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LOCAL DIRECTIONAL PATTERN (LDP) FOR FACE RECOGNITION

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Abstract. *This paper presents a novel local feature descriptor, the Local Directional Pattern (LDP), for recognizing human face. In the proposed feature, different edge responses around each pixel are meticulously encoded to distinguish all kinds of textures available in facial images. The LDP code is also robust enough to provide consistent representation in the presence of random noise and non-monotonic illumination variation. An LDP feature is obtained by computing the edge response values in all eight directions at each pixel position and generating a code from the relative strength magnitude. Each face is divided into small regions, from where LDP histograms are extracted and concatenated into a single feature vector to efficiently represent the facial image. The recognition is performed by template matching in accordance with CSU face identification evaluation system and evaluated with well studied FERET database. The recognition performance demonstrates the robustness of proposed LDP descriptor for representing appearance of facial image over other existing approaches including Local Binary Pattern (LBP).*
Keywords: Facial image representation, Local directional pattern, Texture feature, Face recognition, Local binary pattern

1. **Introduction.** Recent advancement in software and hardware technology has created more demand for personalized interaction with consumer products. Popular method for achieving this is done by identifying the users through human face recognition and enabling appropriate services. There are various services which can be enabled through this kind of recognition system, such as personalized TV program [1, 2], intelligent digital photography [3], smart home [4] and many more. In addition, face recognition does not require the cooperation of the individuals to be recognized. Therefore, it is a more acceptable tool [5] despite the existence of other biometric recognition approaches such as iris scans and fingerprint analysis. A recent survey on face recognition [6] explicates the significance and progress of this research domain [7]. However, robust face recognition system in uncontrolled environment is still a major challenge. The most critical aspect in any face recognition system is to find efficient facial features which can be used to represent the face appearance in changed environment. Any facial feature must meet some constraints to be considered as an efficient one. In short, a good facial feature should have properties like (i) it can discriminate different classes well while tolerating within class variation, (ii) it can be easily extracted from the raw face image to ensure fast processing and (iii) it can be described in a low dimensional feature space to ensure computational speed during classification step. It is not that obvious to find features which concurrently meet all these requirements [8] because the appearance of a face may encounter a large

number of variations due to different pose, different lighting condition, different facial expression, etc. Another problem of automatic face recognition is that facial features have limited distinctive information for personal identification and these features are genetically dependent, which means that genetically identical twins have very similar facial features [9].

Many methods for face recognition have been proposed during last three decades and each of those methods uses different techniques for facial feature representation and classification. These techniques can be broadly classified into two groups according to the number of image areas they use to generate facial features. These two types of features are called – global feature and local feature respectively. In global feature extraction process, the whole image is taken into account, but local feature extraction process considers only local region within the given image. A number of global features are used to describe the face appearance aiming to recognize it from the face database. These features, generated from Principal Component Analysis (PCA) [10], Linear Discriminant Analysis (LDA) [11], Two-dimensional Principal Component Analysis (2D PCA) [12], Independent Component Analysis (ICA) [13], Fast ICA [14], etc., have been widely used in the domain of face recognition. Suitability of different frequency features, e.g., dominant frequency features [15] and polar frequency features [16], are also analyzed for face recognition. Wei et al. [17] proposed a method that extracts features by employing discrete cosine transform (DCT) and Gabor wavelets, and then fused their independent features which are extracted with ICA. Although, the global features are popular in face recognition, their performances degrade in changing environment with different pose, different lighting and with different facial expressions. Hence, local features are also gettting significant attention for their robustness in uncontrolled environment [18]. Local Features Analysis (LFA) [19], Elastic Bunch Graph Match (EBGM) [20], Locally Salient Independent Component Analysis (LS-ICA) [21] are popular among the local methods for locating the local face features. Some local feature based methods need to localize different facial components such as the eyes, nose and mouth before extracting facial features. After recognizing the prominent face components, features are generated from position and/or appearances of these facial components which are then used to classify the images. These methods are known as geometric features, and they require a lot of computation prior to feature extraction to localize the prominent face component. Moreover, error in localizing these local regions may lead to severe performance drops. This computational burden and necessity of accurate localization make these methods inappropriate from being used in real time application. A more generic local appearance based approach also proposed [22] that divides the input face image into non-overlapping blocks, without considering any salient region from which different types of facial feature are extracted. This local appearance based method becomes much popular due to its robustness under environmental change and also it is independent from the location of facial components. Similar to this local appearance based feature extraction method, Ahonen et al. [23] proposed Local Binary Pattern (LBP) which has got a lot of attention from the researchers working in the domain of computer vision [24, 25, 26]. It provides an invariant description in presence of monotonic illumination variation on face image. However, the existing methods still suffer a lot from non-monotonic illumination variation, random noise, and change in pose, age, expression.

