Extraction of Illumination Invariant Features using Fuzzy Threshold based Approach

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ABSTRACT
The field of face recognition is increasingly investigated for access control, face based search, passport processing, security, surveillance, etc. applications. Performance of face recognition systems under constrained environment is quite satisfactory, but face recognition in unconstrained environment is yet a challenging problem due to key technical challenging issues. Varying illumination is one of the key issues in real time face recognition applications. Experimental assessment of various methods developed by research community demonstrates that, yet there is a need and scope for improving methods to handle the varying illumination problem. In this paper, a novel approach, referred to as fuzzy threshold based local binary pattern is proposed for extracting illumination invariant features. Local binary pattern based method is modified by introducing a fuzzy based threshold for generating binary pattern. Effectiveness of proposed method is assessed on extended Yale B face database. Experimental results demonstrate that proposed method performs better than conventional binary pattern under complex illumination conditions.

General Terms
Face Recognition; Fuzzy Techniques; Image Processing; Pattern Recognition.

Keywords
Face Recognition, Feature Extraction, Fuzzy Threshold, Illumination, Local Binary Pattern.

1. INTRODUCTION
Facial feature based biometric recognition applications have emerged as one of the popular recognition methodologies. Though, it is a well accepted solution for facility access, security application, and time crucial application, the 2D facial recognition still remains extremely tricky under different pose and non-uniform illumination conditions. The Face Recognition Vendor Test (FRVT) 2006 [14] highlighted that non-uniform illumination is one of the bottle-neck of face recognition system. To extract discriminant and illumination invariant facial features under such problem is the key problem in face recognition system. Different methods have been proposed for feature extraction in the past, such as principal component analysis (PCA) [7][19], Linear Discriminant Analysis (LDA) [11], Independent Component Analysis (ICA) [2]. Also, various modifications of PCA [4], LDA [21], and ICA [15] have been explored by researchers to extract discriminant features. But, these methods are very sensitive to illumination variations.

It is shown by theoretical analysis that Gradient face is an illumination insensitive measure and is robust to different illumination conditions. Gradient face can discover underlying inherent structure of face images since the gradient domain explicitly considers the relationships between neighboring pixel points. Gradient face has more discriminating power than the illumination insensitive measure extracted from the pixel domain. Zhang et. al. [22] proposed a novel method to extract illumination free feature for face recognition using Gradient faces method. The proposed method is compared with other three methods named Multi-scale Retinex (MR) method, Self Quotient Image (SQI) method and Local Total Variance (LTV) method. Though, proposed method performs better than other methods, its evaluation using error rate like false acceptance rate, false rejection rate, equal error rate etc. is lacking.

Gabor-get with Elastic Bunch Graph Matching (EBGM) is an alternative facet of approaches that addresses non-linear characteristics in real-time face images such as variations in illumination, pose, and expression. Gabor wavelet transform is used to create dynamic link architecture to project the face onto an elastic grid and graph matching is used for recognition. Kela et. al. [9] proposed a novel method which combines the Retinex and color constancy approach with EBGM. The experimental results demonstrate that performance of the method is superior to the known systems. The overall accuracy has shown an increase of 3.14% as compared to the known EBGM based recognition system without using Retinex and Color Constancy method. However, performance has been improved, accurate landmark localization for facial features such as eyes, lips, nose, etc.) is very difficult.

Finding good facial features for the appearance of local facial regions is an open issue. Ideally, these features should be easy to compute and have high inter-class variance and low intra-class variance, robust to non-uniform illumination and other factors. The texture analysis community has explored a variety of different descriptors for the appearance of image patches. Local Binary Pattern (LBP) is one of them. Due to its texture discriminative property and very low computational cost, LBP [12] is becoming very popular in pattern recognition. Many variants of LBPs have been developed by research community. T. Ahonen et. al. [1] proposed an uniform LBP with enhanced histogram based facial features. The proposed LBP feature yields higher recognition rates compared to PCA, Bayesian method and EBGM in all the FERET test sets. Guo et. al. [6] compared the performance of uniform and non-uniform LBP features and found that uniform pattern may miss some of useful features compared to non-uniform. A novel generative approach for face authentication, based on a LBP description of the face is presented by Y. Rodriguez and S. Marcel [16]. They considered collection of LBP-histograms as a generic face model. A client-specific model is obtained by an adaptation technique from this generic model under a probabilistic framework. Experiments were performed on XM2VTS and BANCA. Results show that the approach performed better than state-of-the-art LBP based face recognition techniques. Though, feature vector size of histograms based approach is smaller, it loses spatial neighborhood relationship. Motivated from the illumination invariant property, discrimination power and low computational cost of LBP and advantages of fuzzy set theory [17] and fuzzy threshold in image processing and pattern recognition [3][20], we have investigated the use of fuzzy threshold in LBP based feature extraction method to overcome the limitation of crisp threshold for tackling illumination problem.

