I.J. Image, Graphics and Signal Processing, **2015, 10, 37-46**
Published Online September 2015 in MECS (http://www.mecs-press.org/)
DOI: 10.5815/ijigsp.2015.10.05

Face Recognition Based on Texture Features using Local Ternary Patterns

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Abstract—Face recognition is one of the important and popular visual recognition problem due to its challenging nature and its diverse set of applications. That's why face recognition is attracted by many researchers. Methods based on Local Binary Pattern (LBP) are widely used for face recognition in the literature, and it is sensitive to noise. To address this present paper utilized the powerful local texture descriptor that is less sensitive to noise and more discriminant in uniform regions called as Local Ternary Pattern (LTP). The Uniform Local Binary Pattern (ULBP) derived on LBP treats a large set of LBP under one label called as miscellaneous. This may result some loss of information on LBP and LTP based methods. To address this two Prominent LBP (PLBP) are derived, namely PLBP-Low (L) and PLBP-High (H) on LTP. Based on this the present paper derived eight texture features on facial images. A distance function is used on proposed texture features for effective face recognition. To eliminate most of the effects of illumination changes that are present in human face an efficient preprocessing method is used that preserves the significant appearance details that are needed for face recognition. The present method is experimented on Yale, Indian and American Telephone and Telegraph Company (AT&T) Olivetti Research Laboratory (ORL) data bases and it has given state-of-the-art performance on the three popular datasets.

Index Terms—Face recognition, local binary pattern, uniform LBP, illumination, preprocessing, appearance details, and texture features.

I. INTRODUCTION

Finding significant and discriminative face recognition descriptors is one of the major challenges for the researchers in face recognition. One needs to derive face recognition methods that can deal with large variations in illumination, facial expression, partial occlusions, pose, and ageing. The two main approaches for face recognition are: appearance-based descriptors and geometric feature-based descriptors. Both these methods have their own advantages and disadvantages. Methods like linear [29, 37] and nonlinear [12] subspace approaches, texture [11], Gabor wavelets [18,34], the local structure [9], texture [11,21,37,39] and Local Binary Patterns (LBP) [2,7,47,48] based methods are also studied in the literature. As a nonparametric method, LBP summarizes local structures of images efficiently by comparing each pixel with its neighboring pixels. LBP was originally proposed for texture analysis [26], and has proved a simple yet powerful approach to describe local structures. LBP has been exploited for facial representation in different tasks, which include face detection [2,13], face recognition [6,15,20,25,27,46], facial expression analysis [8,24,32], age classification [10,19,28,40] and other related applications. A dynamic security protocol for face recognition is proposed in the literature [33] by using Random number generator encryption algorithm. A face recognition method by integrating morphological operators or random transforms with Principle Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) [4, 27] is also proposed. The system [4] proved to be robust in different lightning conditions. A simple PCA based face recognition system that recognizes the facial images captures by a normal camera [3] is also proposed. One of the disadvantages of this [3] is it requires a controlled environment, which is not possible always.

Uniform and Non Uniform LBP's are derived on LBP. Uniform LBP (ULBP) are treated as fundamental unit of LBP and the remaining large set of Non Uniform LBP (NULBP) are treated under one label in the literature[2,26,47], which may result loss of some information. The other disadvantage of LBP is a small noise may derive a huge variation in LBP code something from 0 to 255. To overcome this present paper utilized the LTP approach and to overcome the problems related to ULBP and NULBP we have used our previously derived PLBP [41] on LTP for effective face recognition.

The present paper is organized as follows. The section (II) describes the related work, section (III) presents the proposed methodology, section (IV) and (V) presents the results and discussion and conclusions.

II. Related Work

The Local Binary Pattern (LBP) was introduced by Ojala et al [26] in 1996. The LBP is a powerful tool to describe the local attributes of a texture. LBP's are computationally efficient and simple nonparametric local image texture descriptor. Local Binary Pattern (LBP) has been widely used in various computer vision applications including face recognition [1, 2, 5, 30] because of its simplicity and robustness to illumination variations.

In the LBP the grey level image is converted into binary by taking the central pixel value as a threshold and this grey level value is compared with its neighborhood values. The resulting binary valued image is treated as a local descriptor. The basic LBP was initially derived on a 3*3 neighborhood. This LBP operator can also be represented with different variation of (P, R) where P represents the number of neighboring pixels and R is the Radius. By this the basic LBP operator is represented as (8, 1). The 8-bit binary representation or 8-neighboring pixels on a 3*3 neighborhood or (8, 1) derives a LBP code that ranges from 0 to 255 [26]. The LBP operator takes the following form as given in equation (1) [26].

$$\mathrm{LBP}(8,1) = \sum_{n=0}^{7} 2^n \mathrm{S}(\mathrm{P_c} - \mathrm{P_n}) \quad (1)$$

Where 'n' runs over the 8 neighbors (0 to 7) of the central pixel C, $\mathrm{P_c}$ and $\mathrm{P_n}$ are the grey level intensities at c and n and S(u) will be 1 if u $\geq$ 0 and 0 otherwise. The LBP encoding process on a 3*3 neighborhood i.e. (8, 1) is given in Fig.1.

