Local Diagonal Extrema Number Pattern: A new Feature Descriptor for Face Recognition

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Abstract

This paper proposes a simple and novel feature descriptor for face recognition called local diagonal extrema number pattern (LDENP). LDENP produces a compact code of facial features which is obtained by encoding the directional information of the face image. Further, LDENP micro-patterns are created using values and indices of the local diagonal extremas (i.e. minima and maxima) using first order local diagonal derivatives that extract the directional information. Moreover, the proposed algorithm partitions the face into several regions to facilitate extraction of features from each region individually. Consequently, the extracted features are concatenated into a single feature vector which is used as a face descriptor. In this work, only the diagonal neighbours are considered, hence, the dimension of the feature, and the computation time to recognize the face are reduced. Therefore, the curse of dimensionality problem is solved. Experimental results are carried out on standard benchmark databases like FERET, Extended YALE-B, ORL and LFW-a. Moreover, efficiency of LDENP descriptor is asserted by comparing recognition rates of the proposed method with other existing local-descriptor based methods.

Keywords: Face recognition, Local features, Feature descriptor, Local directional pattern, Face descriptor, Local diagonal neighbours.

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1. Introduction

In recent years, biometrics for identifying human features has increased significantly in large populations. Moreover, humans are recognized based on their physiological and behavioral characteristics such as face, fingerprint, palm veins, hand geometry, iris, retina, gait, voice etc [1]. Among biometrics, face recognition is an active research area with noteworthy contributions. Biometric authentication, human computer interaction, surveillance, forensics, and crime investigation are major applications of face recognition [2].

In a face recognition system, representing a face in the form of a face descriptor is an important step [3]. A face descriptor can be able to recognize a suitable representation for every face, moreover, the efficacy of a descriptor can be determined by its ability to extract features from an input image. Additionally, an efficient descriptor must have the ability to differentiate between intra-class and inter-class structures with minimal time complexity. Lately, several researchers have proposed successful methods to extract the representation of a face, and computed efficient face descriptors. However, these methods fail to recognize faces under adverse conditions of illumination, pose, partial occlusions, aging, lighting conditions, expression, etc.

Face recognition methods are broadly classified into geometric-based, holistic, appearance-based, and statistical-based methods [4, 5, 6]. Geometric feature based methods use the local facial features and the relationships to recognize the faces, geometric feature based method is also known as feature based method. Holistic method uses little information from facial features (i.e. the relationship between the features and the whole face is not considered) to recognize the faces. Moreover, algorithms which follow holistic method independently process the facial features. Appearance based methods describe the face in terms of texture information in an image, these features are represented as feature vectors with high dimensionality [7]. Statistical methods use a uniquely identified statistical pattern to represent a feature extracted from a face.

In literature, face recognition methods such as geometric-based, holistic, appearance-based, and statistical-based methods are used in numerous algorithms namely, principal component analysis (PCA), linear discriminant analysis (LDA), locally linear embedding (LLE), locally preserving projections (LPP), independent component analysis (ICA), trace transforms (TT), hidden markov model (HMM), and Kernel PCA algorithm [8, 9, 10, 11]. However, defining a robust descriptor for face recognition remains a challenging goal. Recently, 3D morphable methods have been proposed for face recognition. The distance between a set of query and gallery images is computed to facilitate the face recognition process in image set based face recognition [12]. Further, the low complexity facial image recognition system has been proposed to work in an unconstrained spatial resolution [13]. However, local pattern descriptors are gaining more attention for face recognition in latest trends. A popular local descriptor technique called local binary pattern (LBP) is proposed by Ojala et al. [14]. LBP descriptor encodes every pixel in an image based on the relationship between the centre pixel and neighbouring pixels. Furthermore, LBP extracts a higher order texture micropattern from the locally encoded image. Ojala et al. [15] proposed to increase the efficiency of LBP descriptor by varying the sizes of the neighbourhood. Additionally, bi-liner interpolation technique was considered for different neighbourhood sizes. However, a major drawback of LBP was the loss of brightness information due to the difference between the centre pixel and neighbour pixels. To solve the drawback of LBP, complete modelling of the LBP (CLBP) was developed by Guo et al. [16], and it represents the local descriptor based upon the sign, and magnitude differences between the pairwise pixels. Another form of LBP called the uniform LBP (ULBP) [4] uses descriptor patterns with only two transitions from 1 to 0 or vice-versa. The next variation of LBP is called the local phase quantization (LPQ) [17], in the LPQ method, patterns are generated by quantizing the LBP encoded image. Moreover, LPQ outperforms the LBP in blurred images. Liao et al. [18] presents a multi-Block LBP, which captures both micro and macro patterns. Three/Four path LBP was extended from LBP, it generates the micro pattern descriptor by encoding the patch type of texture information. Later, LBP was extended to neighbourhood intensity based LBP (NI-LBP), centre intensity based LBP (CI-LBP), angular difference based LBP (AD-LBP), and radial difference based LBP (RD-LBP) [19]. These methods generate the micro pattern descriptors for the complete image representation, consequently, they are more robust, and efficient than the LBP descriptor.