Motivated by the success of LBP operator to encode the micro-level information such as edges and spots using intensity changes, researchers recently have started utilizing change of gradient magnitude around the pixels to encode micro-level information of edges, spots, etc. [27, 28]. These methods replace the intensity change with the change of gradient magnitude around the pixel, and then calculate LBP code trivially. Consequently, these are unable to encode the information which is possibly achieved by analyzing different magnitude of edge responses in different directions of the pixel. Researchers also found that LBP code generated from homogenous region is not robust enough in presence of noise. In addition to that, LBP cannot generate robust code in presence of non-monotonic illumination variation. Local ternary pattern (LTP) is also proposed which can tackle problem of less robustness in homogenous region. But while addressing the issue LTP maintains two histograms which create larger feature dimension. Besides this LTP needs threshold to determine homogeneity of the local patch and selection of this threshold influences the performance of LTP code.

Considering all of these drawbacks of existing LBP and its variants, we proposed a new local image feature Local Directional Pattern (LDP) which computes the edge response values in different directions and uses these to encode the image texture. Proposed LDP feature considers edge response value in different direction around a pixel instead of gradient orientation like SIFT. Considering the relative edge response values in different directions the proposed LDP feature encodes the local neighborhood property of image pixel with a binary bit sequence like LBP. Since the code is produced from a collection of gradient responses computed over a local region, it provides a more consistent texture representation in the presence of random noise and non-monotonic illumination variation. The design of the proposed code also takes into account the topmost edge directions motivated by the fact that they are more consistent against error. The directional response calculated with compass mask makes the proposed code less sensitive from orientation variation. Thereafter, it accumulates occurrence of LDP code or feature over the whole input image (or image region) with a histogram, which is called LDP histogram and this histogram acts as the image descriptor for representing the whole image (or image region). The effectiveness of LDP based representation is demonstrated with a gain of increased accuracy in face recognition.

The rest of the paper is organized as follows. Section 2 provides a summary of existing Local Binary Pattern (LBP) and its variant used for face recognition. Section 3 presents our proposed Local Directional Pattern (LDP) and shows its robustness as a feature descriptor. Section 4 describes the method to represent face appearance with LDP feature and its application in face recognition in detail. Section 5 lists the performance of LDP in face recognition with the FERET [29] database in contrast to that of existing LBP and its variants. Finally, the last section provides concluding remarks with direction of future work.

2. Local Binary Pattern (LBP).

The LBP operator, a gray-scale invariant texture primitive, has gained significant popularity for describing texture of an image [30]. It labels each pixel of an image by thresholding its P-neighbor values with the center value and converts the result into a binary number by using Equation (1).

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c) \times 2^p \tag{1}$$

where g_c denotes the gray value of the center pixel (x_c, y_c) and g_p corresponds to the gray values of P equally spaced pixels on the circumference of a circle with radius R. The function $s(x)$ is defined with Equation (2).

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{2}$$

The values of the neighbors that do not fall exactly on pixels are estimated by bilinear interpolation. In practice, Equation (1) means that the signs of the differences in a

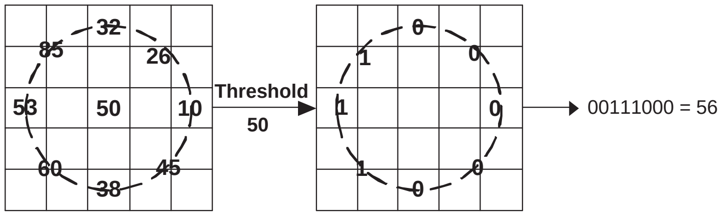


FIGURE 1. The basic LBP operator

$$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

East M_0 North East M_1 North M_2 North West M_3

$$\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

West M_4 South West M_5 South M_6 South East M_7

FIGURE 2. Kirsch edge response masks in eight directions

neighborhood are interpreted as a P-bit binary number, resulting in 2^P distinct values for the binary pattern. This individual pattern value is capable of describing the texture information at the center pixel g_c. The process of generating this P-bit binary number is shown in Figure 1.

One of the variations of this original LBP code is known as uniform LBP. This uniform pattern introduced from the observation that in significant image area certain local binary patterns appear more frequently. These patterns are named as "uniform" as they contain very few transitions from 0 to 1 or 1 to 0 in circular bit sequence. For example, the patterns 00000000 and 11111111 have zero transition, 00011000 has two transitions, and 10001101 has four transitions. Ahonen et al. [17] used this variant of LBP patterns which have at most two transitions (LBP^{u2}) for their face recognition task using FERET database. They have found that 90.6 percent of the patterns in the $(8, 1)$ neighborhood and 85.2 percent of the patterns in the $(8, 2)$ neighborhood are uniform pattern with at most two transitions in case of preprocessed FERET facial images. Though the performance of this feature shows good recognition accuracy in monotonic illumination change this variant of LBP is still sensitive to random noise and non-monotonic illumination variation. The experimental result also shows that this facial feature is not robust enough to represent face image when facial image property changes due to the aging of the person.