172	252	14	$\Rightarrow$ P_c as Threshold P_c =100	1	1	0	Binary Code: $(11001100)_2$
83	100	72		0		0	LBP Code: $(51)_{10}$
65	200	175		0	1	1	
(a)				(b)			(c)

Fig.1. Encoding of Basic LBP Operator

LBP's are invariant to monotonic grey level transformation means they are resistant to lighting or brightening effects. LBP performance is limited because it is sensitive to noise. Sometimes, the reliability of LBP decreases significantly under large illumination variations. Complex local interactions may happen whenever there is a lighting effect. This results the violation of basic LBP assumption that gray-level changes monotonically. To address this in the literature local ternary pattern [36, 37] are proposed. The other disadvantage of the basic LBP is it is sensitivity to random and quantization noise in uniform and near-uniform image regions such as the forehead and cheeks.

LTP overcomes this disadvantage and also it inherits the key advantages of LBP such as computational simplicity by splitting it into two different LBP's. The LBP is prone to noise effect, as it is basically the threshold is considered as the intensity value of the center pixel. A little variation in the grey level intensities due to noise especially in around uniform regions will change the LBP code drastically in some cases. This is illustrated by the following Fig.2 and Fig.3.

75	75	75	$\Rightarrow$ P_c as Threshold P_c =75	1	1	1	Binary Code: $(1111111)_2$
75	75	75		1		1	LBP Code: $(255)_{10}$
75	75	75		1	1	1	
(a)				(b)			(c)

Fig.2. Encoding of Basic LBP Operator without Any Noise

In Fig.2 the basic LBP operator (8, 1) is illustrated without any noise and it is resulted in a LBP code of 255. Assume a simple noise at central pixel changed its intensity value from 75 to 76. In this case the LBP is illustrated in Fig.3.

75	75	75	$\Rightarrow$ P_c as Threshold P_c =76	0	0	0	Binary Code: $(00000000)_2$
75	**76**	75		0		0	LBP Code: $(0)_{10}$
75	75	75		0	0	0	
(a)				(b)			(c)

Fig.3. LBP with Little Noise

From Fig.2 and Fig.3 it is clearly evident that a simple noise may change the LBP code from maximum to minimum. That's the reason the present paper adopted Local Ternary Pattern (LTP) instead of LBP. The LTP mechanism for Fig.2 and Fig.3 are shown in Fig.8 and Fig.9 respectively. Moreover most of the facial regions consist of uniform regions. Therefore by using LBP on them may decrease robustness.

One of the extensions on the original LBP operator is the Uniform LBP (ULBP) [38]. A LBP is treated as ULBP if the circular LBP contains 0 or 2 (maximum of 2) transitions from 0 to 1 or 1 to 0. ULBP is one of the significant concepts of LBP and treated as the fundamental unit, because it represents the primitive structural information such as corners and edges.

Ojala et al [38] observed that there are 58 ULBP's out of 256 LBP's. They provided that almost all textures contain nearly 90% of uniform neighborhoods and they treated all NULBP's to a single bin called miscellaneous. This is one of the important observations because it reduced the dimensionality especially in the methods based on histograms of LBP, from 256 to 59. One of the problems even with ULBP is even a small noise sometimes makes a ULBP into NULBP as shown in Fig.4 and Fig.5. The LTP illustration for Fig.4 and Fig.5 is given in Fig. 10 and Fig. 11 respectively.

70	160	141
138	140	152
10	0	145

(a)

P_c as Threshold P_c=140

0	1	1
0		1
0	0	1

(b)

Binary Code: $(01111000)_2$ LBP Code (ULBP): $(30)_{10}$

(c)

Fig.4. Illustration of transitions on LBP without noise

70	160	141
140	140	152
10	0	145

(a)

P_c as Threshold P_c=140

0	1	1
1		1
0	0	1

(b)

Binary Code: $(01111001)_2$ LBP Code (NULBP): $(158)_{10}$

(c)

Fig.5. Illustration of transitions on LBP with noise of Fig.4.

III. Methodology

The proposed method consists of four major steps as given below.

Step-1: Apply preprocessing methods on facial images to overcome the noise and illuminated problems.

Step-2: Derive two LBP's i.e. LBP-High (LBP-H) and LBP-Low (LBP-L) on the preprocessed LTP, with a lag limit value.

Step-3: Evaluate histograms of ULBP-L, PLBP-L and ULBP-H, PLBP-H and other variants of PLBP separately on LBP-L and LBP-H of LTP.

Step-4: Use a distance function for effective face recognition.

A. Preprocessing

The present paper addressed the effects of illumination variations and local shadowing by using series of preprocessing technique known as gamma correction and Difference of Gaussian (DoG) filtering. The advantage of DOG is it overcomes the above while preserving the essential attributes or elements of the image. Gamma is one of the most important attribute of images. Gamma defines the relationship between a pixel grey level value and its actual luminance. Without gamma, shades captured by digital camera wouldn't appear as they did to our eyes. Gamma Correction (GC) or gamma encoding or gamma compression is a nonlinear grey level transformation. The GC replaces grey level I with I^{γ} (for $\gamma > 0$) or $\log(I)$ for $\gamma = 1$ where $\gamma \in \{0,1\}$. The GC enhances the grey level range of the pixels in dark or shadowed regions. The GC compresses the dynamic range at bright regions. The GC sometimes fails in removing the influence of overall intensity gradients known as shadowing effects. To address this DOG is used on the gamma corrected image. DOG is a very effective and accurate grayscale image enhancement algorithm. In image processing applications DOG is mainly used for enhancing the edges in noisy images and to overcome the illumination related problems present in the image while it is captured. The present paper utilized DOG to overcome the illumination and local shadowing problems.

