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A Comparative Study of Factors Affecting Performance of Local Binary Pattern (LBP) Variant along with Distance Metrics for Face Recognition

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Abstract-Face recognition based on local feature extraction approaches has gained a lot of attention in recent times. Among these approaches, local binary pattern (LBP) is one of the most useful face descriptor. LBP generates threshold binary codes for each image pixel which finally contribute to the feature set. The original LBP stores these binary codes in 256 bins corresponding to each gray scale value. It presents invariance towards monotonic gray scale illumination and computationally simpler approach. However, still the challenge remains in the selection of appropriate set of LBP features along with the precise classifier for recognition task. In this study, our focus is on some major factors which relates to the efficiency of the LBP based face recognition methods: 1) performance analysis of the original LBP (with 256 features) in comparison to uniform LBP (containing 59 features) 2) Include/Exclude non-uniform patterns from final LBP feature set 3) division of face images into optimal sized patches 4) selection of appropriate distance metric. After thorough evaluation of above factors, we have located an effective combination of the LBP feature set and the similarity measure for different kinds of variations present in the face images. The extensive experiments are carried out on three standard face databases namely FERET, ORL and YALE.

Index Terms-*Face Recognition, local feature extraction, Uniform LBP, Region division LBP, Distance Metric,Euclidean Distance, Chi-Square Distance, Histogram Intersection.*

1. INTRODUCTION

Face recognition achieved much interest from researchers in security applications, criminal identification and commercial application because of its non intrusive nature as compared to other biometric techniques like iris scanning, fingerprint detection etc. The techniques and algorithms which were earlier used for texture analysis contributed their effort for recognition also. But texture distributors tend to average over the image area, while face recognition retains the information about spatial relations [1]. So the holistic techniques which were earlier used for texture analysis were updated with their local variants for face recognition problems to justify this fact[2,3,4,5].

As a texture analyzer, LBP already described statistical and structural information quite well and due its low computational complexity and simplicity of expression gained much interest from researchers in face recognition task[6]. In spite of having number of algorithms available for face recognition, the availability of a robust approach invariant to commonly occurring variations like illumination, pose and expression was found a rarity [7,8], but LBP variants gave efficient results in expression recognition [9, 10], gender classification [11], Image Preprocessing and face authentication [12, 13] and many more.

In this work, we illuminate major factors concerning LBP operator which affects its performance towards face recognition. A brief insight about those factors is introduced here:

1) The comparative behavior of LBP feature vector with 256 bins and its variant uniform LBP with 59 bins provided for facial images (Fig. 4) and their performance analysis has been done to justify the results. The uniform LBP histogram is genuinely more stable and dense in case of facial images and their accuracy is significantly higher than the original LBP.

2) Local binary patterns observed in an image can be divided into two categories: uniform and non-uniform patterns. Section 4 presents the detailed analysis of patterns available in an image and their effect in the process of recognition. The histogram and the image concerning uniform and non-uniform image pixel presence have shown the stability of uniform patterns and sensitivity to noise of non-uniform patterns.

3) Holistic approach seems insignificant in case of face recognition due to the presence of spatial relations among pixels in the facial image [1,14]. Ahonen et al. presented the idea of preprocessing the image regions before calculating the final feature set for comparison. This preprocessing includes division of image in regions to generate histogram while the final concatenated histogram prepared from all individual histograms will be taken as the final feature set. The comparative behavior of this technique has been presented in the experimental reviews in section 5. The only challenge involved in this technique is the extent of region division to be observed for efficient results.

4) Distance metrics plays an important role in face recognition as the feature vector generated is insignificant if the concerned

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distance metric is inappropriate to distinguish the images. We extensively evaluate the effect of three distance metrics (Euclidean Distance, Chi-Square Distance and Histogram Intersection) on LBP operator feature vectors.

The insight into all these factors is provided as follows: section 2 covers the original LBP operator and its successor uniform patterns and region based LBP approach with different feature sizes. Section 3 provides insight into distance metrics compared in the experiment. Section 4 states the detailed insight into major issues surfaced. Section 5 gives detailed experiment work done and results obtained. Finally conclusion and future work has been presented.

2. LBP OPERATOR DESCRIPTION

The LBP operator proposed by Ojala et al. proved highly discriminative operator for texture analysis [6]. The operator generates a binary code through the subtraction of each image pixel with its neighboring pixels that provides the information regarding micro patterns available in the image. The occurrence histogram of all these patterns results in establishing difference among facial images.