3. **Local Directional Pattern (LDP).** The proposed LDP feature is an eight bit binary code assigned to each pixel of an input image through the following procedures.

– Compute 8 directional responses using the Kirsch compass edge detectors shown in Figure 2.

– Assign a bit to each of the directional responses depending on the values of directional responses calculated in earlier step.

– Select k most significant response and set the corresponding bits to 1 leaving other $(k - 1)$ bits to 0.

85	32	26
53	50	10
60	38	45

→

Mask Index	m_7	m_6	m_5	m_4	m_3	m_2	m_1	m_0
Mask Value	161	97	161	537	313	97	-503	-393
Rank	6	7	5	1	4	8	2	3
Code Bit	0	0	0	1	0	0	1	1
LDP Code	19							

FIGURE 3. Generating LDP code with $k = 3$

85	32	26
53	50	10
60	38	45

LBP = 00111000 = 56
LDP = 00010011 = 19

(a)

81	29	32
38	58	15
65	43	47

LBP = 00101000 = 40
LDP = 00010011 = 19

(b)

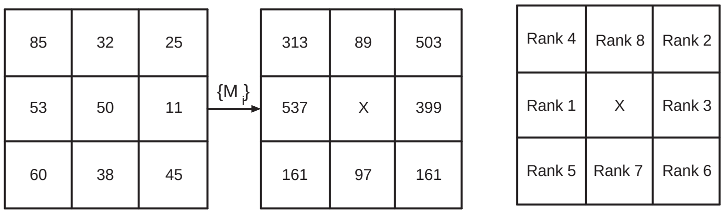
FIGURE 4. Robustness of LDP vs. LBP: (a) original image with LBP and LDP code, (b) noisy image with changed LBP and LDP value

For the computation of 8 directional responses, Kirsch edge detector, Prewitt edge detector, Sobel edge detector can be used [31]. However, the Kirsch compass edge detector is known to detect different directional edge responses more accurately than others because the Kirsch edge detector considers all eight neighbors [32]. Hence, we calculate eight directional edge response values of a particular pixel using Kirsch masks [31] in eight different orientations centered on its own position. These masks are shown in Figure 2.

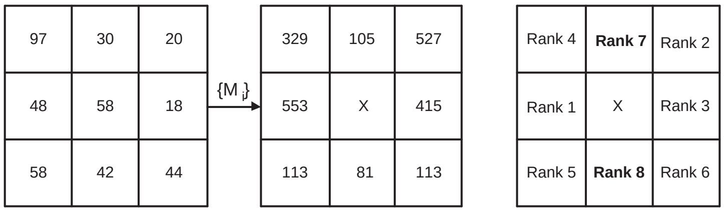
At each direction, the gradient edge response is determined from several intensity values found on a local neighboring region. Similar to the benefits achieved through an averaging mask, the gradient response is less sensitive to random noises. Gradient calculation with basic first order derivative function is not followed because that gradient response is more prone to errors when measured from two pixel values and noise can influence this function more. Thus, the usage of region information results into a more stable directional response. Accordingly, applying eight masks, we obtain eight edge response values m_0, m_1, ..., m_7, each representing the edge significance in its respective direction. The response values are not equally important in all directions. The presence of corner or edge shows high response values in particular directions. We are interested to know the k most prominent directions in order to generate the LDP. Hence, we find the top k values $|m_j|$ and set them to 1. The other $(8 - k)$ bit of 8-bit LDP pattern is set to 0. Figure 3 demonstrates the generation of LDP code considering three most prominent edge responses that is using $k = 3$.

$$LDP_k = \sum_{i=0}^{7} s(m_i - m_k) \times 2^p \tag{3}$$

where, m_k is the k-th most significant response and $s(x)$ is the same as Equation (2).



(a)



(b)

FIGURE 5. Robustness of LDP in presence of random noise: (a) original image and ranking of edge responses, (b) noisy image with new ranking of edge responses

The LDP code produces more stable pattern in presence of noise. For instance, Figure 4 shows an original image and the corresponding image after adding Gaussian white noise. After addition of noise, 5th bit of LBP changed from 1 to 0; thus LBP pattern changed from uniform to a non-uniform code. Since edge response values are more stable than gray value, LDP pattern provides the same pattern value even in the presence of that noise and non-monotonic illumination changes.