B. Local Ternary Pattern (LTP)

To overcome the noise related problems of LBP, LTP is proposed in the literature [36, 37]. LTP is a ternary or 3-valued code. In LTP the neighborhood pixel values are compared with central pixel using a lag limit value *'l'*. Based on this comparison the neighborhood values will be assigned one of the three values +1 or 0 or -1, as given in equation (2) [37].

$$LTP\ (T_i) = \begin{cases} 1 & P_i \geq (i_c + l\ ) \\ 0 & |P_i - i_c| < l \\ -1 & P_i \leq (i_c - l\ ) \end{cases} \quad (2)$$

Where P_i and i_c represents the grey level intensity values of the neighboring pixels and the central pixel respectively, l represents the lag limit value and T_i represents the one of the ternary value assigned to the neighboring pixel i. LTP encoding is illustrated in Fig.6 with $l=5$.

37	30	26
25	31	35
36	28	45

(a)

$(P_c + l, P_c - l)$ (31+5,31-5)

1	0	-1
-1		0
1	0	1

(b)

LTP Ternary Code: $(10(-1)0101(-1))_3$

(c)

Fig.6. Illustration of transitions on LTP with l=5.

The LTP with ternary representation generates a total of 0 to 3^n-1 valued codes and also the LTP generates more number of ULBP's and it leads to lot of complexity in the methods involved with histograms. To gain simplicity some of the researchers [22, 36, 37] split LTP into two different channels of LBP and named them as Positive or High LBP (LBP-H) and Negative or Low LBP (LBP-L) as shown in Fig.7 for ternary code 10(-1)0101(-1). The Fig.7 is an extension process for Fig.6. This representation of LBP-H and LBP-L overcomes the complexity and dimensionality related problems of LTP. This phenomenon of using lag limit value in LTP improves the resistance to noise.

1	0	-1
-1		0
1	0	1

Positive or High LBP (LBP-H)

1	0	0
0		0
1	0	1

Binary Code: $(10001010)_2$
LBP-H Code: $(81)_{10}$

Negative or Low LBP (LBP-L)

0	0	1
1		0
0	0	0

Binary Code: $(00100001)_2$
LBP-L Code: $(132)_{10}$

Fig.7. Splitting of LTP into LBP-H and LBP-L

By observing Fig. 8 and Fig.9 of LTP and Fig.2 and Fig.3 of LBP, it is evident that a small noise have no effect in LTP and whereas the same may result a drastic effect on LBP code.

75	75	75
75	75	75
75	75	75

$(P_c + l, P_c - l)$ (75+5,75-5)

0	0	0
0		0
0	0	0

Binary Code: $(00000000)_2$ LTP Code: $(0)_{10}$

(a) (b) (c)

Fig.8. Encoding of basic LTP operator without any noise

75	75	75
75	76	75
75	75	75

$(P_c + l, P_c - l)$ (76+5,76-5)

0	0	0
0		0
0	0	0

Binary Code: $(00000000)_2$ LTP Code: $(0)_{10}$

(a) (b) (c)

Fig.9. Encoding of basic LTP operator with noise

A small noise may not convert a ULBP into Non ULBP in LTP, whereas it is highly possible in LBP, which is evident from Fig.10 and Fig.11 and Fig.4 and Fig.5. If the small noise by chance extends on the more portion of the image, many ULBP's will be converted in to NULBP or under miscellaneous label. This drastically reduces the overall face recognition rate and also other classification problems.

70	160	141
138	140	152
10	0	145

$(P_c + l, P_c - l)$ (140+5,140-5)

-1	1	0
0		1
-1	-1	1

LTP Ternary Code: $((-1)1011(-1)(-1)0)_3$

(a) (b) (c)

Fig.10. Illustration of transitions on LTP without noise

70	160	141
141	140	152
10	0	145

$(P_c + l, P_c - l)$ (140+5,140-5)

-1	1	0
0		1
-1	-1	1

LTP Ternary Code: $((-1)1011(-1)(-1)0)_3$

(a) (b) (c)