2. METHODOLOGY

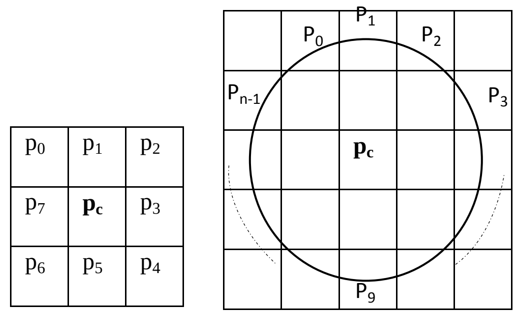
2.1 Local Binary Pattern

Local Binary Pattern method is based on local neighborhood of pixel in a small window of digital image. Let *I* be an image. $W_I(p_0, p_1,\ldots,p_{n-1}, p_c)$ be a window in image *I*, *n* is the number of neighboring pixels, *R* is the radius of the neighborhood, p_c is center pixel in the window W_I, and p_0 to p_{n-1} are neighboring pixels of p_c. Then, an LBP is defined as

$$LBP(n,R) = \sum_{j=0}^{n-1} s(p_c - p_j) \times 2^j \qquad (1)$$

where $$s(x) = \begin{cases} 1\, if\ x \ge 0 \\ 0\, if\ x < 0 \end{cases} \qquad (2)$$

Neighborhood around a center pixel may be square or circular as shown in Fig. 1. For circular neighborhood larger than 8 pixel, the pixel values p_j are computed using $\{(R*\cos(2\pi p/n), R*\sin(2\pi p/n))\}$ and interpolation.



(a) (b)

Fig 1: (a) Square Neighborhood (b) Circular Neighborhood

Fig.2(a) shows a 3*3 local window from a face image. Center pixel p_c has neighborhood size n = 8 pixels. Fig.2 (b) shows binary window generated by taking center pixel as threshold value. Pixels whose value is greater than or equal to center pixel are represented as '1' and other as '0'. Binary pattern for Fig. 2(b) is generated by scanning the window given in Fig. 2(a) clockwise, starting from top-left corner. LBP is computed by finding decimal equivalent of binary pattern. The binary pattern is 00011100 and its LBP is 28.

This simple LBP just considers sign of a neighboring pixel with respect to center pixel and do not considers the magnitude by which the neighboring pixels are larger or smaller. Hence, in [22] Zhang et. al. proposed an operator to find LBP based on magnitude of difference between center pixel and neighboring pixel. The window derived from difference of center pixel and neighboring pixel is referred to as magnitude window and the LBP generated based this window is referred to as LBP_M. Fig. 2(c) is magnitude window. Say, we take global mean of the difference windows as a threshold (Let it be '7'), then binary pattern is 11000000 and LBP_M is 192 (Fig. 2(d)).

