	74.19	6.45	0	16.12
<b>Sadness</b>	<b>LBP</b>	3.22	3.22	6.45	3.22	67.74	3.22	12.90
	<b>LTP</b>	3.22	0	6.45	3.22	70.96	3.22	12.90
	<b>LTrPs</b>	3.22	3.22	3.22	3.22	77.14	3.22	6.45
<b>Surprise</b>	<b>LBP</b>	6.66	0	13.33	3.33	3.33	66.66	6.66
	<b>LTP</b>	3.33	0	10	6.66	3.33	73.33	3.33
	<b>LTrPs</b>	3.33	0	3.33	3.33	3.33	73.33	13.33
<b>Neutral</b>	<b>LBP</b>	6.66	0	13.33	3.33	6.66	3.33	66.66
	<b>LTP</b>	0	6.66	3.33	0	13.33	6.66	70
	<b>LTrPs</b>	0	0	0	0	3.33	3.33	93.33

Table.1(d). Confusion Matrix for Facial Expression Recognition obtained by LTDF<sub>c</sub><sup>s</sup> for JAFFE database

(%)		Anger	Disgust	Fear	Happiness	Sadness	Surprise	Neutral
<b>Anger</b>	<b>LBP<sub>(6)</sub></b>	93.33	0	0	0	0	0	6.66
	<b>LTP<sub>(6)</sub></b>	96.66	0	0	0	0	0	3.33
	<b>LTrPs<sub>(5)</sub></b>	96.66	0	0	0	3.33	0	0
<b>Disgust</b>	<b>LBP<sub>(6)</sub></b>	0	93.10	3.44	0	3.44	0	0
	<b>LTP<sub>(6)</sub></b>	0	96.55	0	0	3.44	0	0
	<b>LTrPs<sub>(5)</sub></b>	3.44	89.65	6.89	0	0	0	0
<b>Fear</b>	<b>LBP<sub>(6)</sub></b>	0	0	96.87	0	0	3.12	0
	<b>LTP<sub>(6)</sub></b>	0	0	96.87	0	0	3.12	0
	<b>LTrPs<sub>(5)</sub></b>	0	6.25	90.62	0	0	0	3.12
<b>Happiness</b>	<b>LBP<sub>(6)</sub></b>	0	0	0	83.87	9.67	0	6.45
	<b>LTP<sub>(6)</sub></b>	0	0	0	87.09	6.45	6.45	0
	<b>LTrPs<sub>(5)</sub></b>	0	0	0	83.87	3.22	3.22	9.67
<b>Sadness</b>	<b>LBP<sub>(6)</sub></b>	0	0	3.22	3.22	90.32	0	3.22
	<b>LTP<sub>(6)</sub></b>	0	3.22	0	3.22	90.32	0	3.22
	<b>LTrPs<sub>(5)</sub></b>	3.22	0	3.22	3.22	90.32	0	0
<b>Surprise</b>	<b>LBP<sub>(6)</sub></b>	0	0	3.33	3.33	0	93.33	0
	<b>LTP<sub>(6)</sub></b>	0	0	0	3.33	0	96.66	0
	<b>LTrPs<sub>(5)</sub></b>	0	0	0	10	3.33	76.66	10
<b>Neutral</b>	<b>LBP<sub>(6)</sub></b>	0	0	0	0	0	0	100
	<b>LTP<sub>(6)</sub></b>	0	0	0	0	0	0	100
	<b>LTrPs<sub>(5)</sub></b>	0	0	0	0	3.33	3.33	93.33

Table.1(e). Confusion Matrix for Facial Expression Recognition using LTDF<sub>c</sub><sup>s</sup> on JAFFE database