Fig.11. Illustration of transitions on LTP with noise of Fig.10

C. Prominent LBP (PLBP)

The present paper derived our previous LBP variant called PLBP's "in press" [41] on the preprocessed LTP facial image. ULBP is treated as the fundamental unit of a texture and researchers considering this treated all NULBP's (198 out of 256) on a 3*3 neighborhood or (8, 1) as a miscellaneous label. Some researchers in the literature [16, 17, 41, 45, 49] argued that treating such a huge number of NULBP's as miscellaneous may lose some of the significant local information. They conducted experiments using all ULBP's and some of the NULBP's and treated the remaining NULBP's under one label [16, 17, 41, 45, 49]. Recently we attempted to derive significant NULBP's out of NULBP's and evaluated face recognition by integrating significant with ULBP [14]. The present paper by extending this argument used our derived PLBP's [41] on the LTP. A Prominent LBP (PLBP) is based on circular transitions on LBP. A LBP is a PLBP if it contains transitions that occur after two or more consecutive zeros immediately followed by two or more consecutive ones and vice versa. For example the following LBP codes constitutes the PLBP 14(00001110), 27(00011011), 35(00100011), 51(00110011), 177(10110001), 243(11110011) and the following are Non PLBP (NPLBP) 26(00011010), 53(00110101), 65(01000001), 148(10010100), 202(11001010), 244(11110100). The LBP code 26(00011010) does not fall in to PLBP because it consists of transitions from two or more consecutive zero's to two or more consecutive one's and vice versa is not there. The LBP code 202 (11001010) does not fall in to PLBP because it consists of transitions from two or more consecutive one's to two or more consecutive zero's and vice versa is not there. The LBP code 65(01000001) does not fall in to PLBP because it neither consists of transitions from two or more consecutive one's to two or more consecutive zero's nor vice versa is there. The PLBP contains a total of 92 patterns of LBP with 8 neighboring pixels with a radius of 1 out of which 40 are ULBP's and 58 are NULBP's. Based on ULBP and PLBP, we have derived Maximum PLBP (ULBP U PLBP) and Small PLBP (ULBP ∩ PLBP) [41]. The Maximum PLBP (MPLBP) contain a total of 110 LBP out of which 58 are ULBP's and 52 are NULBP's on (8,1) i.e. on a 3*3 neighborhood. The Small PLBP (SPLBP) contains a total of 40 ULBP's only. The SPLBP treats the remaining 18 ULBP's and 198 NULBP's as miscellaneous label. The present paper derived Prominent LBP's (PLBP) on the LTP facial images.

For efficient face recognition on the test image the histograms of the above four texture features are derived and compared with data base images using chi-square distance method as given in equation (3).

$$R(d,t) = \min(\sum_{i=1}^{n}((d_i - t_i)^2/(d_i + t_i))/2) \quad (3)$$

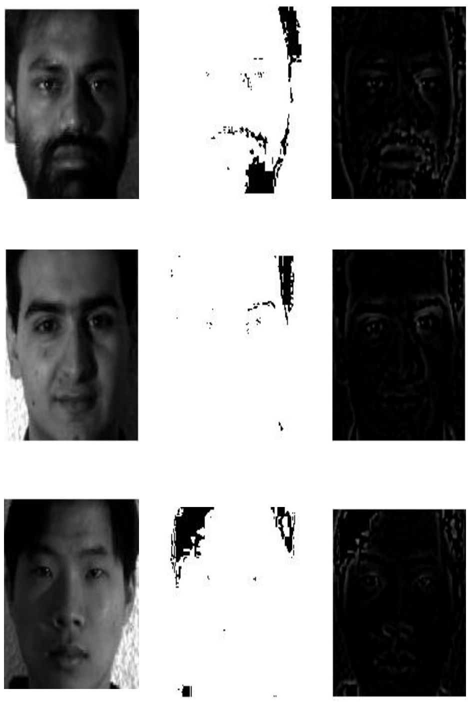
Where d, t are image features (histogram vectors) and *R(d,t)* is the histogram distance for recognition. The same process is adopted on both the Low LBP and High LBP images derived on LTP. We tested face recognition by using lag limit values i.e. 2, 3, 4, 5 and we obtained best results when lag limit is 3 and all tables are based on with a lag limit value l=3.

IV. RESULTS AND DISCUSSIOSNS

For effective face recognition, the present paper utilized the above new derivatives on LTP on three different databases as mentioned below.

The present paper considered 120 facial images out of 15 persons with 11 different facial expressions per person as training set from Yale data base [43], 472 facial images as training set from Indian database [42]. These 472 facial images correspond to 59 different individuals of both male and female, and on each individual 11 different expressions of Indian database. The present paper also considered 320 facial images as training set from AT&T ORL database [31] for face recognition.

The present paper on all the three facial databases applied the preprocessing using Gamma correction, with $'\gamma'$ value of 0.2. After this DoG is used on the gamma corrected facial images, to overcome the illumination and other realted problems. The Fig.12 shows the original facial images of yale database and its corresponding $'\gamma'$ correction and DoG images.



(a) (b) (c)

Fig.12. Preprocessed Images: (a) Original Images, (b) After Gamma Correction with γ = 0.2 (c) DoG Images on (b)

The present paper evaluated the histograms of the above eight texture features on the above three databases with different combinations of (P,R): (8,1), (8,2), (8,3), (8,4), (16,1), (16,2), (16,3) and (16,4) using different lag values *l*= 2, 3, 4 and 5 and placed the results in feature library. The table 1 and 2 shows the face recognition rate for Yale database on LBP Low and LBP High derived on LTP of facial images with different (P, R) using *l*=3. In the same way the table 3, 4 and 5, 6 represents the face recognition rates for AT&T ORL and Indian databases on LBP low and LBP high facial images derived on LTP.