107	107	110
110	**115**	115
112	115	115

(a) Intensity values in 3*3 Window

0	0	0
0		1
0	1	1

(b) Binary Pattern (LBP_S)

8	8	5
5		0
3	0	0

(c) Magnitude Window

1	1	0
0		0
0	0	0

(d) Binary Pattern (LBP_M)

Fig 2: Local Binary Pattern Generation for LBP_S and LBP_M scheme

8	8	5
5		0
3	0	0

(a) Magnitude Window

0.54	0.54	0.78
0.78	**0.82**	1
0.91	1	1

(b) Fuzzy Membership Window

0	0	0
0		1
1	1	1

(c) Binary Pattern (LBP_F)

Fig 3: Computation of LBP_F Binary Pattern

2.2 Fuzzy Threshold based LBP

Fuzzy threshold based LBP (LBP_F) is similar to local binary pattern. In LBP_F, the binary pattern is based on fuzzy threshold which is computed using bell shaped membership function (Fig. 4). Membership value is assigned to difference of neighboring pixel and center pixel. The mean of memberships of differences is taken as fuzzy threshold. The algorithm given in Fig. 5 for computing LBP_F was proposed in our previous work in [10]. The inputs *I*, *n*, and *R* refer to an input image, neighborhood size, and radius respectively. $Diff_j$ is the difference between *j*th neighbor p_j and center pixel p_c. *Norm* is a mean of differences, $Diff_j$ and μ_j in Step 6 is the bell shaped membership function shown in Fig.4. Fig. 3(a) to Fig. 3(c) shows how LBP_F is computed. The window in Fig. 3(a) is generated from local window given in Fig. 2(a) by finding difference of center pixel and neighboring pixels. For Fig. 3(b), neighboring values in window are fuzzy membership values for corresponding pixels in Fig. 3(a) and the center value (0.82) is the mean of these neighboring values, which is used as threshold for generating binary pattern shown in Fig. 3(c). Fuzzy binary pattern the window is 000111100 and its LBP is 120.

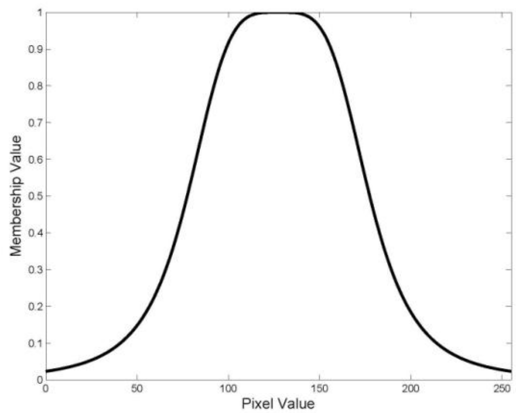


Fig 4: Bell shaped membership function

Algorithm: **Fuzzy Threshold based LBP** (LBP_F)
Input: Image (*I*), Neighborhood size (*n*) , Radius (*R*)
Steps:

1. While not end of image *I*
2. Get window $W_I(p_0, p_1, \ldots, p_{n-1}, p_c)$ from image *I*.
3. Compute $Diff_j = p_j - p_c$ where $0 < j < n$
4. $D_j = \sum_{j=0}^{n-1} Diff_j$
5. $Norm = D_j$ ^2 / n
6. $\mu_j = e^{-Diff_j^2 / Norm}$
7. $fThrd = \frac{1}{n} \sum_{j=0}^{n-1} \mu_j$ where *fThrd* is fuzzy threshold
8. $\mathrm{FtLBP}_j(n, R) = \sum \mathrm{S}(\mu_j) \times 2^j$

   where $s(\mu_j) = \begin{cases} 1 & if\ \mu_j \geq fThrd \\ 0 & if\ \mu_j < fThrd \end{cases}$
9. EndWhile

Fig. 5: Fuzzy threshold based LBP Algorithm [10]

Zhang et. al. [22] proved that LBP_M provides additional discrimination power to simple sign based LBP (LBP_S). Also they proved that, LBP_S contains more discriminative information than LBP_M. Here, our main objective is to analyze and compare global mean threshold based LBP and fuzzy threshold based and hence we have omitted LBP_S. Otherwise LBP_S alone or LBP_S with LBP_M / LBP_F can definitely gives better performance.