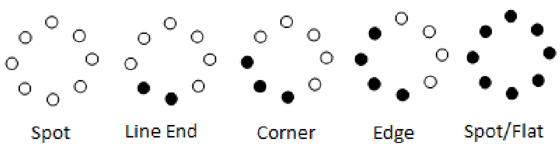


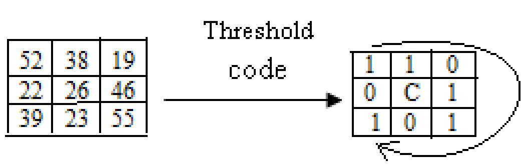
Fig 1: Micro Patterns available in the facial images

The $LBP_n^r(x_c, y_c)$ operator that works in 3×3 neighborhood of an image pixel can be defined as:

$$LBP_n^r(x_c, y_c) = \sum_{n=0}^{7} sig(z_n - c).2^n \quad (1)$$

where z_n is the neighboring pixel to the center pixel c.

$$sig(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases} \quad (2)$$



$$LBP\ code(c) = 1\times2^0 + 1\times2^1 + 0\times2^2 + 1\times2^3 + 1\times2^4 + 0\times2^5 + 1\times2^6 + 0\times2^7 = 91$$

Fig 2: 3×3 matrix representing binary code generated by LBP operator

where n is the size of neighborhood and r is the radius of the neighboring pixels from center pixel. The gray scale values of out of boundary pixels are calculated using bilinear interpolation. The gray scale value based on 3×3 neighborhood ranges between 0-256 resulting in 256 bins in the occurrence histogram of LBP operator.

The circularly symmetric neighborhood property of $LBP_n^r(x_c, y_c)$ was used in the next extensions i.e. rotation invariant and Uniform pattern LBP operator. This property of $LBP_n^r(x_c, y_c)$ make it beneficial than the original LBP [15].

2.1 Uniform Local Binary Patterns

The micro patterns available in the facial images are divided into two categories: uniform and non-uniform. uniform patterns are powerful because all these patterns accounts into the maximum two transitions of '0' and '1' bit string in it.

$$LBP_{n,r}^{u2} = \begin{cases} \sum_{n=0}^{7} sig(z_n - c)., & if\ U(LBP_{n,r}) \leq 2 \\ n+1, & otherwise \end{cases} \quad (3)$$

where

(4)

The Uniform LBP operator is represented as $LBP_{n,r}^{u2}$ where $u2$ stands for uniform patterns. There are 58 uniform patterns in 256 LBP codes and rest of the 198 has been named as non-uniform patterns.

2.2. Region Division based LBP operator

Ahonen et al. proposed a new approach for face recognition with region division based LBP operator [16]. During this technique, an image is divided into uniform non overlapping regions and Final histogram in this technique has been generated by concatenating the individual feature set into the final set.

The region divisions and corresponding concatenated histogram is represented by:

R0,R1,R2,…,Rn-1 and

$$H_{i,j} = \sum_{x,y} I\{f_l(x,y) = i\}\, I\{(x,y) \in R_j\}$$
$$i = 0,\ldots,n-1,\ j = 0,\ldots,m-1 \quad (5)$$

$$U(LBP_{n,r}) = |sig(z_{n-1} - c) - sig(z_n - c)| + \sum_{n=0}^{7} |sig(z_n - c) - sig(z_{n-1} - c)|$$

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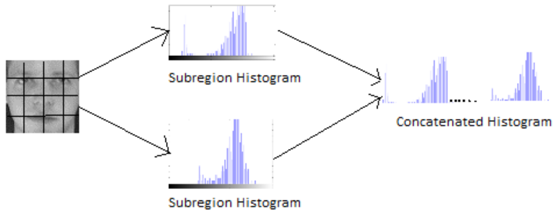

Fig 3: Region division in facial image, their respective histogram and concatenated histogram

This histogram labels presents information about the patterns on a pixel level, labels are summarized over a small region to produce information on a regional level and the regional histograms are concatenated to build a global description of the face [16]. This technique increases the size of feature set based on the extent of divisions e.g. in case of 64×64 image size if 4 divisions are made of 32×32 image size each. For original LBP the feature set will be 4×256=1024 and in case of uniform LBP it will be 4×59=236. Similarly, the size increases abruptly with 16 divisions, its 16×256=4096 and 16×59=944 and so on. So the extent of divisions brings a real issue of concern to the researchers to bring an optimal sized feature set as well as efficiency of result.

3. DISTANCE METRICS

For face recognition applications, distance metrics are applied more often than any trained classifiers, because of the limited number of availability of images [17]. The three distance measures Euclidean Distance, Chi-Square Distance and Histogram Intersection are the frequently used measures in image analysis and report effective results.

Euclidean Distance measures the summation of difference among the paired values of the feature set. After taking the square root of the summation the closest distance measure is taken as the final result for that particular image [18].

$$ED_{(x,y)} = \sqrt{\sum_{i,j} (x_{i,j} - y_{i,j})^2} \quad (6)$$

Chi-Square Distance metric [16] is a non parametric test to measure the goodness of fit for data specific to a class. The minimum distance found between two feature set gives the maximum similarity measure between them.

$$\chi^2_{(x,y)} = \sum_{i,j} \frac{(x_{i,j} - y_{i,j})^2}{x_{i,j} + y_{i,j}} \quad (7)$$

In presence of dominant patterns at some specified parts of face image like eyes, nose, mouth etc. the higher weights can be given to the specified partition for more effective results.