The robustness of LDP code showed in the previous example is mainly achieved because it is generated from eight different edge response values computed by using 3×3 mask operators, which is more resistant to noise compared with the intensity differences between the center pixels and neighboring pixels used in LBP. The consistency of the LDP code is further increased by excluding weak responses, which are more vulnerable to noise. In presence of noise it is most unlikely that a high ranking edge response will change its ranking. Even if any change in position occurs in the magnitude ranking, it is most likely to occur in less significant directions. Figure 5(a) shows the ranking of each edge directional response for the give input image whilst Figure 5(b) shows the same with the noisy image. The example shows that high ranking directional responses do not change their positions while low ranking responses, such as direction 2 and 6, change their positions, in the presence of strong noise. Hence, the proposed LDP with $k = 3$ produces the same code for the noisy image.

4. **Face Recognition with LDP Descriptor.** The LDP feature which is robust against different variations like non-monotonic changes in illumination and in random noise is used to represent the face for the application of face recognition. The LDP method for face representation demonstrates robustness to variations inexpression, illumination, aging and noise. This robustness is achieved due to combining of stability of edge response value in place of intensity value, considering local pattern instead of single pixel value, and local region histogram. This section presents how to use this proposed LDP operator for representing the appearance of a face image and use that representation to recognize it.

4.1. **Face representation using LDP.** There are three steps to represent the face using LDP feature from a raw face image. First, the LDP operator is applied on the face image

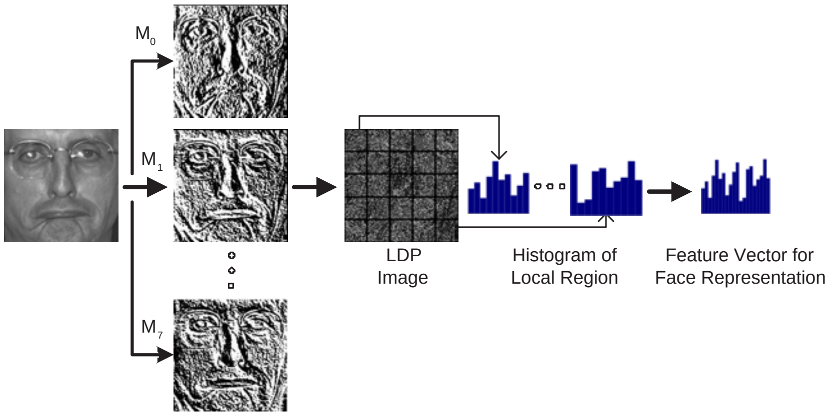
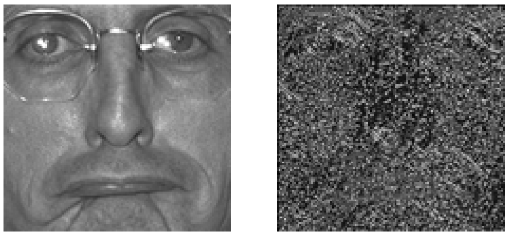


FIGURE 6. Flowchart of face representation using LDP descriptor



(a) (b)

FIGURE 7. (a) Original face image, (b) LDP image

to get LDP image. Second, histogram is extracted from each local region of LDP image to build the local representation of the face. Third, all the histograms are concatenated into one feature vector to build the global representation. The tolerance of local histogram to puzzle-like movement implies that face representation with LDP is insensitive to shape variation, such as expression and aging. The whole procedure of the proposed method for face representation is illustrated in Figure 6, in which it can be seen how an example face image converted into LDP images, partition into different regions, generate region-based histograms and then produce final face representation which is the concatenated histogram of all the local region histograms.

4.1.1. *Generating LDP face image.* At the beginning face image is represented using LDP operator, and the LDP operator is applied in the raw face image using Equation (3). In our experiment we use $k = 3$ to generate the LDP code. Figure 7 shows an example of LDP image generated from raw face image.

4.1.2. *Histogram of LDP.* After encoding an image with the LDP operator we get an encoded image $I_L(x, y)$. We use $k = 3$ which generates ${}_8C_3 = 56$ distinct values in our encoded image. So histogram H of this LDP labeled image $I_L(x, y)$ is a 56 bin histogram and can be defined

$$H_i = \sum_x \sum_y P(I_L(x, y) = C_i) \tag{4}$$

where $C_i = i^{\text{th}}$ LDP pattern value, $i = 0, 1, \ldots, {}_8C_k$. Here ${}_8C_k$ is the number of different labels produced by the LDP operator and

$$P(A) = \begin{cases} 1 & \text{if } A = \text{true} \\ 0 & \text{if } A = \text{false} \end{cases} \tag{5}$$

4.1.3. *Concatenated LDP histogram.* Each face is represented by an LDP histogram. LDP histogram contains fine detailed information of an image, such as, edges, spot, corner and other local texture features. However, histogram computed over the whole face image encodes only the occurrences of the micro-patterns without any knowledge about their locations. In order to incorporate some degree of location information, we divide face images into n number of small regions R_0; R_1; $\ldots$; R_n and extract the LDP histograms H_{Ri} from each region R_i. These n LDP histograms are then concatenated to get a spatially combined LDP histogram which plays the role of a global face feature for the given face image. The process is illustrated in the second part of Figure 6.