3. EXPERIMENTAL RESULTS

To validate the effectiveness of proposed methods, we have performed various experiments. Our objective is to test performance of fuzzy based approach among different lighting conditions and to analyze its performance on different enrolled datasets having varying lighting condition. For this purpose extended Yale B face database [8] is selected for experimentation, which contains 38 faces of different persons each with 64 different lighting conditions. Table-1 gives details of lighting condition distribution among different subsets. Lighting condition complexity increases as we move from subset-1 to subset-5. Three images of each subject are used for creating feature template during enrollment phase. Table-2 provides information of images used during enrollment phase of face recognition process. In first, second and third experiment, three images per subject was selected from subset-1, subset-3, and subset-5 respectively. In fourth experiment, out of three images to be used for enrollment, one image per subject is selected from each of the subsets (subset-1, subset-3, and subset-5). This variation in images for enrollment phase is to study and analyze effect of lighting on performance due to enrolled datasets having varying illumination.

Imposter face image of 38 persons each with 5 images are selected from CMU PIE face database [18]. Performance of the methods is compared using parameters like Recognition Rate (RR), False Acceptance Rate (FAR), and False Rejection Rate (FRR), and Equal Error Rate (EER) [7]. Two different neighborhood sizes of local window are considered. The performance of the methods is evaluated under different lighting conditions and different neighborhood sizes.

In Table-3 and Table-4, Exp. # refers to the experiment number and LBP scheme refers to different variations of LBP (The variation is either due to neighborhood size or threshold type). Bold face content in tables shows better performance. Rank one recognition rate of four experiments on five subsets of extended Yale B database is given in Table-3. In first experiment, where enrolled images belong to subset-1, performance of LBP_M is better than LBP_F for first three subsets but its performance is poor than LBP_F for other two subset. Performance for experiment #2 is similar to first experiment except for subset three, where LBP_F is better. The Rank one RR for experiment #3 is poor compared to first two experiments because enrolled images are from subset-5, which has complex lighting conditions. Overall performance of LBP_F in experiment #4 is better compared to LBP_M. Also performance of experiment #4 is better than first three experiments, due to enrollment dataset, which has varying lighting conditions from three different subsets (Table-2).

EER plays important role in deciding trade-off between performance requirements for some specific application. It the error rate at which FAR is equal to FRR. Table-4 gives EER at RR of four experiments.

Table 1. Lighting condition distribution among subsets of extended Yale B database (*IPS: Images Per Subject)

Subsets	*IPS	Lighting Source Direction	No. of images
Subset-1	14	0° to 12°	529
Subset-2	10	13° to 25°	380
Subset-3	12	26° to 50°	449
Subset-4	10	51° to 77°	380
Subset-5	18	Above 77°	669

Table 2. Images used per subject during enrollment phase of different experiments

Exp. #	Enrollment Images used from Subset(s)
1	Subset-1 (#3)
2	Subset-3 (#3)
3	Subset-5 (#3)
4	Subset-1 (#1) Subset-3 (#1) Subset-5 (#1)

Table 3. Rank one recognition rate of four experiments on extended Yale B face database

Exp. #	LBP Scheme	Rank One Recognition Rate				
		Subset-1	**Subset-2**	**Subset-3**	**Subset-4**	**Subset-5**
1.	LBP_M8	**93.25301**	**98.42105**	**83.51893**	54.21053	13.90135
	LBP_F8	90.12048	89.73684	79.95546	**57.63158**	**37.81764**
	LBP_M16	**92.04819**	**95.0000**	**82.18263**	39.21053	10.76233
	LBP_F16	88.43373	88.42105	75.72383	**41.57895**	**23.76682**
2.	LBP_M8	**78.44991**	**72.63158**	61.79104	38.15789	10.76233
	LBP_F8	74.85822	69.73684	**74.02985**	**56.31579**	**35.87444**
	LBP_M16	**76.37051**	**70.52632**	**67.16418**	40.52632	12.70553
	LBP_F16	59.16824	48.42105	61.79104	**57.89474**	**37.07025**
3.	LBP_M8	26.8431	**30.52632**	30.73497	45.26316	14.05405
	LBP_F8	**27.78828**	21.31579	**44.32071**	**57.10526**	**56.57658**
	LBP_M16	20.79395	25.26316	29.39866	46.57895	14.59459
	LBP_F16	**35.72779**	**34.21053**	**59.6882**	**68.94737**	**57.83784**
4.	LBP_M8	93.48269	**99.21053**	76.88564	50.78947	16.64025
	LBP_F8	**97.35234**	98.42105	**86.86131**	**69.47368**	**67.35341**
	LBP_M16	93.68635	**100.0000**	80.04866	49.21053	17.7496
	LBP_F16	**96.74134**	98.42105	**87.10462**	**72.36842**	**66.24406**