Histogram Intersection was first provided by Swain et al. [21] for object recognition. Further it has been used for image classification [19]. Though simple, this method is very useful in similarity measure where a large database is involved and quick replies are required. The Histogram Intersection is represented as:

$$HI_{(x,y)} = \sum_{i,j} \frac{\min(x_i, y_j)}{x_i + y_j} \quad (8)$$

The x, y parameters used in all the three distance metric equations give the representation of an image histogram.

The effects of all the three distance metrics are collectively observed on all the implemented techniques and documented their results on each of the methodology.

4. MAJOR FACTORS DISCUSSED

In this paper, we have addressed certain issues those will limit the performance of LBP operator. These issues have been worked out on facial images and their properties. If the below mentioned issues have been taken care of, the statistical and spatial information retrieved from the LBP feature set can be effectively used for face recognition.

1. The LBP operator histogram presents a highly discriminative feature of differentiating facial images on the basis of occurrence of various micro patterns in the image. As stated earlier, LBP operator generates a threshold binary code for image pixel that represents the micro patterns available in the image. The gray scale values generated through this binary code has been distributed in the histogram with 256 bins in original LBP technique. The histograms shown in Fig. 4.b for various facial images clearly show the non-uniformity of the availability of the micro patterns across the whole image. Ojala et al. verified that more the number of bins in the histogram more will be the chances of getting small number of values in individual bin, resulting in sparse and unstable histogram leading to less discrimination for micro patterns [20]. Ojala et al. noticed that almost 90.6% of all the patterns in facial images were uniform, so they extended the LBP technique to consider only 58 uniform patterns to draw the histogram and rest of the non-uniform patterns to be considered in 59^{th} bin.

The LBP histogram shown below for four different facial images have shown sparse histograms in case of LBP and dense one in case of uniform patterns.

(a)

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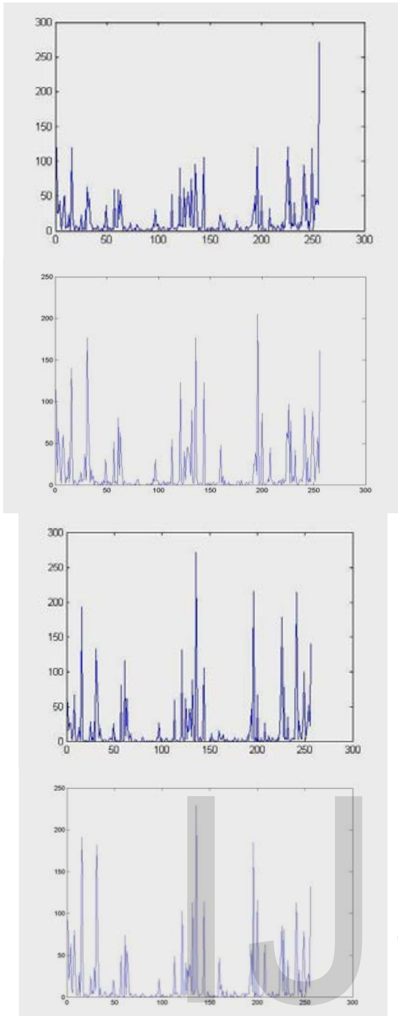
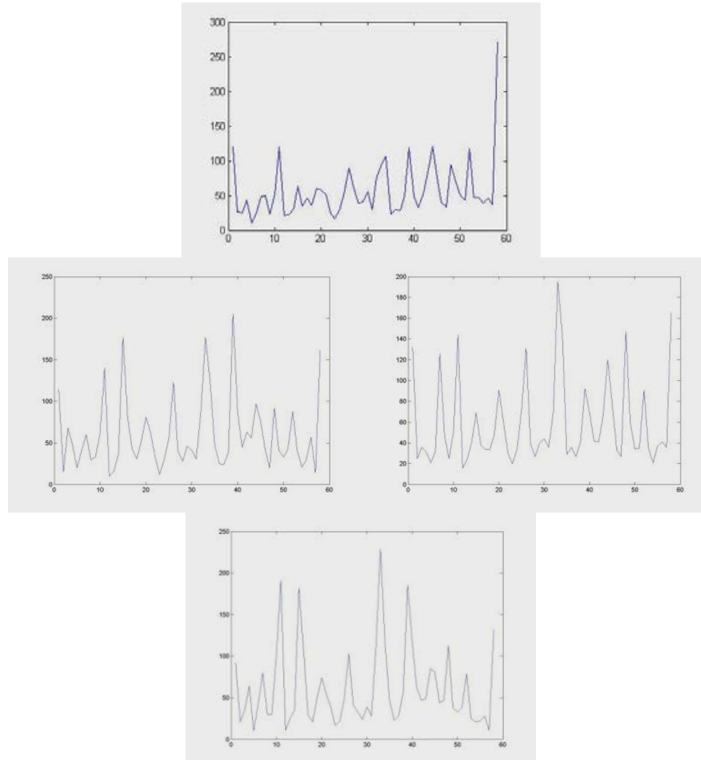