4.2. **Similarity measure based on LDP.** From the pattern classification perspective, a natural problem of face recognition is having a large number of classes but only a few, sometimes only one, number of training sample(s) are available for per class. In this situation, more sophisticated classifier is not applicable rather simple nearest-neighbor classifier is used in classifying the face. Several dissimilarity measures have been proposed to compare closeness between two histograms named as – Histogram intersection, Log-likelihood statistics and Chi square statistics (χ^2):

Histogram intersection:

$$D(S,M) = \sum_i \min(S_i, M_i) \tag{6}$$

Log-likelihood statistics:

$$L(S,M) = -\sum_i S_i \log M_i \tag{7}$$

Chi square statistics:

$$\chi^2(S,M) = \sum_i \frac{(S_i - M_i)^2}{(S_i + M_i)} \tag{8}$$

Though the original form of this measure is applicable to compare a single histogram but all these dissimilarity measures can be applied on the spatially enhanced LDP histogram by simply summing over i and j.

Relevant studies in psychophysics and neuroscience have revealed that different facial features have different degree of significance to face recognition [7]. For example, it has been found that hair, face outline, eyes and mouth are more important for perceiving and remembering faces, while the nose plays a relatively unimportant role [33]. Inspired by this knowledge, weighted dissimilarity measures [34] are used which provide different weight in different face block regions. Hence, the dissimilarity measures equations are slightly modified to incorporate weight of each block's histogram. So weighted dissimilarity measures between two spatially encoded LDP histograms SLH^1 and SLH^2 can be defined by:

Weighted Histogram intersection:

$$D_w(SLH^1, SLH^2) = \sum_{i,j} w_i\{\min(SLH^1_{i,j}, SLH^2_{i,j})\} \tag{9}$$

Weighted Log-likelihood statistics:

$$L_w(SLH^1, SLH^2) = -\sum_{i,j} w_i(SLH^1_{i,j} \log SLH^2_{i,j}) \tag{10}$$

Weighted Chi square statistics:

$$\chi^2_w(SLH^1, SLH^2) = \sum_{i,j} w_i \frac{(SLH^1_{i,j} - SLH^2_{i,j})^2}{(SLH^1_{i,j} + SLH^2_{i,j})} \tag{11}$$

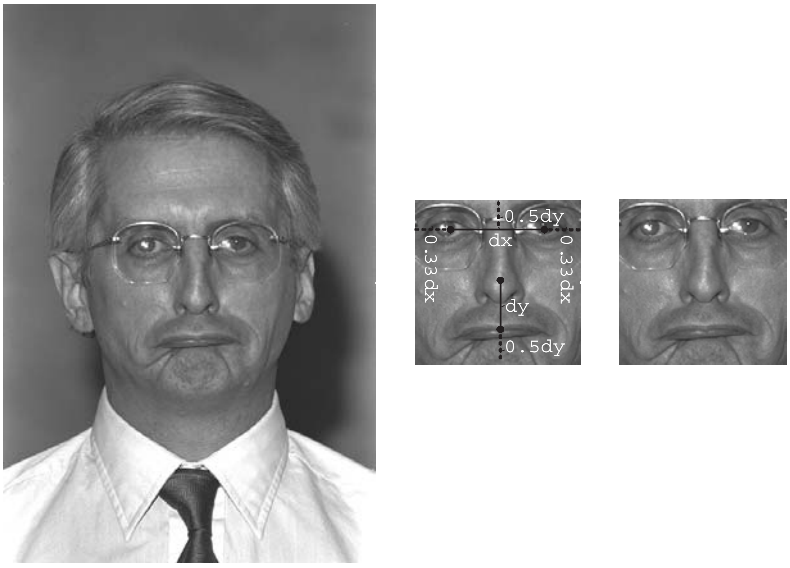


FIGURE 8. Original face and cropped region of the face image

For all three equations indices i refer to the region number, j indicates histogram bin number of that region and w_i is the associated weight of region i.

5. **Experimental Result.** The performance of proposed LDP pattern is tested in the face recognition problem in accordance with the Colorado State University Face Identification Evaluation System [35] using images from the FERET [29] database. Many approaches, such as Principle Component Analysis (PCA) [10], Bayesian approach and Elastic Bunch Graph Match (EBGM) [20] are available for comparisons. LBP-based methods [8, 23, 25] have also been recently proposed and have achieved the state-of-the-art results on the FERET database. Hence, in this section, we have conducted experiments on FERET face database (with 1196 subjects) and compared our result with the results found applying existing methods. We have found our method performing significantly better than these methods especially in adverse environment like illumination change and with aging effects.