(%)		Anger	Disgust	Fear	Happiness	Sadness	Surprise	Neutral
Anger	LBP <sub>(5,7)</sub>	96.66	0	0	0	0	0	3.33
	LTP <sub>(5,8)</sub>	96.66	0	0	0	0	0	3.33
	LTrPs <sub>(2,4)</sub>	96.66	0	0	0	3.33	0	0
Disgust	LBP <sub>(5,7)</sub>	0	93.10	3.44	0	0	0	3.44
	LTP <sub>(5,8)</sub>	0	96.55	0	0	3.44	0	0
	LTrPs <sub>(2,4)</sub>	0	89.65	10.34	0	0	0	0
Fear	LBP <sub>(5,7)</sub>	0	0	100	0	0	3.12	0
	LTP <sub>(5,8)</sub>	0	0	96.87	0	0	3.12	0
	LTrPs <sub>(2,4)</sub>	0	3.12	96.87	0	0	0	0
Happiness	LBP <sub>(5,7)</sub>	0	0	0	87.09	6.45	6.45	0
	LTP <sub>(5,8)</sub>	0	0	0	90.32	3.22	0	6.45
	LTrPs <sub>(2,4)</sub>	0	0	0	83.87	6.45	3.22	6.45
Sadness	LBP <sub>(5,7)</sub>	3.22	0	0	3.22	90.32	0	3.22
	LTP <sub>(5,8)</sub>	0	0	0	3.22	93.54	0	3.22
	LTrPs <sub>(2,4)</sub>	3.22	3.22	3.22	3.22	80.64	0	6.45
Surprise	LBP <sub>(5,7)</sub>	0	0	0	3.33	0	96.66	0
	LTP <sub>(5,8)</sub>	0	0	0	3.33	0	96.66	0
	LTrPs <sub>(2,4)</sub>	0	0	0	6.66	3.33	83.33	6.66
Neutral	LBP <sub>(5,7)</sub>	0	0	0	0	0	0	100
	LTP <sub>(5,8)</sub>	0	0	0	0	0	0	100
	LTrPs <sub>(2,4)</sub>	0	0	0	0	3.33	3.33	93.33

Table.2(a). Performance evaluation of LTDF<sub>c</sub><sup>m</sup> (loosely coupled DAISY) using LBP for illumination variation

		Recognition rate (%)					
No: Rings		1 (LTDF <sub>c</sub> <sup>s</sup> )	2	3	4	5	6
Bins		10	20	30	40	50	60
Distance between rings (d)	1 (DAISY)	77.77	84.77	90.94	93	95.88	97.11
	2	88.06	95.06	97.11	97.11	97.53	97.11
	3	95.06	97.53	97.94	97.53	97.94	97.94
	4	97.94	97.94	97.53	97.94	97.11	95.88
	5	<b>98.35</b>	97.94	97.94	97.53	95.06	95.06
	6	98.35	97.94	97.94	96.29	95.06	95.06
	7	97.94	98.35	97.11	95.47	95.06	95.06

As observed, LTDF<sub>c</sub><sup>s</sup> using LBP is sufficient to attain a maximum recognition accuracy of 98.35%. LTDF<sub>c</sub><sup>s</sup> and LTDF<sub>c</sub><sup>m</sup> produce similar results and so the system achieves high speed when LTDF<sub>c</sub><sup>s</sup> is used.

The best recognition rates obtained by the proposed LTDF<sup>s</sup>, in comparison with the experimented base models are given in Table.2(b), in which LTDF<sup>s</sup> performs better than the base models in face recognition with different lighting conditions. Most of the pixels in face images lie on skin areas and are similar in closest neighborhood. This causes the proposed LTDF to gain high recognition rate by relating pixels that are at certain distance apart.

### 5.3 RESULTS ON POSE VARIATION

In this section, effectiveness of the proposed LTDF on pose variant images is evaluated with Indian Face database [30]. The database constitutes two main directories separately for male and female. There are eleven different images of 22 distinct females in female directory. For every subject, there are seven images in different poses. All the 22 female subjects' images are used for the experiment by placing one frontal pose image per subject in the gallery set and the remaining subjects in the probe set.