(b)



(c)

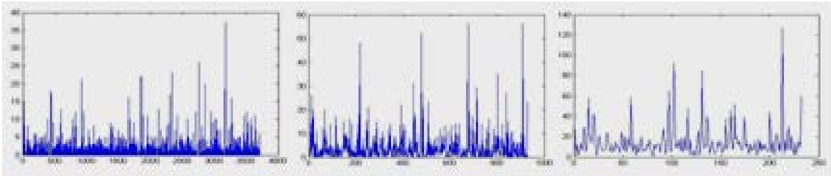
Fig 4: (a) Facial Images (b) corresponding LBP_{256} histogram (c) Uniform LBP Histogram

The experiments performed in section 5 have justified the results of LBP original operator and uniform patterns on face recognition.

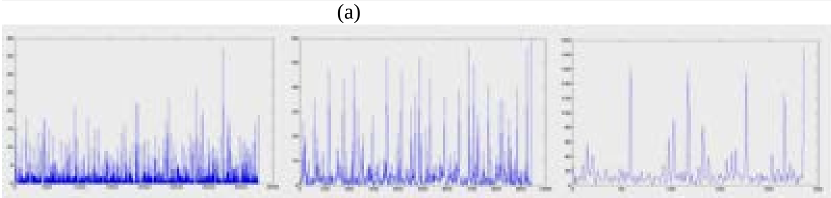
2. As uniform patterns are kept in 58 bins, the distribution of non-uniform patterns was made in rest of the 198 bins which has been collectively taken in a single bin for final feature vector used. The presence of large number of patterns in a single bin makes the corresponding histogram value to make an abrupt rise that leads to variation and sensitivity to noise. It has been observed that most of the non-uniform pattern values contribute to noise and unessential patterns available in the image. Fig. 5 shows original image, image with uniform pattern gray scale pixels and image with non-uniform pattern image pixel.

Fig 5: (a) Original Image (b) Uniform Patterns in the image (c) Non-Uniform Patterns in the Image

The Fig. 6 shows the histograms of original image presented in Fig. 5.a without including non-uniform patterns (Fig. 6.a) and including non-uniform patterns (Fig. 6.b) with various region divisions. The presence of non-uniform patterns shows the abrupt variations in the values (Fig. 6.b).



(a)

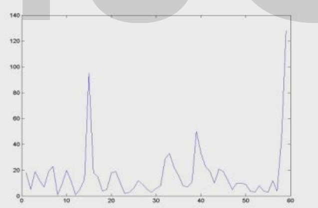


(b)

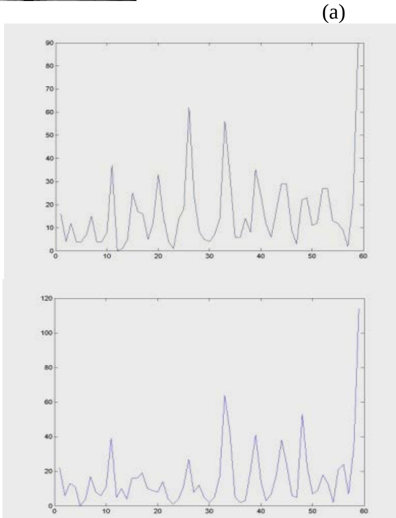
Fig 6: Facial image histograms of 8,16,32 patch sizes (a) without including Non-uniform patterns (b) with non-uniform patterns

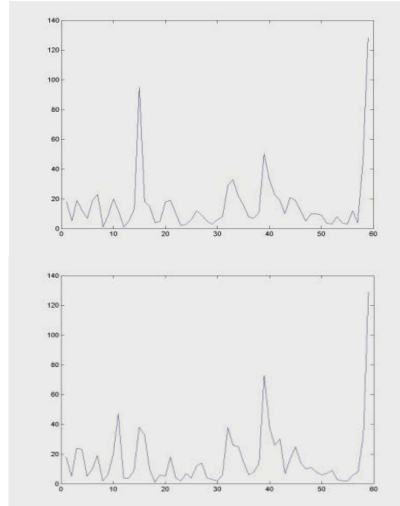
During experiments, it has been found that presence of non-uniform patterns does not make any difference in result when one to one image comparison has been done and during special variation observation, many times the results get decreased with the presence of non-uniform patterns as the presence of all the non-uniform patterns in a single bin makes the histogram unstable.