5.1. **Experimental setup.** The FERET database consists of a total of 14,051 gray-scale images representing 1,199 individuals. The images contain variations in lighting, facial expressions, pose angle, aging effects, etc. In this work, we mainly focused on showing applicability of our method in the consumer product. In consumer application, user generally supposed to co-operate with the system; however, environmental changes may appear a lot. Hence, in this work, only frontal faces are considered with different lighting condition, different expression and with aging effects on the face image. These facial images can be divided into five sets as follows:

(i) fa set, used as a gallery set, contains frontal images of 1,196 people.

(ii) fb set (1,195 images). The subjects were asked for an alternative facial expression than in the fa photograph.

(iii) fc set (194 images). The photos were taken under different lighting conditions.

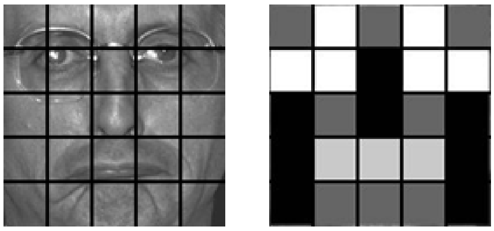
(iv) *dupI* set (722 images). The photos were taken later in time.

(v) *dupII* set (234 images). This is a subset of the *dupI* set containing those images that were taken at least a year after the corresponding gallery image.

After choosing the images, automatic face cropping and resizing have been done from the original image by utilizing the positions of two eyes, mouth and nose with equal height

(a) (b) (c) (d) (e)

FIGURE 9. Example face image from FERET database: (a) image from fa set, (b) image from fb set, (c) image from fc set, (d) image from $dupI$ set, (e) image from $dupII$ set



(a) (b)

FIGURE 10. (a) A facial image divided in 5×5 sub-regions, (b) the weights assigned for the weighted χ^2 dissimilarity measure. Black, dark gray, light gray and white indicates weight of 0.0, 0.5, 1.0 and 1.5 respectively.

and width. Finally images are resized into 100×100 pixels. In the FERET database, the ground-truth data of eye, mouth and nose are provided. For the real-time system, we can use an existing eye detection technique that provides good detection accuracy [36]. For automatic face cropping we have used the horizontal distance between two eyes (termed as dx) and vertical distance between mouth and nose (termed as dy). A distance of $\frac{1}{3}dx$ between the boundaries and both eyes has been maintained. The upper boundary has maintained a distance of $\frac{1}{2}dy$ from the eye position and the bottom boundary also has maintained a distance of $\frac{1}{3}dy$ from the mouth position. The whole cropping measurement is shown in Figure 8. No further alignment of facial features such as alignment of mouth [37] is performed in our algorithm. Since LDP is robust in illumination change, no attempt is made to remove illumination changes.

Five example cropped images, one from each of those five groups is shown in Figure 9. In our experimental setup, every image is partitioned into $M \times N$ sub-blocks. We used fa image set as gallery image and other four sets (fb, fc, $dupI$ and $dupII$) as probe images. One image from probe set is compared using mentioned dissimilarity measure with all the images from gallery image set (fa set). The classification result is achieved through the nearest neighbor classification method. Table 1 shows recognition performance of proposed method along with other methods which ascertain the superiority of the proposed method.

5.2. **Parameters of the LDP method.** There are some parameters which can be tuned to optimize the performance of LDP based face recognition. Some of these parameters are the number of prominent edge response set during LDP code generation, number of sub-regions the face image should be divided into, weight associated for every sub-region, choice of dissimilarity measure used during nearest neighbor classification.

Table 1. The recognition result of the LDP and comparison algorithm in FERET database

Methods	fb	fc	dupI	dupII
LDP, weighted	0.97	0.82	0.72	0.69
LDP, un-weighted	0.97	0.80	0.70	0.66
LBP	0.97	0.79	0.66	0.64
PCA	0.85	0.65	0.44	0.22
Bayesian	0.82	0.37	0.52	0.32
EBGM	0.90	0.42	0.46	0.24