Furthermore, various variants of LBP exist in literature such as local ternary pattern (LTP) [20], local directional pattern (LDP) [21], local directional number pattern (LDNP) [22], local derivative pattern (LDeP) [23], local vector pattern (LVP) [24]. Tan and Triggs [20] proposed the LTP method which extends on LBP by generating micropatterns with the three codes -1, 0, 1. LDP [21] local descriptor extracts the intensity variation and structural information by encoding the centre pixel and the neighbourhood pixels in eight directions using kirsch masks. Therefore, LDP increases recognition rate for noise images. Moreover, LDP was extended to enhanced LDP (ELDP) [25], which uses local edge information to represent the face. The resultant ELDP generates the double-digit octal number by choosing the most prominent and the second most prominent edge response value from the eight directions. Furthermore, ELDP uses dimensionality reduced patterns as descriptors, hence, it works better than LDP. LDNP is another variation of the LDP [22]. LDNP works like LDP, however, the top most positive direction and top most negative direction are chosen from the convolved krisch masks image to extract the face descriptor. LDNP reduces the eight-bit LDP code to six-bit per pixel. Furthermore, the researcher modified LDP into LDNP with Gaussian function (LDNPG) which uses gaussian masks instead of kirsch masks. Zhang et al. [23] introduces LDeP which contains directional information rather than intensity values, and it overcomes the problem of LBP by proving its efficiency on images with varying levels of random noise, illumination variation, and pose variation. LVP [24] was proposed to identify the relationships between the referenced pixel and the local neighbourhood pixels in terms of higher order derivative space. In most of the descriptors methods discussed, masks were used to encode the image and compute the code pattern for a centre pixel of an encoded image. In addition, a large database was used for the face recognition. The use of algorithms like LBP, LTP, LDP, and LVP on databases resulted in an increase in length of the feature, and increase in feature extraction time, moreover, the performance of the recognition system was degraded. The above demerits has motivated us to propose the new local diagonal extrema number pattern (LDENP) descriptor for face recognition. In the proposed descriptor, the centre pixel and its local diagonal neighbours are considered only, and dimension of the descriptor can be reduced. The information among the local diagonal neighbours is encoded by finding the values and indices of the local diagonal extremas using first-order local diagonal derivatives. From the encoded local diagonal neighbours pixel, a micro pattern for binary value of the local extremas is computed. The novelty and advantages of the proposed descriptor is as follows:

- The proposed descriptor uses first order derivatives to encode the image rather than using masks.
- The proposed descriptor considers only the local diagonal pixels values rather than the local neighbour pixels. Hence, it reduces the dimensionality of the feature descriptor.
- The proposed descriptor calculates the micro-patterns based on the first order local diagonal extrema number pattern.
- To the best of knowledge, first order derivative based local descriptors have not been applied for face recognition by researchers.
- The proposed descriptor yields a high face recognition rate.

The rest of the paper is organized as follows: Section 2 presents the computation of the proposed descriptor, Section 3 demonstrates the results of the proposed descriptor on several different face images. The overall performance of the proposed descriptor and comparison results with other local descriptors are presented in Section 3, Section 4 concludes the paper.

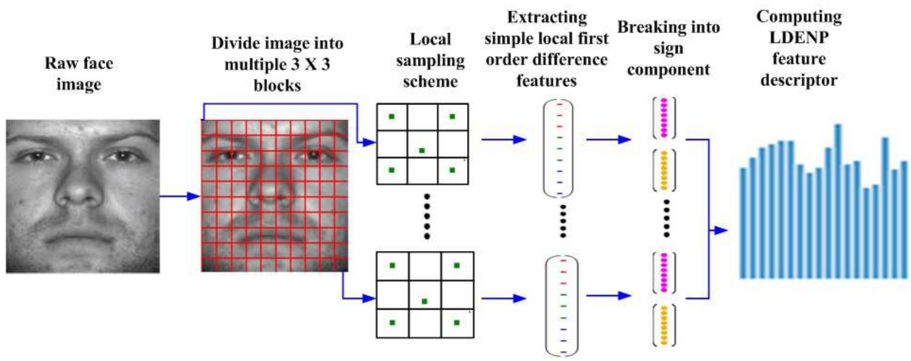

Figure 1: Framework of the proposed feature extraction method.

2. Local Diagonal Extrema Number Pattern

In this section, we propose a new and well-organized image feature descriptor using local diagonal extrema number pattern (LDENP). The LDENP compute the pattern only using the local diagonal neighbours of the centre pixel. The local diagonal extremas i.e. maxima and minima are extracted from the image using first-order local diagonal derivatives [26]. Moreover, the local direction numbers are extracted using the top most positive and top most negative direction number, which are computed by the direction of the local diagonal extremas. Further, the relationship of local diagonal extrema pixels with the local directional number is used to encode the LDENP feature descriptor. The framework of the proposed (LDENP) feature extraction method is shown in Fig. 1.