Table-4: Recognition Rate at Equal Error Rate for four experiments on subsets of extended Yale B face database

Exp. #	LBP Schemes	Subset-1		Subset-2		Subset-3		Subset-4		Subset-5	
		EER	RR	EER	RR	EER	RR	EER	RR	EER	RR
1.	LBP_M8	11.37	88.67	**12.88**	**87.11**	25.12	74.83	**28.14**	**71.57**	**46.57**	**53.51**
	LBP_F8	**10.78**	**89.39**	15.36	84.74	**23.02**	**76.87**	28.49	71.57	46.37	53.81
	LBP_M16	23.57	76.62	**18.37**	81.84	33.15	67.26	37.85	62.11	42.78	57.25
	LBP_F16	**20.36**	**79.27**	18.74	80.78	37.01	62.58	40.99	58.95	45.99	53.81
2.	LBP_M8	**17.82**	**82.42**	24.08	75.78	**31.65**	**68.05**	46.27	53.68	47.18	52.91
	LBP_F8	20.48	79.21	25.26	74.73	30.72	69.25	44.47	55.26	45.34	54.56
	LBP_M16	27.64	72.21	**23.75**	**76.05**	33.23	66.86	**40.56**	**59.47**	43.47	56.35
	LBP_F16	32.32	68.05	32.38	67.63	33.56	65.97	40.61	59.22	**42.85**	**56.95**
3.	LBP_M8	34.95	65.41	38.98	61.05	48.19	51.89	50.04	50.00	55.37	44.68
	LBP_F8	41.89	58.22	41.57	58.42	46.30	53.67	49.97	50.00	56.02	43.96
	LBP_M16	33.87	66.35	35.01	65.26	35.29	65.03	**46.68**	**53.42**	48.07	51.89
	LBP_F16	**33.65**	**66.54**	**32.31**	**68.15**	**31.52**	**68.82**	47.28	52.63	**47.89**	**52.25**
4.	LBP_M8	10.19	90.02	9.73	90.26	35.80	64.23	49.27	50.78	48.74	51.03
	LBP_F8	**8.69**	**91.24**	**7.55**	**92.36**	31.37	68.61	48.69	51.35	48.98	51.03
	LBP_M16	18.53	81.67	11.34	88.68	**30.08**	**70.31**	40.65	59.47	43.73	56.26
	LBP_F16	18.32	81.67	13.25	86.84	32.42	68.36	**40.64**	**59.21**	**42.52**	**57.37**