Table 1. Face Recognition Rate on Yale Database on LBP Low (LBP-L) Of LTP

(P,R)	LBP-L	ULBP-L	PLBP-L	SPLBP-L	MPLBP-L
(8,1)	80.00	80.00	77.78	77.78	80.00
(8,2)	80.00	75.56	75.56	80.00	84.44
(8,3)	91.11	80.00	84.44	75.56	86.67
(8,4)	84.44	77.78	77.78	71.11	84.44
(16,1)	75.56	68.89	71.11	68.89	71.11
(16,2)	80.00	84.44	75.56	77.78	80.00
(16,3)	80.00	82.22	86.67	88.89	80.00
(16,4)	80.00	80.00	82.22	77.78	82.22
AVERAGE	81.39	78.61	78.89	77.22	81.11

Table 2. Face Recognition rate on Yale Database on LBP High (LBP-H) of LTP

(P,R)	LBP-H	ULBP-H	PLBP-H	SPLBP-H	MPLBP-H
(8,1)	73.33	68.89	73.33	73.33	68.89
(8,2)	84.44	75.56	75.56	68.89	82.22
(8,3)	82.22	73.33	75.56	68.89	77.78
(8,4)	80.00	77.78	73.33	68.89	75.56
(16,1)	77.78	71.11	68.89	68.89	68.89
(16,2)	82.22	80.00	80.00	77.78	80.00
(16,3)	77.78	80.00	77.78	80.00	80.00
(16,4)	82.22	82.22	82.22	84.44	86.67
AVERAGE	80.00	76.11	75.83	73.89	77.50

Table 3. Face Recognition rate on AT&T ORL Database on LBP Low (LBP-L) of LTP

(P,R)	LBP-L	ULBP-L	PLBP-L	SPLBP-L	MPLBP-L
(8,1)	86.67	80.00	83.33	83.33	80.00
(8,2)	90.00	80.00	83.33	90.00	80.00
(8,3)	96.67	100.0	90.00	90.00	96.67
(8,4)	96.67	100.0	86.67	86.67	93.33
(16,1)	96.67	93.33	96.67	96.67	93.33
(16,2)	93.33	93.33	96.67	96.67	93.33
(16,3)	96.67	100.0	100.0	96.67	100.0
(16,4)	100.0	96.67	93.33	90.00	100.0
AVERAGE	94.58	92.92	91.25	91.25	92.08

Table 4. Face Recognition rate on AT&T ORL Database on LBP High (LBP-H) of LTP

(P,R)	LBP-H	ULBP-H	PLBP-H	SPLBP-H	MPLBP-H
(8,1)	86.67	90.00	80.00	80.00	90.00
(8,2)	93.33	93.33	86.67	86.67	93.33
(8,3)	100.00	93.33	86.67	83.33	96.67
(8,4)	100.00	96.67	93.33	86.67	96.67
(16,1)	96.67	90.00	86.67	86.67	90.00
(16,2)	93.33	100.00	96.67	100.00	100.00
(16,3)	86.67	96.67	100.00	96.67	100.00
(16,4)	86.67	96.67	100.00	100.00	96.67
AVERAGE	92.92	94.58	91.25	90.00	95.42

Table 5. Face Recognition rate on Indian Database on LBP Low (LBP-L) of LTP

(P,R)	LBP-L	ULBP-L	PLBP-L	SPLBP-L	MPLBP-L
(8,1)	91.11	91.11	84.44	84.44	91.11
(8,2)	91.11	84.44	97.78	86.67	91.11
(8,3)	91.11	88.89	86.67	88.89	86.67
(8,4)	91.11	88.89	82.22	82.22	86.67
(16,1)	91.11	88.89	91.11	91.11	91.11
(16,2)	86.67	93.33	91.11	91.11	93.33
(16,3)	95.56	91.11	88.89	86.67	91.11
(16,4)	93.33	93.33	88.89	86.67	88.89
AVERAGE	91.39	90.00	88.89	87.22	90.00

Table 6. Face Recognition rate on Indian Database on LBP High (LBP-H) of LTP

(P,R)	LBP-H	ULBP-H	PLBP-H	SPLBP-H	MPLBP-H
(8,1)	86.67	77.78	77.78	77.78	77.78
(8,2)	91.11	86.67	88.89	86.67	88.89
(8,3)	91.11	88.89	86.67	84.44	88.89
(8,4)	91.11	84.44	77.78	80.00	82.22
(16,1)	86.67	91.11	91.11	91.11	91.11
(16,2)	88.89	84.44	91.11	88.89	91.11
(16,3)	93.33	86.67	91.11	88.89	91.11
(16,4)	91.11	91.11	88.89	84.44	88.89
AVERAGE	90.00	86.39	86.67	85.28	87.50

The present paper also derived face recognition rate for the above three databases on combining LBP-low and LBP-high. By Combining LBP-L and LBP-H (LBP-LH) of LTP there will be 116, 184, 80 and 220 patterns of ULBP-LH, PLBP-LH, SPLBP-LH and MPLBP-LH respectively. The tables 7, 8 and 9 shows face recognition rates for lag value 3 for the three considered databases on LBP-LH of LTP. From the tables 1 to 9, it is clearly evident that all four texture features derived on LBP-LH of LTP on all three considered databases shows higher face recognition rate. The reason for this is the ULBP-LH, PLBP-LH, SPLBP-LH and MPLBP-LH consist twice number of patterns than their counter parts of LBP-L and LBP-H of LTP. That is the reason for a little improvement of face recognition rates i.e. approximately by 2% and also increases complexity. The recognition rates are displayed in Fig.13, Fig.14 and Fig.15 for the above methods.