2.1. First-Order Local Diagonal Derivative

The first order local diagonal derivative is used to find the local diagonal extremas of any centre pixel. The diagonal neighbours are used to extract the local diagonal information. In this paper, we have only used diagonal neighbours, it significantly reduces the dimension of the descriptor, further, the diagonal neighbours contain most of the local information [27]. Let $F_{m,n}$ be the centre pixel and its corresponding ith diagonal neighbours $F^{i}_{m,n}$ at a distance

R, where $i \in [0,3]$ and $F_{m,n}$ is the pixel at mth row and nth column of any gray scale image F with m_1 rows and m_2 columns. The intensity value positions of $F^i_{m,n}$ and $F_{m,n}$ are shown in the Fig.2(a). The definition of $F^i_{m,n}$ is given in Eq. (1).

$$F^i_{m,n} = F_{m+\alpha,n+\beta} \tag{1}$$

where α and β are constants having values either $+R$ or $-R$ depending on the values of i and it is defined in Eq. (2)

$$\alpha,\beta = \begin{cases} +R,-R & i=0 \\ -R,+R & i=1 \\ -R,-R & i=2 \\ +R,+R & i=3 \end{cases} \tag{2}$$

There are three first-order diagonal derivatives that are defined as $T = 0, 1$ and 2 respectively. First order local diagonal derivatives are calculated in three directions by finding the relationship of each diagonal pixel value with the remaining diagonal pixels. The first-order diagonal derivatives for $T = 0$ can be defined as follows.

$$F^{0,0}_{m,n} = F^1_{m,n} - F^0_{m,n} \tag{3}$$

$$F^{1,0}_{m,n} = F^2_{m,n} - F^1_{m,n} \tag{4}$$

$$F^{2,0}_{m,n} = F^3_{m,n} - F^2_{m,n} \tag{5}$$

$$F^{3,0}_{m,n} = F^0_{m,n} - F^3_{m,n} \tag{6}$$

The first-order diagonal derivatives for $T = 1$ can be defined in Eqs. (7)–(10).

$$F^{0,1}_{m,n} = F^{2}_{m,n} - F^{0}_{m,n} \tag{7}$$

$$F^{1,1}_{m,n} = F^{3}_{m,n} - F^{1}_{m,n} \tag{8}$$

$$F^{2,1}_{m,n} = F^{0}_{m,n} - F^{2}_{m,n} \tag{9}$$

$$F^{3,1}_{m,n} = F^{1}_{m,n} - F^{3}_{m,n} \tag{10}$$

Similarly, the first-order diagonal derivatives for $T = 2$ can be defined as follows.

$$F^{0,2}_{m,n} = F^{3}_{m,n} - F^{0}_{m,n} \tag{11}$$

$$F^{1,2}_{m,n} = F^{0}_{m,n} - F^{1}_{m,n} \tag{12}$$

$$F^{2,2}_{m,n} = F^{1}_{m,n} - F^{2}_{m,n} \tag{13}$$

$$F^{3,2}_{m,n} = F^{2}_{m,n} - F^{3}_{m,n} \tag{14}$$

The general formula to define the first-order diagonal derivatives of the $T = 0, 1, 2$ can be given in Eq. (15)

$$F^{i,T}_{m,n} = F^{(mod(1+i+T,4))}_{m,n} - F^{i}_{m,n} \tag{15}$$

where $i \in [0, 3]$, $T = [0, 2]$, and $mod(A, B)$ is the remainder of division of A by B.

2.2. Computation of Local Diagonal Extrema Number Pattern

The local diagonal extremas (i.e. maxima and minima) of the centre pixel $F_{m,n}$ are represented by $F^{\tau^{max}}_{m,n}$ and $F^{\tau^{min}}_{m,n}$ based on intensity pixel values, where τ^{max} is the index of the local diagonal maxima and τ^{min} is the index of the local diagonal minima of the centre pixel $F_{m,n}$ and it is computed as follows:

$$\tau^{max} = \underset{i}{argmax}(sign(F^{i,T}_{m,n}) = 0, \forall T \in [0, 2]) \tag{16}$$

$$\tau^{min} = \underset{i}{argmin}(sign(F_{m,n}^{i,T}) = 1, \forall T \in [0,2]) \tag{17}$$

where *sign* is a function used to find the sign of the number and it is defined in Eq. (18).

$$sign(\lambda) = \begin{cases} 1, & \lambda \geq 0 \\ 0, & \lambda < 0 \end{cases} \tag{18}$$

Now, computed values and indices of the local diagonal extremas for the centre pixel $F_{m,n}$ will be used to compute the LDEDNP.

For each region, LDENP is encoded using the most positive and most negative position values to define a meaningful descriptor. The most important values are computed using the local diagonal extremas (i.e. maxima and minima) information–the most significant bit is assigned the positive direction and least significant bit is used for the negative direction. It is defined in Eq. 19

$$LDENP(m,n) = 4\tau^{max} + \tau^{min} \tag{19}$$

where (m,n) is the centre pixel value of the region, τ^{max} is the position of the top most negative direction and τ^{min} is the position of the top most positive direction which are defined in Eqs. (16) and (17) respectively.