3. Ahonen [16] described that the texture descriptors used for face recognition applications have been motivated by the local approach towards feature selection. Holistic techniques are the one in which single feature vector has been used for an image description while local approach divides the image into regions and individual region feature vectors are then concatenated to draw the final feature vector so that to preserve the spatial relations among the regional patterns available in the image. Now facial images observe the collection of micro patterns non-uniformly distributed across the image. The histograms have been shown below to clearly present the distribution of patterns across the image.



(a) (b)





(c)

Fig 7: (a) Original Facial Image (b) Full Image Histogram (c)Histograms of divisions showing spatial relations.

Ahonen et al. states that the local methods are more robust against the variations in the pose and illumination than holistic methods [1]. Also it's important to retain the spatial relations in case of facial images. In Fig. 7, the variational images of a person shows much difference when holistic approach has been maintained while the histograms tend to be more stable with region divisions in case of local approach.

4. Two types of classifiers are mainly taken into consideration: Distance Metrics and training classifiers. Both are used for measuring the similarity among the images. Trainable classifiers require large number of training samples which is usually unavailable in case of face recognition so only few trainable combinations have been used for these applications [17]. Three major distance metrics explored in our work are: Euclidean Distance that calculates difference between corresponding values of two images to check similarity factor among them. Chi-Square distance is a non parametric test used to compare the feature vectors of different images using normalized measure. Histogram Intersection firstly used by [21] worked for colored histograms. The experiments performed in section VI covers the effectiveness of these three distance metrics on feature vector descriptor for face recognition.

5. EXPERIMENTAL RESULTS

In this section, we evaluated the factors limiting the performance of LBP operator along with the classifier approach by several experiments on different databases. Under the same experimental conditions, we have compared the performance for detecting rotation and expression variations for ORL, YALE and FERET databases respectively. In this study we apply Euclidean distance, Chi-Square distance and Histogram Intersection on various LBP operator approaches to check the efficient combination among them.

5.1. Operator Description

In all the experiments the neighborhood setting has been taken as (8,1) and the region division has been made in a uniform non overlapping manner. In LBP approaches with feature vector size 256 and 59/58 for image size 64×64, the region divisions have been made as 32×32, 16×16 and 8×8. While in case of image size 128×128 the

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divisions made are 64×64, 32×32 and 16×16. During experiments it has been found that face recognition approach is sensitive to the region division.
The methods description has been taken in experiments as: LBP, ULBP59 and ULBP58 in case of holistic LBP approach for original LBP operator, uniform pattern operator with 59 bins and uniform pattern operator for 58 bins respectively.
During Region divisions, original LBP is written in patch sizes (32×32), (16×16) and (8×8) while uniform patterns are mentioned as u59(32×32),u59(16×16),u59(8×8) and u58(32×32),u58(16×16),u58(8×8) for uniform patterns with 59 and 58 bins respectively.
Similarly distance Metrics have been mentioned as ED, CS, HI for Euclidean Distance, Chi-Square Distance and Histogram Intersection Respectively.

5.2 Experiments on ORL database

ORL database contains 40 subjects having 10 images each with large within class lighting, pose and appearance due too presence/absence of glasses/facial hair and different times of capture[23] experimental images have been taken in 64×64 size and work has been done in two phases, one with equal distribution of images in training and testing set and second with near frontal images in training set and pose variation images in test set to check the efficiency of the method to changes in pose.

Fig 8: ORL Database Images

For the first Experiment, Table 1 and 2 shows the Holistic and Region division based LBP approaches respectively. As earlier discussed the holistic approach has shown less efficient results as compared to when the images have been divided into regions. But in case of region division, the size of image divisions is the main concern. Very small region divisions do not present efficient result. In case of ORL database the best results have been obtained for uniform pattern based LBP operator worked on 16×16 divisions. As far as distance metric is concerned, Chi-Square has performed better than Euclidean distance and Histogram Intersection.

TABLE 1
ORL RESULTS WITH SINGLE FEATURE VECTOR FOR LBP, $ULBP_{59}$, $ULBP_5$ WITH THREE DISTANCE METRICS

Method Name	ED	CS	HI
LBP	74.5	**78.5**	23
$ULBP_{59}$	68	77.5	72.5
$ULBP_{58}$	74.5	77.5	71.5

TABLE 2
REGION DIVISION BASED LBP APPROACHES COMPARED FOR ORL DATASET ALONG WITH DISTANCE METRICS (ED, CS, HI)

Method Name	ED	CS	HI
$_{u59}$ (32×32)	83	90	88.5
$_{u59}$ (16×16)	91	**97**	88.5
$_{u59}$ (8×8)	92.5	94.5	91.5
$_{u58}$ (32×32)	83	90.5	88.5
$_{u58}$ (16×16)	92	96.5	88
$_{u58}$ (8×8)	92	95	91.5
(32×32)	83	90.5	53.5
(16×16)	91.5	96	71
(8×8)	93	94	92