Table.2(b). Recognition rate (%) on the Essex-illu dataset for one sample training problem on several methods

Methods	Recognition accuracy
LBP	77.77
LTP	93.82
LTrPs	93.41
LTDF <sub>c</sub> <sup>s</sup> _LBP <sub>(5)</sub>	98.35
LTDF <sub>c</sub> <sup>s</sup> _LTP <sub>(5)</sub>	100
LTDF <sub>c</sub> <sup>s</sup> _LTrPs <sub>(3)</sub>	97.53
LTDF <sub>c</sub> <sup>s</sup> _LBP <sub>(4,8)</sub>	98.35
LTDF <sub>e</sub> <sup>s</sup> _LTP <sub>(2,6)</sub>	100
LTDF <sub>e</sub> <sup>s</sup> _LTrPs <sub>(2,5)</sub>	97.53

It can be understood from Table.3 that the proposed LTDF is more suited for pose variant images. For instant, the proposed LTDF<sub>c</sub><sup>s</sup> using LBP yields an accuracy of 36.36% whereas the base model LBP gives an accuracy of 19.69%. This shows that the proposed model performs better producing an accuracy of 17% greater than that of LBP and hence it has higher discrimination power.

It is also noticed that LTDF<sub>c</sub><sup>m</sup> and LTDF<sub>e</sub><sup>s</sup> using LBP produce an accuracy of 47.92% and 42.42% respectively. LTDF<sub>c</sub><sup>m</sup> give highest result with four rings when  $d$  is 5 for all the rings. Both the models seem to be more efficient when compared with LTDF<sub>c</sub><sup>s</sup> for pose variant images. This is due to the fact that for pose variant images certain information can be lost and so facial features are captured differently when these models are used. By this analysis, it is very well understood, that LTDF<sub>e</sub><sup>s</sup> performs better for the pose variant images. The results prove the effectiveness of LTDF<sub>e</sub><sup>s</sup>.

Table.3(a). Performance evaluation of LTDF<sub>c</sub><sup>m</sup> (loosely coupled DAISY) using LBP on pose variation

		Recognition rate (%)					
No: Rings		1 (LTDF <sub>c</sub> <sup>s</sup> )	2	3	4	5	6
Bins		10	20	30	40	50	60
Distance between rings (d)	1 (DAISY)	19.69	17.42	20.45	29.54	35.60	34.84
	2	15.15	28.78	37.12	37.12	42.42	42.42
	3	28.03	37.87	41.66	42.42	45.45	44.69
	4	28.78	37.87	42.42	43.93	46.21	43.93
	5	32.57	43.93	43.18	<b>47.92</b>	44.69	45.45
	6	<b>36.36</b>	43.18	46.96	44.69	43.93	42.42
	7	36.36	45.45	45.45	46.96	44.69	43.18

Table.3(b). Recognition rate (%) on the Indian Face database for one sample training problem (one frontal image per subject) on several methods

Methods	Recognition accuracy
LBP	19.69
LTP	36.36
LTrPs	29.54
LTDF <sub>c</sub> <sup>s</sup> _LBP <sub>(6)</sub>	36.36
LTDF <sub>c</sub> <sup>s</sup> _LTP <sub>(6)</sub>	47.72
LTDF <sub>c</sub> <sup>s</sup> _LTrPs <sub>(6)</sub>	43.18
LTDF <sub>e</sub> <sup>s</sup> _LBP <sub>(9,7)</sub>	42.42
LTDF <sub>e</sub> <sup>s</sup> _LTP <sub>(5,1)</sub>	49.24
LTDF <sub>e</sub> <sup>s</sup> _LTrPs <sub>(4,5)</sub>	45.45

## 5.4 RESULTS ON PARTIAL OCCLUSION WITH OBJECTS

Occlusions appear as local distortion away from a common face representing human population [9]. In order to study the capability of the model for recognizing faces occluded with objects, frontal face images of 13 persons with spectacles are collected from Essex database [7] and the image set is referred in this paper as Essex-po. One image per individual is randomly chosen as gallery set and 12 images per person are kept in the probe set. Table.4 gives the experimental results.