LDENP computes a four bit code for each pixel in a 3×3 sub-image. In the LDENP, the four bit binary code per region contains at most three 1's. Hence, the number of unique patterns formed are $\binom{4}{3} + \binom{4}{2} + \binom{4}{1} + \binom{4}{0} = 15$. This forms the resulting feature vector with a size of $n \times 15$ where n is the number of blocks in the image.

2.3. Illustrative Example

In the proposed LDENP feature descriptor method, an image F of size 100×100 is divided into 3×3 blocks. The working mechanism of LDENP code for 3×3 image is shown in Fig. 2. The intensity value position of the $F_{m,n}^{i}$ and $F_{m,n}$

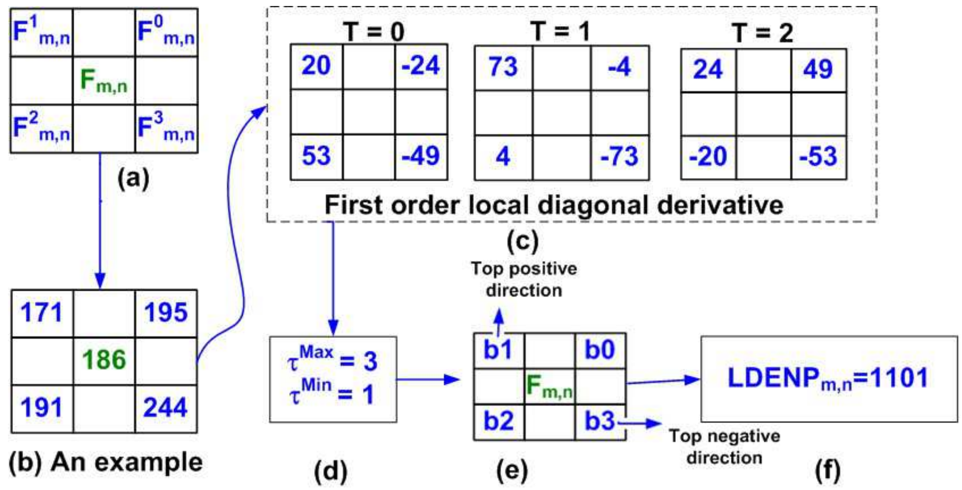

Figure 2: An example of the computation of $LDENP_{m,n}$ pattern for centre pixel $F_{m,n}$

are presented in the Fig. 2(a). The intensity values of the example 3×3 for $F^i_{m,n}$ and $F_{m,n}$ are displayed in Fig. 2(b). Fig. 2(c) shows the first order diagonal derivatives for $T = 0, 1$ and 2 computed on an example of Fig. 2(b). Fig. 2(d) displays the indices of the local diagonal extremas computed from Fig. 2(c) (i.e. first-order local diagonal derivatives). Fig. 2(e) displays the top most positive direction and top most negative direction position values, which are identified from the Fig. 2(c). Finally, LDENP pattern is depicted in Fig. 2(f) for the given example. Further, the encoded image F of size 100×100 is divided into the 4×4 regions and the histogram of each region is computed to get the final LDEDNP feature descriptor. Finally, the histogram bins are concatenated to extract the face image. The proposed descriptor is smaller in length than the other descriptors. Hence, it reduces the dimensionaly of the feature vector.

2.4. Face Description

After generating LDENP code in every pixel of an image, LDENP feature is used to generate an image descriptor. In this regard, histogram has been used to represent, analyze and characterize images. The reasons for choosing histogram are 1) It can be computed easily and efficiently, 2) It is robust to

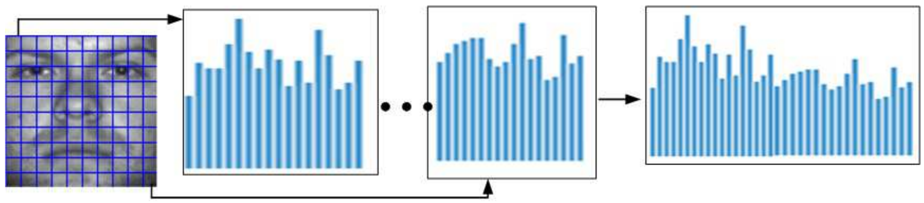

Figure 3: Face description by LDENP histogram

noise and local image transformations, and 3) It reduces the data to be processed significantly. In this work, the face is represented by LDENP histogram and it is shown in Fig. 3. The LDENP histogram contains high quality information of an image such as edges, corners, spots and other local texture features of the face. Histogram encodes only the number of occurrences of micro-patterns without location information, to aggregate the location information of the descriptor, the face image is divided into small regions $R_1, R_2, \cdots, R_N$ and extraction of individual histogram H_i from each region R_i is implemented. The histogram H_i is created by accumulating all the codes in the region with respective bin and it is defined in Eq. (20).

$$H_i(c) = \sum_{\substack{(m,n)\in R_i \\ LDEDNP(m,n)=c}} \upsilon, \forall c \tag{20}$$

where c is a LDENP code, (m, n) is a pixel position in the region R_i, $LDENP(m, n)$ is the LDENP code for the position (m, n), and υ is the accumulation value. Finally, LDENP histogram (LDENPH) is computed by concatenating those histograms, and it is defined in Eq. (21).

$$LDENPH = \prod_{i=1}^{N} H_i \tag{21}$$

where N is the number of regions of the divided face and Π is the concatenation operator.