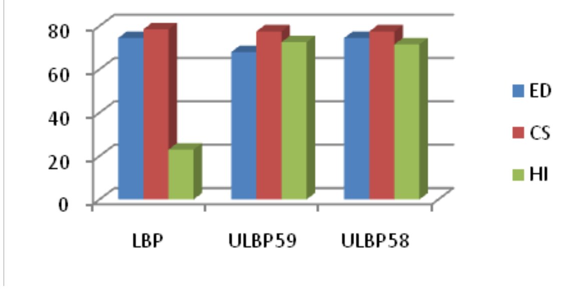


Fig 9: ORL Results of LBP,$ULBP_{59}$,$ULBP_{58}$ feature vectors for full image

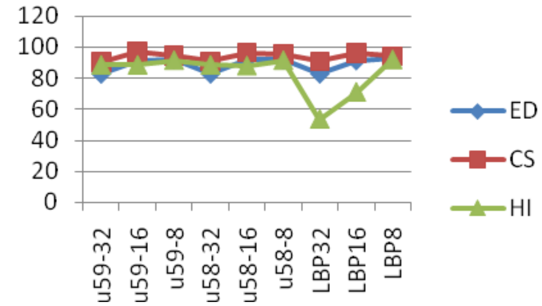


Fig 10: Comparative results of region division LBP original and uniform pattern based approaches for ORL dataset

The charts presented in Fig. 9 and Fig. 10 clearly shows the difference in results.
In the second experiment, an important issue concerning uniform patterns has been observed. As earlier stated non-uniform patterns have been collectively taken in single bin in the final feature vector, the results with feature vector 58 and 59 shows that either inclusion of non-uniform patterns does not affect the result or the results are more in case of exclusion of non-uniform patterns.

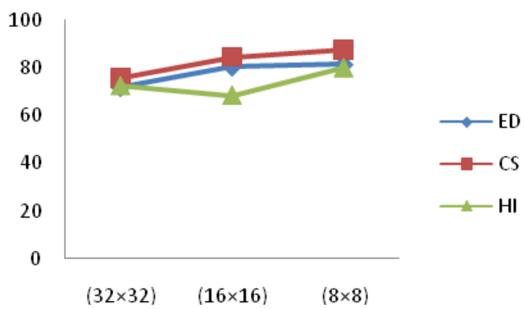
TABLE 3
ROTATION SPECIFIC RESULTS FOR ORL WITH SINGLE FEATURE VECTOR FOR LBP, $ULBP_{59}$, $ULBP_{58}$

Method Name	ED	CS	HI
LBP	63.4	65.6	13.4
$ULBP_{59}$	57.1	67.1	66.2
$ULBP_{58}$	63.4	**68.1**	66.5

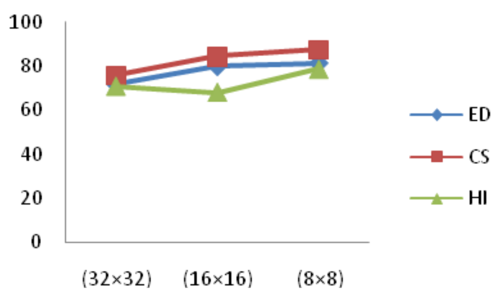
TABLE 4
ROTATION SPECIFIC COMPARATIVE ASPECTS OF ORL DATASET FOR LBP APPROACHES WITH DISTANCE METRICS

Method Name	ED	CS	HI
$_{u59}$ (32×32)	71.8	75.9	72.5
$_{u59}$ (16×16)	80.6	84.6	68.4
$_{u59}$ (8×8)	81.5	**87.5**	80
$_{u58}$ (32×32)	71.8	75.9	70.9
$_{u58}$ (16×16)	80	84.4	68.1
$_{u58}$ (8×8)	81.5	**87.5**	78.7

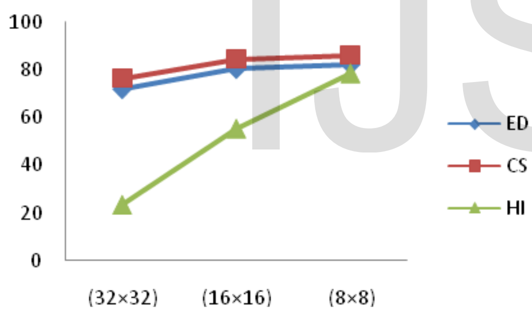
(32×32)	72.1	76.5	23.7
(16×16)	80.3	84.6	55.6
(8×8)	82.1	86.2	78.7



(a)ULBP$_{59}$



(b)ULBP$_{58}$



(c)LBP

Fig 11: Region division based comparative LBP approaches (32×32, 16×16, 8×8) for rotational variation images of ORL dataset