Table 7. Face Recognition rate on Yale Database on LBP-LH of LTP

(P,R)	LBP-LH	ULBP-LH	PLBP-LH	SPLBP-LH	MPLBP-LH
(8,1)	75.56	73.33	73.33	73.33	75.56
(8,2)	86.67	77.78	77.78	75.56	84.44
(8,3)	84.44	82.22	84.44	82.22	86.67
(8,4)	88.89	82.22	77.78	73.33	80
(16,1)	71.11	71.11	68.89	68.89	68.89
(16,2)	77.78	82.22	84.44	86.67	84.44
(16,3)	75.56	80.00	80.00	84.44	80.00
(16,4)	86.67	86.67	80.00	86.67	82.22
AVERAGE	80.83	79.44	78.33	78.89	80.28

Table 8. Face Recognition Rate on AT&T ORL Database on LBP-LH of LTP

(P,R)	LBP-LH	ULBP-LH	PLBP-LH	SPLBP-LH	MPLBP-LH
(8,1)	86.67	83.33	83.33	83.33	83.33
(8,2)	90.00	93.33	83.33	86.67	90.00
(8,3)	100.0	100.0	96.67	100.0	100.0
(8,4)	100.0	96.67	90.00	93.33	96.67
(16,1)	96.67	93.33	96.67	96.67	93.33
(16,2)	93.33	100.0	100.00	96.67	100.0
(16,3)	96.67	100.0	100.00	96.67	100.0
(16,4)	96.67	100.0	96.67	96.67	100.0
AVERAGE	95.00	95.83	93.33	93.75	95.42

Table 9. Face Recognition Rate on Indian Database on LBP-LH of LTP

(P,R)	LBP-LH	ULBP-LH	PLBP-LH	SPLBP-LH	MPLBP-LH
(8,1)	86.67	84.44	82.22	82.22	84.44
(8,2)	91.11	88.89	93.33	86.67	88.89
(8,3)	91.11	86.67	86.67	86.67	91.11
(8,4)	88.89	88.89	84.44	84.44	84.44
(16,1)	88.89	9111	91.11	91.11	91.11
(16,2)	88.89	88.89	91.11	88.89	91.11
(16,3)	95.56	93.33	91.11	93.33	91.11
(16,4)	95.56	88.89	88.89	86.67	93.33
AVERAGE	90.83	88.89	88.61	87.50	89.44

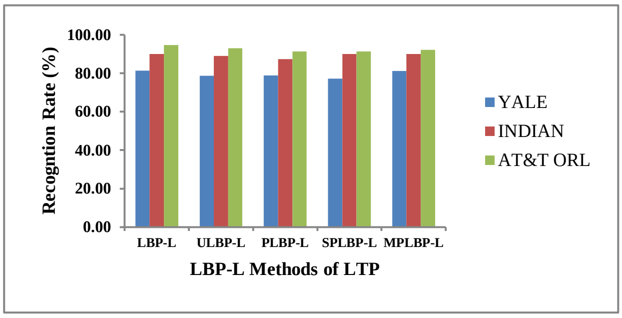


Fig.13. Recognition Rate for Different Databases on LBP-L Of LTP

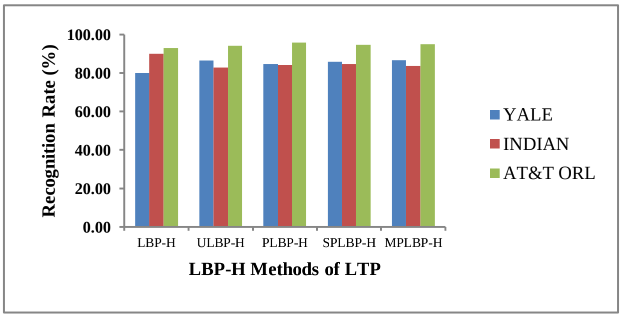


Fig.14. Recognition Rate for Different Databases on LBP-H Of LTP

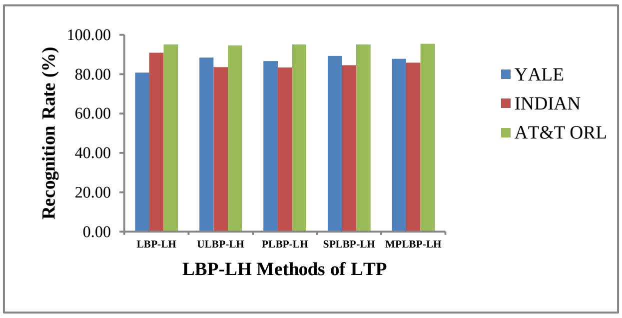


Fig.15. Recognition Rate for Different Databases on LBP-LH Of LTP

Furhter the present paper ecaluated the face reocngition on the above three data bases using four test cases with different lag values (*l*) 2,3, 4 and 5. The graphs of fig.16 to fig.18 shows the face recognition rates for four different test cases of lag values i.e. *l*= 2,3,4 and 5 on yale data base.