2.5. Face Recognition

LDENPH is used for the face recognition process. The objective of face recognition is to compare the extracted encoded feature vector from the given query image with all other stored database candidate's feature vector using dissimilarity measure. Many dissimilarity measures are presented such as euclidean distance, city-block distance, chebyshev distance, minkowski distance, quadratic distance, canberra distance, non-linear distance, angular separation, log-likelihood, histogram intersection and chi square. From literature, it is evident that the chi square attains the better accuracy when compared to other dissimilarity measure. chi square measure between two vectors f_1 and f_2, of length L is defined in Eq. (22).

$$\chi^2(f_1, f_2) = \sum_{i=1}^{L} \frac{(f_1(i) - f_2(i))^2}{f_1(i) + f_2(i)} \tag{22}$$

The corresponding face of the feature vector with the minimum distance (lowest measured) value indicates the match found.

3. Experimental Results and Analysis

In this section, experimental results are described to show the performance of the LDENP feature descriptor for face recognition. The proposed LDENP descriptor was tested on four publicly available databases: FERET [28], Extended YALE-B [29], ORL [30] and LFW-a [31]. Regarding the length of the LDENP descriptor, the LDENP has a 15 different value, and length of the final descriptor will be a multiple of this length. Note that the similar methods has the greater lengths. For example, the basic length of: LBP [4] is 59, LTP [20] is 3^8, LD$_i$P [21] is 56, LD$_e$P [23] is 1024, LPQ [32] is 256, GGPP [33] is $256n_s$, where n_s is the number of scales, LDN^K [22] is 56, LDN^G [22] is 56 n, where n is the number of sigma, LDEP [26] is 24. In addition, all these lengths should be multiplied by the grid size. In comparison, the proposed LDENP is compact and reduces length of feature vector. Further, the proposed LDENP descriptor significantly improves the accuracy of the recognition system. We have analyzed the LDENP descriptor under different environmental conditions such as illumination variation, time lapse, different lighting conditions, pose and expressions. Moreover, the face images from these databases are cropped and normalized into 100×100 using eye location and mouth location provided by ground truth of each database or using a face detector. The experimental results are represented using recognition rate and accuracy. The recognition rate and accurcy are defined in Eqs (23) and (24) respectively.

$$RecognitionRate = \left(\frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \right) \times 100 \tag{23}$$

$$Accuracy = \left(\frac{\text{True Positive} + \text{True Negative}}{\text{Total number of images}} \right) \times 100 \tag{24}$$

3.1. Performance Analysis on FERET Database

The performance of LDENP feature descriptor for face recognition is tested with the FERET database in accordance with the CSU identification system. FERET database contains $14,501$ images of $1,010$ individuals with everyone's face image labelled. These images are divided into 5 set namely fa, fb, fc, dup I and $dup\ II$, moreover, five images are captured under various illumination conditions, poses, aging and expressions. Here, fa set is used as gallery images and the remaining sets $fb, fc, dup\ I$ and $dup\ II$ are used as probe images. fa contains frontal images of $1,010$ images. fb conatins $1,009$ images the expression variation, fc has 194 images with illumination variation, $dup\ I$ and $dup\ II$ contain time lapse variation images, there are 722 and 234 images in $dup\ I$ and $dup\ II$ respectively [28]. Fig. 4 shows the sample images of FERET database. Fig. 5 shows the sample single person image from different sets of the FERET database. Fig. 5(a) shows a sample image from fa set, Fig. 5(b) is a sample image from fb set, Fig. 5(c) displays the sample image from fc set, Fig. 5(d) show the sample images from $dup\ I$ set, which is captured within the one year of fa image and Fig. 5(e) exhibits the sample image from $dup\ II$ set, which was the subset of $dup\ I$ set and it has been captured at least 18 month after the corresponding fa image.