It has been found that LBP being a pixel value based local pattern can handle only small pose variations, in case of large variations spatial regions suffers misalignment [25]

5.3 Experiments on YALE database

Yale database has been the collection of frontal images of 15 persons having 11 images each with various expression variations like happy, sad, sleepy, surprise, wink and normal [24]. Image size has been 64×64. Our work here concerns LBP operator variants effect on expression variations. Again the experiments have been conducted in two chunks, first set takes near equal training and testing sets. As in YALE database we have 11 images each of 15 persons. So the sets have been taken as 5 images per person in training and 6 images per person in testing set (75/90). The second set takes frontal images in training and expression images in testing (30/90)

Fig 12: YALE Database Images

In the first experiment, we have observed both LBP and ULBP$_{58}$presenting the effective results in case of 8×8 region division. Again in this case the effectiveness of uniform patterns has been observed without the inclusion of non-uniform patterns in feature set. Another observation made in our experimental results has been regarding abrupt reaction of histogram intersection technique in case of original LBP operator. During holistic and near holistic approach the results of HI technique have been very low that shows ineffectiveness of this method towards LBP$_{256}$ approach.

TABLE 5
YALE RESULTS WITH SINGLE FEATURE VECTOR FOR LBP, ULBP$_{59}$, ULBP$_{58}$ WITH THREE DISTANCE METRICS

Method Name	ED	CS	HI
LBP	57.7	**63.3**	21.1
ULBP$_{59}$	57.7	62.2	53.3
ULBP$_{58}$	57.7	**63.3**	53.3

TABLE 6
REGION DIVISION BASED LBP APPROACHES COMPARED FOR YALE DATASET ALONG WITH DISTANCE METRICS (ED, CS, HI)

Method Name	ED	CS	HI
$_{u59}$ (32×32)	77.7	84.4	81.1
$_{u59}$ (16×16)	83.3	91.1	82.2
$_{u59}$ (8×8)	84.4	94.4	88.8
$_{u58}$ (32×32)	77.7	81.1	81.1
$_{u58}$ (16×16)	81.1	91.1	81.1
$_{u58}$ (8×8)	85.5	**95.5**	88.8
(32×32)	77.7	81.1	34.4
(16×16)	82.2	94.4	74.4
(8×8)	85.5	**95.5**	87.7

The second experiment covers the effect of LBP operators on expression variation. The results show that division approach rises 22.2% in its accuracy than holistic approach. Similarly Chi-Square outperforms Histogram Intersection and Euclidean Distance with 6.6% accuracy rate. Others have also experimented LBP on expression variation [9,10] and provided effective results.

TABLE 7
EXPRESSION VARIATION SPECIFIC YALE DATASET RESULTS WITH SINGLE FEATURE VECTOR FOR LBP, ULBP$_{59}$, ULBP$_{58}$

Method Name	ED	CS	HI
LBP	65.5	77.7	27.7
ULBP$_{59}$	64.4	74.4	67.7
ULBP$_{58}$	**65.5**	**75.5**	67.7

TABLE 8

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EXPRESSION VARIATION SPECIFIC COMPARATIVE ASPECTS OF YALE DATASET FOR LBP APPROACHES WITH DISTANCE METRICS

Method Name	ED	CS	HI
u59 (32×32)	87.7	93.3	90
u59 (16×16)	87.7	96.6	77.7
u59 (8×8)	91.1	96.6	91.1
u58 (32×32)	88.8	94.4	90
u58 (16×16)	87.7	**97.7**	77.7
u58 (8×8)	86.6	96.6	91.1
(32×32)	91.1	94.4	45.5
(16×16)	88.8	**97.7**	73.3
(8×8)	90	96.6	88.8

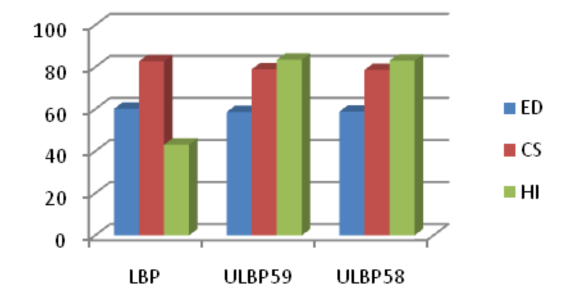


Fig 14: FERET fb results of LBP, $ULBP_{59}$, $ULBP_{58}$ feature vectors for full image

5.4 Experiments on FERET database

FERET database has been quite frequently used in many researches regarding evaluation of face recognition techniques. During experimental work the images of 128×128 size have been divided into two sets of training and testing with nearly equal number of images [2, 22]. During experiments on FERET we have taken the database as it is and not preprocessed the way it's been done in [16]