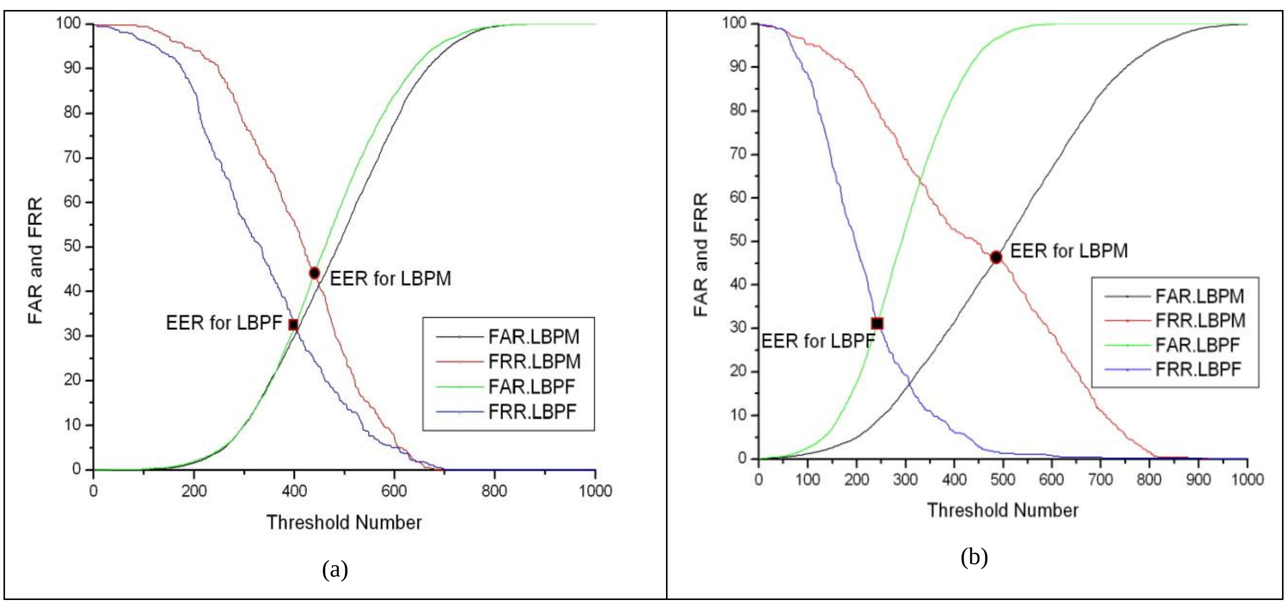
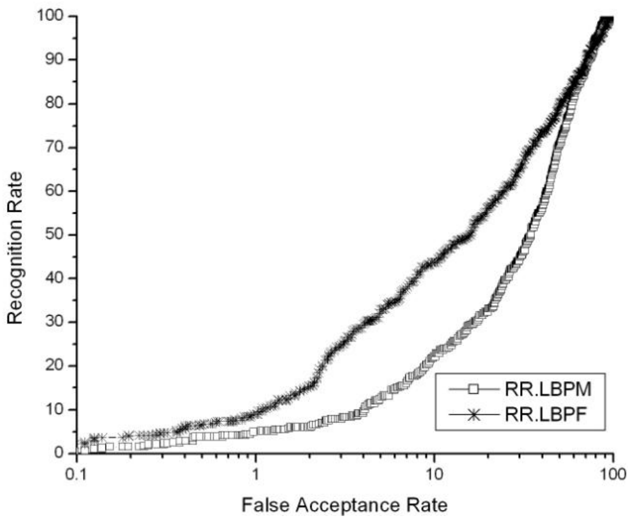
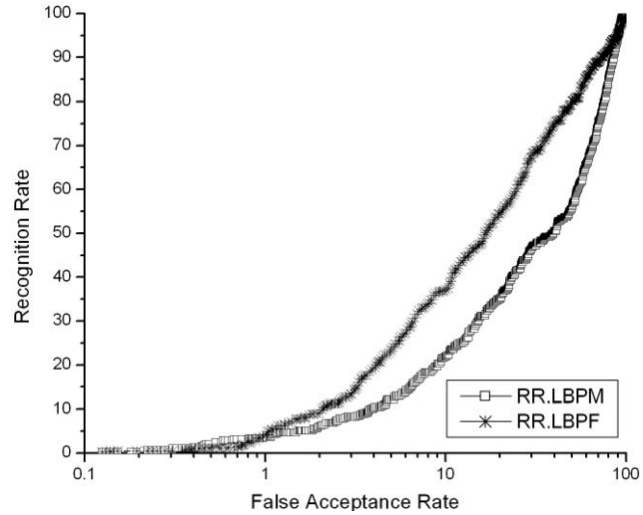