Figure 4: Sample images of FERET database

Table 1 shows the performance in terms of recognition rate when LDENP is compared with the PCA [34], LBP [4], LBP$_w$ [35], LTP [20], LD$_i$P [21], LD$_e$P [23], LPQ [32], GGPP [33], LDN^K [22], LDN$^G_{0.3,0.6,0.9}$ [22], LDN$^G_{0.5,1.0,1.5}$ [22], LDN$^G_{1.0,1.3,1.6}$ [22], LDEP [26]. The LDENP code outperforms other methods in the expression (fb) and time lapse variation sets (*dup I*, *dup II*). For the intensity variation set (fc), LDEP has the same accuracy as the best LDENP code, but not as fine as GGPP. However, LDENP code performance considerably drops compared to GGPP in illumination variation. Additionally, GGPP produces the leading result becuase it does not depend on the intensity. Therefore, we can say that the improvement of LDENP is the pre-processing of an image. From the result, it can be observed that the LDENP code works better for facial expression characteristics, and it matches similar face expression with different pose. To facilitate easier understanding, Fig. 6 shows a pictorial comparison between recognition rates of LDENP and other methods. Furthermore, performance of the LDENP code is evaluated using accuracy and false negative rate (miss rate) metrics and its result presented in Fig. 7 and Fig. 8 respectively. From the Fig. 7 and Fig. 8, it can be inferred that LDENP is more efficient than the other methods.

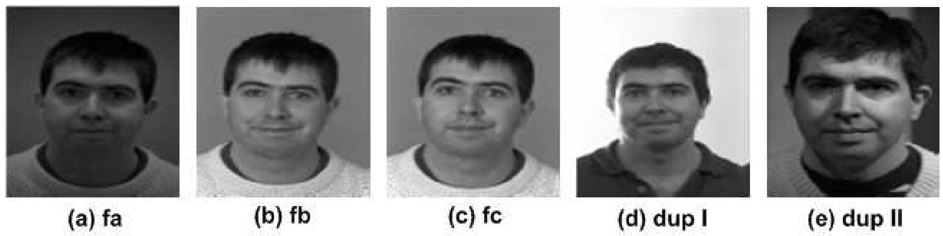

Figure 5: Example of different categories of single image from FERET database: (a) Sample fa image, (b) Sample fb image, (c) Sample fc image, (d) Sample $dupI$ image was taken within one year of fa image, (e) Sample $dupII$ image was taken atleast 18 months later.

Table 1: Comparison of recognition rate of the LDENP code and other methods in the FERET database

Method	fb	fc	dup I	dup II
PCA [34]	80.42	78.75	40.30	22.22
LBP [4]	80.99	84.69	64.9	48.62
LBP_w [35]	79.93	84.18	50.55	19.72
LTP [20]	84.30	36.22	52.26	22.94
LD_iP [21]	83.12	71.94	66.61	58.26
LD_eP [23]	85.10	79.35	63.45	61.21
LPQ [32]	84.89	88.78	63.34	46.79
GGPP [33]	87.60	**92.86**	70.67	66.97
LDN^K [22]	82.88	86.22	65.21	50.46
$LDN^G_{0.3,0.6,0.9}$ [22]	87.84	84.69	72.86	69.27
$LDN^G_{0.5,1.0,1.5}$ [22]	88.55	81.12	73.32	71.10
$LDN^G_{1.0,1.3,1.6}$ [22]	88.43	78.06	72.08	70.18
LDEP [26]	96.64	89.72	82.35	81.85
LDENP	**97.75**	89.97	**82.95**	**86.84**

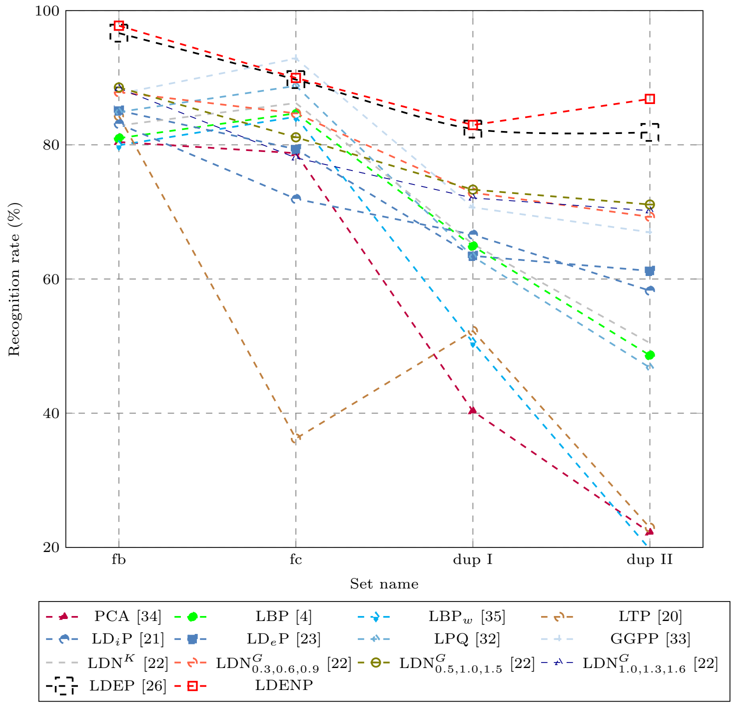

Figure 6: Graphical comparison of recognition rate of the LDENP code and other methods in the FERET database