We may get different LDP encoded features by varying k values, i.e., number of significant responses set for coding. In presence of noise it is most unlikely that a high ranking edge response will change its relative ranking and consequently generate stable code. Even if some positional changes occur in the magnitude ranking, it is most likely to occur in less significant directions. However, we need to consider the fact that value of k is also related to the descriptive power of the code. As we incorporate more number of edge responses the descriptive power starts to increase, because with higher number of k we become more capable of differentiating between more local micro patterns. However, at the same time by incorporating comparatively less significant response it becomes more noise prone. Hence, the optimal value of k should be selected from a good trade-off between reliability of the LDP code over noise and the descriptive power of the code. Therefore, to select the value of k we carry out another experiment by varying k value. It may be noted that, number of prominent directions, i.e., $k = 1$ gives the symmetric descriptor as $k = 7$ because ${}^8C_1 = {}^8C_7$. Therefore, the parameter k needs to be verified with the value from $\{1, 2, 3, 4\}$. It is also worthwhile to mention that number of prominent edge response used to generate the LDP code leads to a change in the number of histogram bins and consequently changed the feature vector length. In order to determine the optimal number of prominent edge response, we fix the number of regions g, and find the optimal value for k. Table 2 shows the performance for different k values with the facial images divided 100 equal regions. It can be observed that the best recognition rate is achieved when $k = 3$.

LDP based method is quite robust with respect to dividing the whole image into different number of sub-regions as long as it divides the face into prominent facial components like eye, lip and nose. Recognition performances with different number of sub-regions are shown in Table 3. When comparing different distance measures, the χ^2 measure was found to be performed better than histogram intersection or log-likelihood distance. The recognition result of various dissimilarly measures are also shown in Table 4. In that experiment we divide the image into 10×10 sub-regions and set three prominent edge response value to generate LDP code. To find the weight for every sub-region, a simple technique is applied where only each sub-region is used to recognize the face image. The recognition performance of each block is used to assign the weight of that sub-region in various dissimilarly measures. The obtained weights for weighted chi-square measure are illustrated in Figure 10. The weights were selected without utilizing an actual optimization procedure and thus they are probably not optimal. Despite that, in comparison with the non-weighted method, an improvement is found in weighted method.

5.3. **Robustness to face localization error.** In actual face recognition systems face detection is performed prior to face recognition. Automatic face detection method does not provide exact location of the face and it contains some small error in localization

TABLE 2. The recognition result using different number of prominent direction (k) in FERET database

	fb	fc	dupI	dupII
$k = 1$	0.90	0.72	0.60	0.57
$k = 2$	0.93	0.77	0.64	0.60
$k = 3$	0.97	0.82	0.72	0.69
$k = 4$	0.96	0.80	0.70	0.66

TABLE 3. The recognition result using different sub-region size in FERET database

Block Number	fb	fc	dupI	dupII
3×3 block	0.96	0.78	0.66	0.61
5×5 block	0.96	0.79	0.68	0.65
10×10 block	0.97	0.82	0.72	0.69
15×15 block	0.94	0.80	0.69	0.65

TABLE 4. The recognition result using different similarity measure in FERET database

Similarly Measure	fb	fc	dupI	dupII
Histogram Intersection	0.95	0.78	0.66	0.66
Log-Likelihood	0.95	0.80	0.66	0.65
Chi-Square	0.97	0.82	0.72	0.69

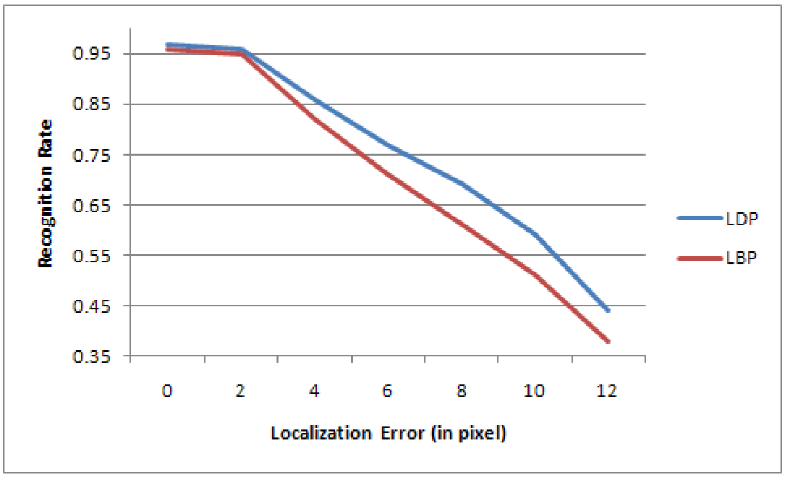


FIGURE 11. The recognition rate for the images of fb probe set with different face localization error

step. So proposed face recognition method should provide robust enough performance in presence of small face localization error.

Our proposed face recognition method generated histograms over the local regions of the face image. So small changes of face position will only lead to changes in the labels which come from border of the local regions. However, labels of inner part of the local region, which are major part of those regions, will not change. Therefore, it is expected that the proposed method is robust in presence of small changes in face localization steps. This assumption is further verified with Figure 11.