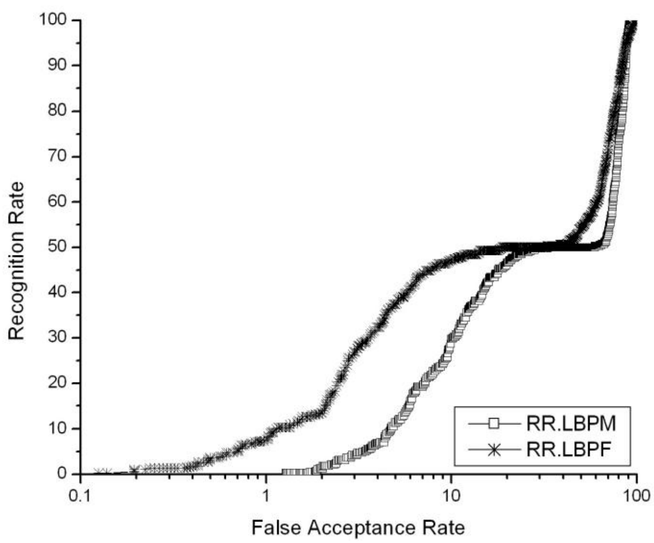
Fig. 6. ROC curve showing performance of LBP_M and LBP_F schemes with neighborhood size 16 on extended Yale B face database. X-axis represents threshold number and Y-axis represents FAR and FRR.



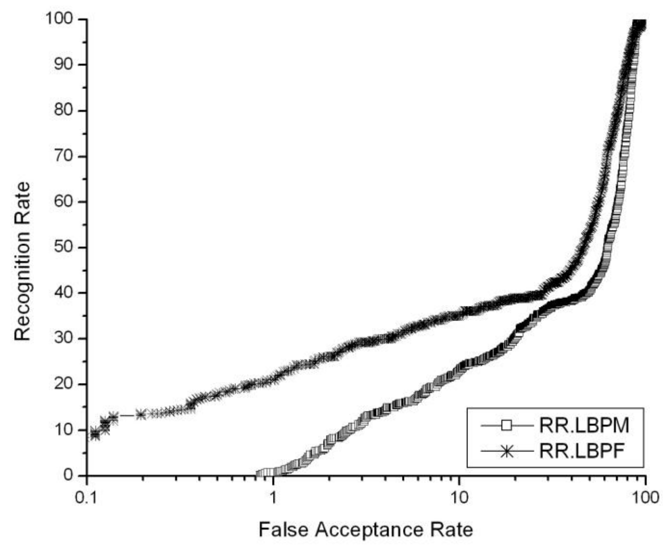
(a) Subset-2



(b) Subset-3



(c) Subset-4



(d) Subset-5

Fig. 7 ROC curves showing performance of LBP_M and LBP_F schemes on four subsets of extended Yale B face database with neighborhood size 16. X-axis represents false acceptance rate and Y-axis represents recognition rate.

Overall performance of first three experiments is poor compared to experiment #4. For experiments #3 and #4, LBP_F gives better RR at given EER except two cases. The lowest EER achieved is 7.55% at RR of 92.36% for LBP_F (exp #4, Table-4). Crossing point of FAR and FRR represents EER.

ROC curve is a very important tool to analyze the performance of any biometric recognition applications. ROC can be plotted for FAR versus RR with FAR on X-axis and RR on Y-axis. Recognition performance of LBP schemes is shown in Fig 6(a) and (b). The round circle/small square near cross point of curves represents EER. Fig. 6(a) and (b), both empirically proves that LBP_F is superior to LBP_M. It can be observed that LBP_F performs better compared to LBP_M in terms of EER. Fig. 7 also presents an ROC curve with FAR on X-axis and RR on Y-axis. It is quite evident from the figure that, performance of LBP_F is almost better than LBP_M on all the four subsets.

4. CONCLUSIONS

To assess the effectiveness of proposed fuzzy based method (LBP_F), four different experiments have been performed on extended Yale B face database. Performance of LBP_F is compared with LBP_M using performance matrices such as RR, FAR, FRR, and EER.

Enrolled dataset has great effect on the performance of the method. Table-3 empirically proves that, enrolled dataset with varying illumination which covers more illumination condition like experiment #4 would give better performance. Also, careful observation reveals that LBP_F performs better for complex lighting conditions. Rank one recognition rate above 65% for LBP_F (Table-3) shows importance of fuzzy based approach compared to LBP_M. Again, ROCs in Fig. 6 and Fig. 7 proves the effectiveness of LBP_F compared to LBP_M.

Work in this paper can be extended in following dimensions:

In future, our goal is to combine LBP_M and LBP_F with LBP_S binary pattern to improve performance of face recognition under varying lighting conditions. Also, a hybrid approach which combines LBP with some Retinex based method may improve performance.

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