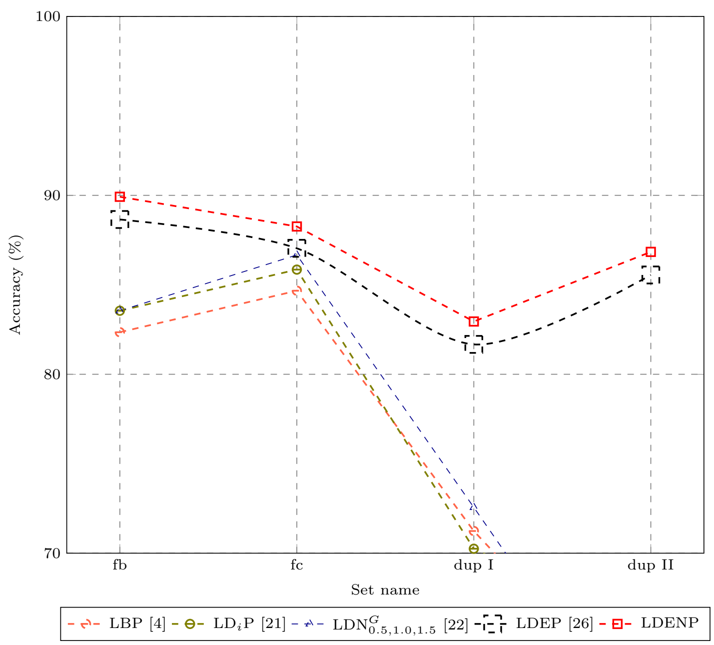

Figure 7: Graphical comparison of accuracy of the LDENP code and other methods in the FERET database

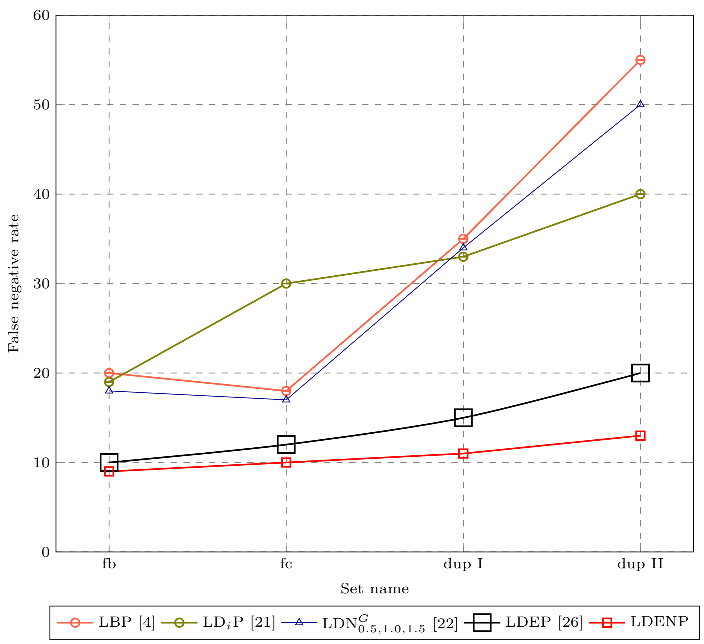

Figure 8: Graphical comparison of false negative rate of the LDENP code and other methods in the FERET database

3.2. Performance Analysis on Extended YALE-B Database

Furthermore, we tested the LDENP feature descriptor on the Extended YALE-B database. This database consists of $16,128$ images of 38 subjects and it is captured under varying illumination. Each subject has 9 poses with 64 different illuminations per pose. This database divides images into five subsets based on the angle of light directions. The five subsets are: $Sub1$ ($0°$ to $12°$), $Sub2$ ($13°$ to $25°$), $Sub3$ ($26°$ to $50°$), $Sub4$ ($51°$ to $77°$), and $Sub5$ (above $78°$). The difficulty of this database increases for subsets 4 and 5 because angles of illumination cover half of face with shadows. Here, $Sub1$ image set is used for gallery images and the other four sets $Sub2, Sub3, Sub4$, and $Sub5$ are used for probe images [29].

Fig. 9 shows the sample images of Extended YALE-B database. The difficulty of the database increases in sets four and five because illumination covers half of face with shadows and it is shown in Fig. 9 as the first two images. Moreover, the proposed descriptor reveals the result without preprocessing which proves the robustness of the descriptor. The proposed descriptor is evaluated against other methods: PCA [34], LBP [4], LBP_w [35], LTP [20], LD_iP [21], LD_eP [23], LPQ [32], LDN^K [22], $\text{LDN}^G_{0.3,0.6,0.9}$ [22], $\text{LDN}^G_{0.5,1.0,1.5}$ [22], $\text{LDN}^G_{1.0,1.3,1.6}$ [22], LDEP [26] and the results are shown in Table 2 as well as Fig. 10. Most of the methods perform well in the $Sub2$ and $Sub3$ sets, however, in $Sub4$ and $Sub5$, LDENP, GGPP, $\text{LDN}^G_{0.5,1.0,1.5}$ and LDEP give optimal performance. The LDENP takes the advantages of the first order diagonal extremas, which is robust in angle illumination variations, and uses the directional information to encode and produce the discriminative code. Furthermore, GGPP, $\text{LDN}^G_{0.5,1.0,1.5}$ and LDEP also perform well, but LDENP uses reduced feature length, hence, LDENP obtained the maximum recognition rate. Fig. 11 and Fig. 12 shows the accuracy and false negative rate results of the LDENP and the other methods. Therefore, recognition rates, accuracy and false negative rate metrics asserts that LDENP performs better than the other existing methods.