From the experimental results in Table.4(a), it is observed that the proposed LTDF<sub>c</sub><sup>s</sup> is able to achieve a highest recognition accuracy of 97.43% for faces partially occluded with spectacle. By knowing the effectiveness of LTDF<sub>c</sub><sup>s</sup>, the experiment is conducted with LTDF<sub>e</sub><sup>s</sup>. Experimental results reveal that the recognition accuracy obtained by LTDF<sub>e</sub><sup>s</sup> is very similar to that of LTDF<sub>c</sub><sup>s</sup>. In addition it is noticed that the result produced by circular model using LBP is about 21% greater than that of its base model which produces an accuracy of 76.28%. This shows the efficiency of LTDF<sub>e</sub><sup>s</sup> in recognizing images partially occluded with spectacle.

## 5.5 RESULTS ON GENERAL RECOGNITION

After observing the effects of the proposed LTDF<sub>c</sub><sup>s</sup> and LTDF<sub>e</sub><sup>s</sup> on various issues in face recognition, performance of the models are experimented for general recognition using AT&T [24] and Georgia Tech [12] databases. The AT&T database has 400 images of 40 subjects that demonstrate expression variation, illumination variation, and partial occlusion with spectacle and pose variation. The Georgia Tech database contains 750 different images of 50 subjects which demonstrate different issues in face recognition like facial expression, occlusion, different lighting condition, and change in pose. All the images are used for the experiment. The results on one sample training problem is obtained by keeping one frontal image per subject in the gallery set and remaining in the probe set and is shown in Table.5(a).

Table.4(a). Performance evaluation of LTDF<sub>c</sub><sup>m</sup> (loosely coupled DAISY) using LBP on partial occlusion with spectacle

Recognition rate (%)							
No: Rings	1 (LTDF <sub>c</sub> <sup>s</sup> )	2	3	4	5	6	
Bins	10	20	30	40	50	60	
Distance between rings (d)	1 (DAISY)	76.28	80.76	83.33	91.02	94.23	94.87
	2	81.41	93.58	95.51	96.15	96.15	96.79
	3	94.23	96.15	96.79	96.79	96.79	96.79
	4	96.15	97.43	96.79	96.79	96.79	95.51
	5	96.79	96.15	96.79	96.15	95.51	94.23
	6	96.79	96.79	96.79	95.51	94.23	93.58
	7	<b>97.43</b>	97.43	95.51	94.87	94.23	93.58

Table.4(b). Recognition rate (%) on the Essex-po dataset for one sample training problem on several methods

Methods	Recognition accuracy
LBP	76.28
LTP	88.46
LTrPs	87.17
LTDF <sub>c</sub> <sup>s</sup> _LBP <sub>(7)</sub>	97.43
LTDF <sub>c</sub> <sup>s</sup> _LTP <sub>(4)</sub>	94.87
LTDF <sub>c</sub> <sup>s</sup> _LTrPs <sub>(3)</sub>	96.79
LTDF <sub>e</sub> <sup>s</sup> _LBP <sub>(4,7)</sub>	96.79
LTDF <sub>e</sub> <sup>s</sup> _LTP <sub>(2,4)</sub>	97.43
LTDF <sub>e</sub> <sup>s</sup> _LTrPs <sub>(4,3)</sub>	95.51

Table.5(a). Recognition rate (%) on the AT&T and Georgia Tech databases for one sample training problem (one frontal image per subject) on several methods

Methods	AT&T	Methods	Georgia Tech
LBP	57.77	LBP	41.14
LTP	60.55	LTP	49.14
LTrPs	58.88	LTrPs	57.57
LTDF <sub>c</sub> <sup>s</sup> _LBP <sub>(4)</sub>	70.55	LTDF <sub>c</sub> <sup>s</sup> _LBP <sub>(4)</sub>	52.42
LTDF <sub>c</sub> <sup>s</sup> _LTP <sub>(4)</sub>	68.61	LTDF <sub>c</sub> <sup>s</sup> _LTP <sub>(5)</sub>	59.42
LTDF <sub>c</sub> <sup>s</sup> _LTrPs <sub>(3)</sub>	60.27	LTDF <sub>c</sub> <sup>s</sup> _LTrPs <sub>(5)</sub>	59.85
LTDF <sub>e</sub> <sup>s</sup> _LBP <sub>(7,2)</sub>	71.11	LTDF <sub>e</sub> <sup>s</sup> _LBP <sub>(4,8)</sub>	53.71
LTDF <sub>e</sub> <sup>s</sup> _LTP <sub>(5,3)</sub>	68.88	LTDF <sub>e</sub> <sup>s</sup> _LTP <sub>(6,3)</sub>	60.28
LTDF <sub>e</sub> <sup>s</sup> _LTrPs <sub>(1,2)</sub>	60.55	LTDF <sub>e</sub> <sup>s</sup> _LTrPs <sub>(4,3)</sub>	60.14