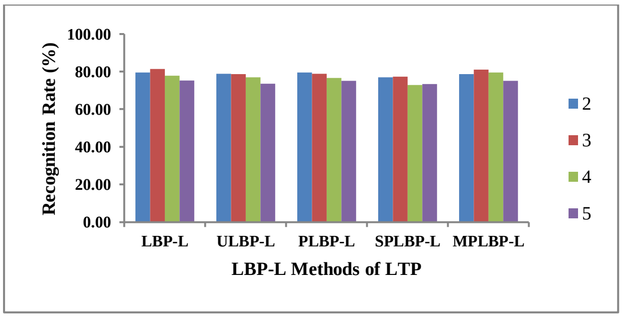


Fig.16. Recognition Rate for Different Lag Values on LBP-L of LTP for Yale Data Base

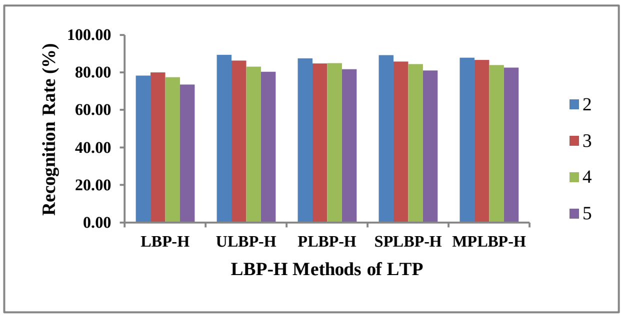


Fig.17. Recognition rate for different lag values on LBP-H of LTP for Yale Data base

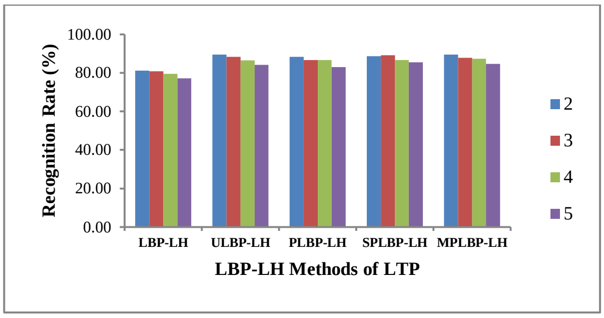


Fig.18. Recognition rate for different lag values on LBP-LH of LTP for Yale Data base

The graphs of fig.19 to fig.21 shows the face recognition rates for four different test cases of lag values i.e. *l*= 2,3,4 and 5 on AT&T ORL data base. Similarly the graphs of fig.22 to fig.24 shows the face recognition rates for four different test cases of lag values i.e. *l*= 2,3,4 and 5 on Indian data base.

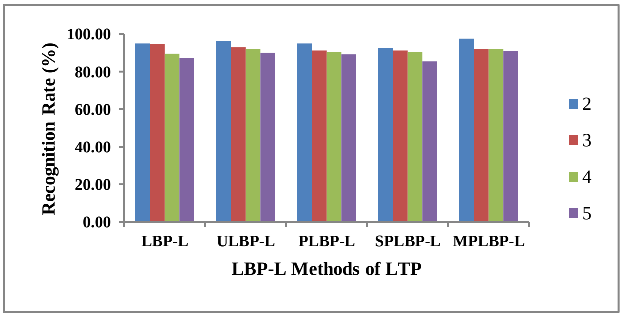


Fig.19. Recognition rate for different lag values on LBP-L of LTP for AT&T ORL Data base

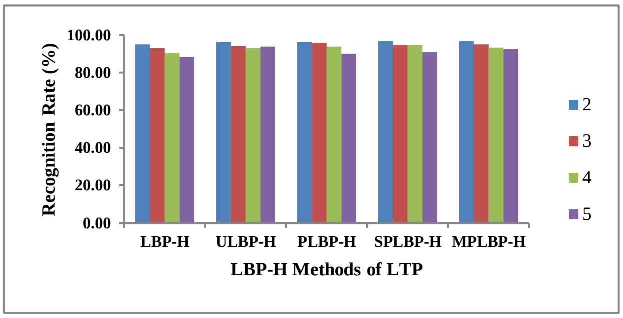


Fig.20. Recognition rate for different lag values on LBP-H of LTP for AT&T ORL Data base

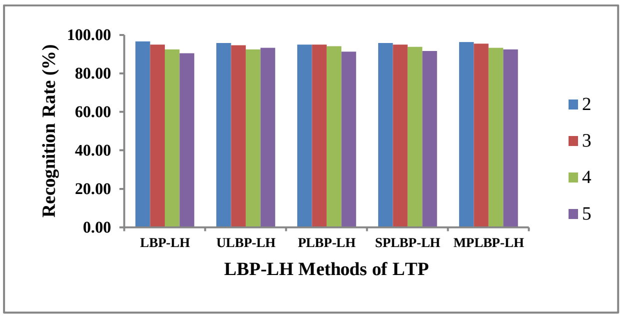


Fig.21. Recognition rate for Different lag values on LBP-LH of LTP for AT&T ORL Data base