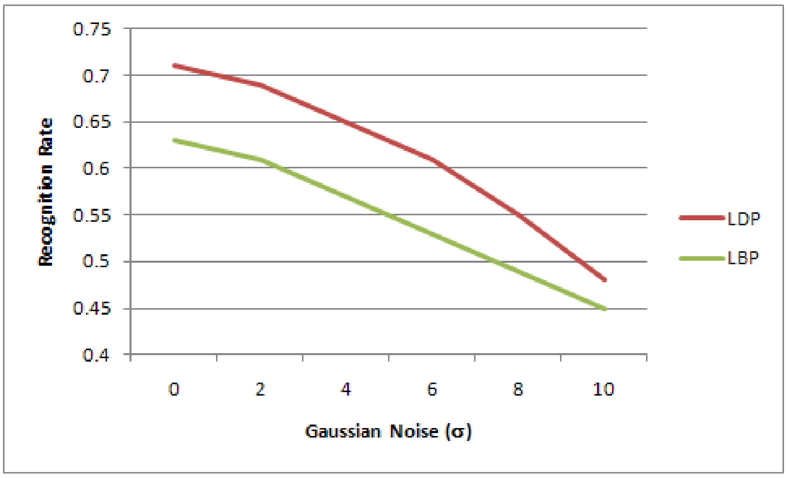


FIGURE 12. The average recognition rate of images all probe set with different noise level

5.4. **Robustness to noise.** In our earlier discussion, we have shown the robustness of LDP over LBP in presence of Gaussian noise. This robustness of LDP code generation should reflect into recognition accuracy of face images. Therefore, to further investigate the sensitivity of LBP and LDP to noise, an experiment was conducted on the images from the same FERET datasets. For this experiment, Gaussian white noise with different noise variance ($\sigma = 0, 2, \ldots, 10$) are added to all the images in the probe sets. The images in the gallery set (i.e., fa set) remained unchanged. The average recognition rates on the four probe sets against different Gaussian noise are illustrated in Figure 12 and it exhibits the robustness of LDP over LBP in face recognition with presence of noise in the image. The results show that LDP sometimes provides over 10.0% higher recognition accuracy over LBP.

5.5. **Robustness to rotation.** The proposed LDP feature is calculated using Kirsch mask which inherently can tolerate some level of rotation. Therefore, to investigate the sensitivity of LBP and LDP to in-plane rotation, an experiment was conducted on the same FERET datasets. For this experiment, all the images in the probe sets are rotated with different rotation angle ($\phi = 5°, 10°, \ldots, 25°$). The images in the gallery set (i.e., fa set) remained unchanged. The average recognition rates on the four probe sets against different in-plane rotation angle are illustrated in Figure 13 exhibiting the robustness of LDP over LBP.

6. **Conclusions.** This paper describes a new local face feature based on LDP descriptor for face recognition. The LDP operator is used to represent face image by dividing the image into small regions and computing a description for each region. These descriptors are then combined into a spatially combined histogram which is used as feature vector for recognition task. The proposed LDP descriptor is insensitive to noise and non-monotonic illumination variations and therefore the face recognition system using this LDP feature also recognizes face with higher accuracy under different expressions and aging conditions, allowing the system to run reliably in uncontrolled environment. Although high performance is achieved by the proposed method, still there are some issues which should be furthered addressed. We trivially divide the face image into small regions. So, more focus should be given for advanced methods to divide the facial image into local regions in more meaningful blocks. Finding optimal weights for all the regions will also be worthwhile to look at. The AdaBoost method presented in [38] can be a good basis for this research.

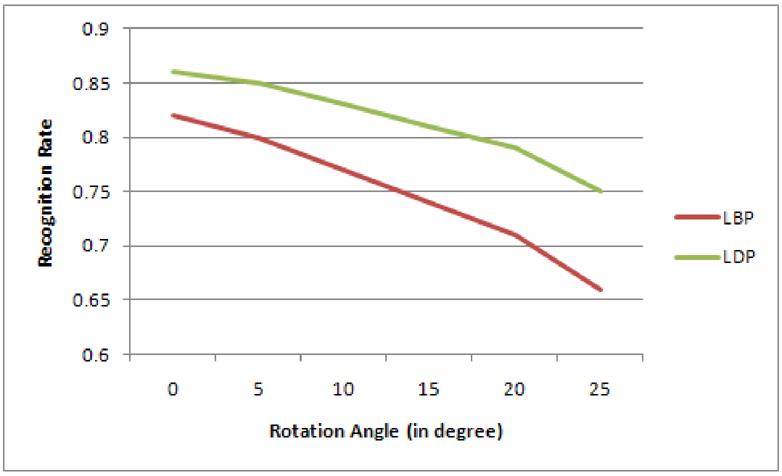


FIGURE 13. The average recognition rate of images all probe set with different noise level

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