Table.5(b). N-fold Cross-Validation result on AT&T database for several methods

Methods	Recognition rate (%)
LBP	92.25±3.8
LTP	93.25±2.89
LTrPs	94±3.76
LTDF <sub>c</sub> <sup>s</sup> _LBP <sub>(4)</sub>	97.75±2.75
LTDF <sub>c</sub> <sup>s</sup> _LTP <sub>(4)</sub>	98±2.83
LTDF <sub>c</sub> <sup>s</sup> _LTrPs <sub>(4)</sub>	96.5±3.16
LTDF <sub>e</sub> <sup>s</sup> _LBP <sub>(7,2)</sub>	99±1.74
LTDF <sub>e</sub> <sup>s</sup> _LTP <sub>(7,2)</sub>	98.5±2.1
LTDF <sub>e</sub> <sup>s</sup> _LTrPs <sub>(7,2)</sub>	96.75±2.8

It is noticed from Table.5(a) that the proposed LTDF<sub>c</sub><sup>s</sup> and LTDF<sub>e</sub><sup>s</sup> outperforms the tested base models even with one sample per subject in the gallery set. To prove the generalization performance of face recognition with general conditions that include all type of variations, an n-fold cross-validation test is conducted on AT&T database by dividing the dataset into 10 groups. Each group has exactly one exemplar per 40 subjects and for each run one group is used for probe set and the remaining for the gallery set. The process is repeated 10 times and the mean recognition rate with standard deviation error is reported in Table.5(b). The results are evident for the proposed LTDF<sup>s</sup> and illustrates that the single ring circular and elliptical models are capable of achieving high recognition rate than its base model by using the same number of patterns. Thus with less number of bins the model is able to achieve better results.

## 6. CONCLUSION

Texture features capture the micro primitive patterns present in the face. This paper proposes a new texture description method referred as Local Texture Description Framework for an effective representation of face images. This descriptor encodes images based on eight pixels that are certain distance apart from the referenced pixel. The descriptor is analyzed for two different shapes, circle and ellipse. It is also analyzed for various levels of neighborhood. Any texture descriptors that use nearest neighbors for describing a texture pattern around a pixel will fit in this model. Therefore effectiveness of the model is verified for standard LBP, LTP and LTrPs. Face recognition issues such as illumination variation, expression variation and variation with partial occlusion and pose variation are detailed in this work. Experiments are also carried out for general cases.

Experimental results demonstrate that the proposed LTDF model based on any existing local texture descriptor provides more accuracy of recognition than that of its conventional ones for all the issues discussed. This is due to its ability in determining many number of important local texture primitives that could discriminate the texture patterns present in different face images. It is found from the experiment that LTDF<sup>s</sup> excels LTDF<sup>m</sup> thereby producing better recognition accuracy with less

number of bins. Moreover it is observed that for LTDF<sup>8</sup>, elliptical shape performs better than the circular shape. Computation of patterns using eight pixels at certain distance apart from a pixel causes many patterns to fall outside the boundary of an image. This decreases the number of patterns in every bin which results in high speed.

Proposed texture descriptor can be viewed as a new approach in describing texture pattern and hence it is applicable for all the texture descriptors which use nearest neighbors of a pixel to describe a texture. In this paper the proposed method is experimented for face recognition, but this can also be suitable for other pattern recognition application such as fingerprint analysis, iris recognition etc. In this work, nearest neighborhood classifier with chi-square distance metric is used. But performance of the model can be improved by using other classifiers and distance metrics.

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