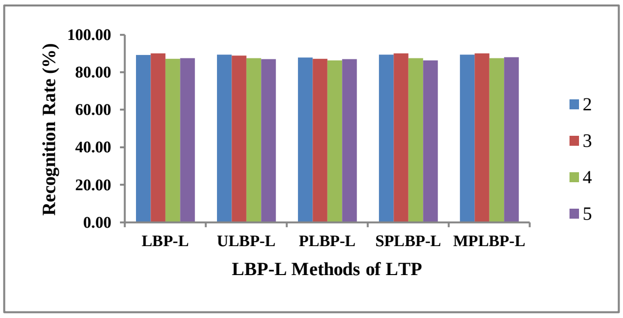


Fig.22. Recognition rate for Different lag values on LBP-L of LTP for Indian Data base

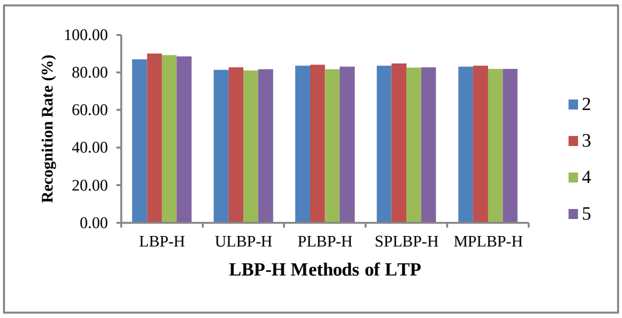


Fig.23. Recognition rate for Different lag values on LBP-H of LTP for Indian Data base

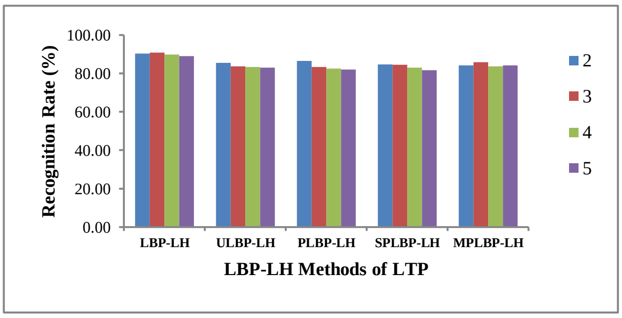


Fig.24. Recognition rate for Different lag values on LBP-LH of LTP for Indian Data base

V. CONCLUSIONS

The present paper derived eight different texture features on facial images based on LBP-L and LBP-H of LTP and another four texture features combining LBP

Low and High (LBP-LH) of LTP, with different combinations of (P, R) and with different lag values. Most of the LBP and LTP based methods suffers with illumination related problems and also with the dark regions. To overcome this i.e. to enhance the grey level range in dark regions the gamma correction is used and to overcome the illumination problems DoG is applied on the facial images in this paper. The lag values 2 and 3 showed almost similar and high face recognition rates for all texture features when compared to the lag values 4 and 5. This fact is clearly evident from the graphs of fig.15 to fig.23. When compared to LBP-L and LBP-H the recognition rate is slightly higher for LBP-LH for all derived texture features and LBP-LH increases the number of codes or units for all texture features. Most of the researchers [1,23,44] in face recognition used the following combinations of (P, R) i.e. (8, 1), (8, 2), (16,1) and (16,2). In this case the average recognition rate for derived texture features on SPLBP and ULBP are almost same where as PLBP and MPLBP shows a slightly high recognition rate. The Yale database [43] and Indian database [42] shows slightly high recognition rate in LBP-L, whereas for AT&T ORL database [31] shows a slightly high recognition rate in LBP-H.

ACKNOWLEDGEMENT

The Authors would like to express their gratitude to Sri K.V. Vishnu Raju, Chairman, Sri Vishnu Educational Society (SVES) and Management of BVRIT Hyderabad College of Engineering for Women, Hyderabad, T.S. India, for promoting the young staff members towards research activities and stressing the need of research and development for the overall development of the nation. The authors would like to thank Dr. P. Rajeshwara Reddy, Chairman, Anurag Group of Institutions (AGOI), Hyderabad for establishing Center for Advanced Computing and Research (CACR) centre under the leadership of Dr.V.Vijaya Kumar, which is providing a roof for exchanging and modeling of research ideas among various research scholars all over the nation in various disciplines like Big-Data, Image Processing and Cloud Computing. Authors would like to thank authorities of Yale database, Indian database and AT&T ORL database.

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How to cite this paper: K. Srinivasa Reddy, V. Vijaya Kumar, B. Eswara Reddy,"Face Recognition Based on Texture Features using Local Ternary Patterns", IJIGSP, vol.7, no.10, pp.37-46, 2015.DOI: 10.5815/ijigsp.2015.10.05