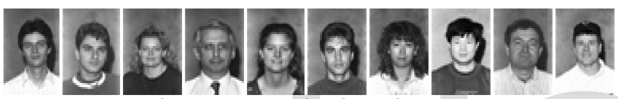


Fig 13: FERET database images

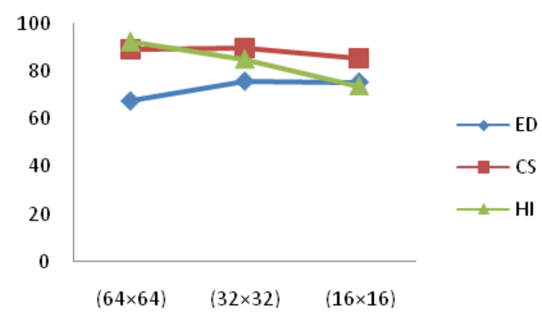
FERET dataset has 1196(fa) images in training and 1195 (fb) in testing set. The results have been shown in table 9 and 10.

TABLE 9
FERET RESULTS WITH SINGLE FEATURE VECTOR FOR LBP APPROACHES

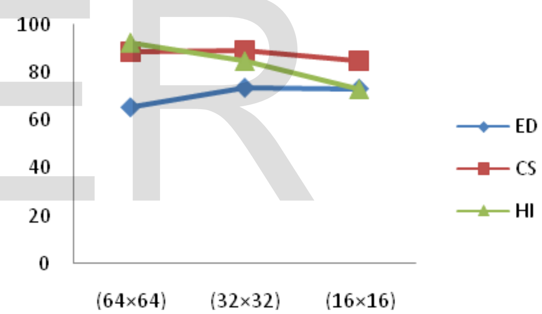
Method Name	ED	CS	HI
LBP	60.2	82.8	43.1
$ULBP_{59}$	58.7	79	**83.5**
$ULBP_{58}$	58.9	78.7	83.1

TABLE 10
FERET RESULTS WITH REGION DIVISIONS FOR LBP, $ULBP_{59}$, $ULBP_{58}$WITH DISTANCE METRICS

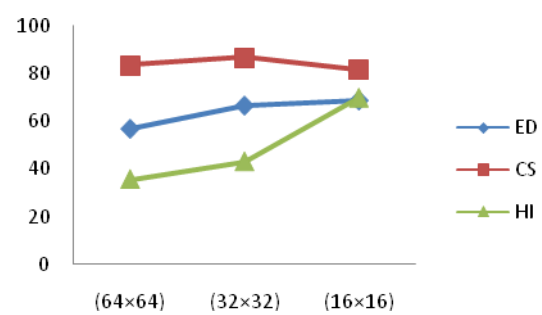
Method Name	ED	CS	HI
u59 (64×64)	67.6	88.9	**92.4**
u59 (32×32)	75.9	89.7	85.1
u59 (16×16)	75.5	85.2	73.8
u58 (64×64)	65.4	88.7	92.4
u58 (32×32)	73.5	89.3	84.7
u58 (16×16)	73.1	84.9	72.9
(64×64)	57.1	83.6	35.7
(32×32)	66.6	86.8	43.1
(16×16)	68.7	81.8	69.7



(a)$ULBP_{59}$



(b)$ULBP_{58}$



(c)LBP

Fig 15: Results for Region divisions with different divisions.

Earlier it has been checked that histogram intersection presented comparable results with chi-square distance measure but in case of FERET (fb) data set, the results of histogram intersection have outperformed in comparison to other distance metric. For FERET dataset experiments have been performed on original images with no preprocessing like cropping or normalization but still results have been 92.4% which shows the efficiency of LBP operator towards face recognition. Ahonen et al. has presented better approach with weighted chi-square distance metric with processed dataset and also compared the results with other methods like PCA, EBGM and Bayesian MAP and have shown the better results through LBP operator [1].

6. CONCLUSION AND FUTURE WORK

The key idea behind this work has been to thoroughly evaluate the factors affecting the performance of LBP operator for face recognition. The five major factors listed in beginning have been checked with extensive experiments on three databases. We would like to list down the concluding remarks:

i) Uniform patterns have definitely been a better approach than the original LBP.

ii) The facial image taken for recognition must be preprocessed with divisions to actually observe the spatial relations among different regions.

iii) The results of Histogram Intersection have been comparative with Chi-Square distance metric but in case of Original LBP operator, its results have been drastically low. The effectiveness of Chi-Square distance metric in all the experiments has shown its real worth for face recognition problems.

Another important issue that we raised in our experiments was the inclusion of non-uniform patterns in a single bin does not seems to benefit as it presents abrupt variation in the feature vector resulting in instability in the LBP histogram. The experiment done in [26,27] for texture analysis has shown work on non-uniform patterns. That instead of taking in single bin non-uniform patterns must be processed according to their properties like near uniform patterns. Further studies include the experiments on non-uniform patterns to be utilized for better results.

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