Figure 9: Sample images from Extended YALE-B database

Table 2: Comparison of recognition rate of the LDENP code and other methods in the Extended YALE-B database

Method	Sub2	Sub3	Sub4	Sub5
LBP [4]	100	100	90	85
LBP_w [35]	100	100	58	24
LTP [20]	100	100	89	58
LD_iP [21]	100	99	50	48
LD_eP [23]	100	98	65	62
LPQ [32]	100	100	83	55
GGPP [33]	100	100	95	95
LDN^K [22]	100	100	93	82
$\text{LDN}^G_{0.3,0.6,0.9}$ [22]	100	100	95	94
$\text{LDN}^G_{0.5,1.0,1.5}$ [22]	100	100	95	95
$\text{LDN}^G_{1.0,1.3,1.6}$ [22]	100	100	95	94
LDEP [26]	100	100	95	95
LDENP	**100**	**100**	**95**	**95**

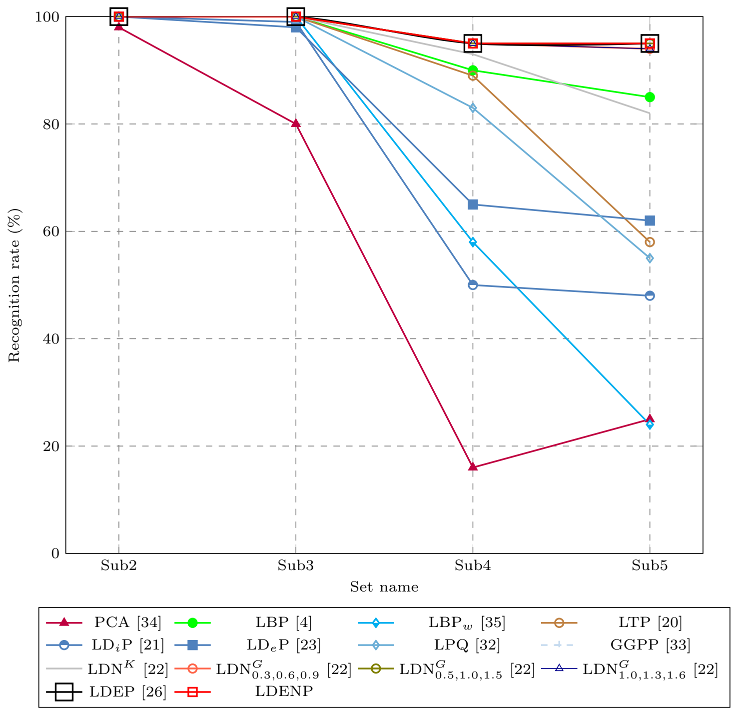

Figure 10: Graphical comparison of recognition rate of the LDENP code and other methods in the Extended YALE-B database

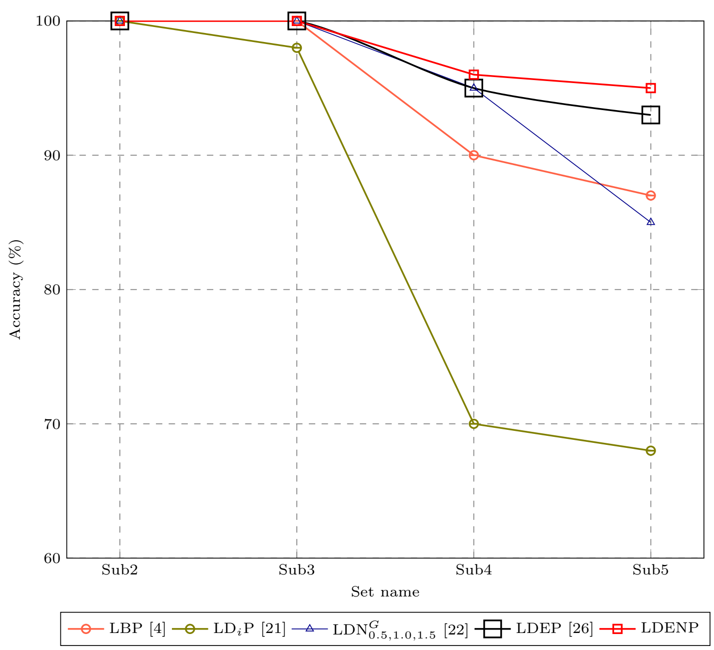

Figure 11: Graphical comparison of accuracy of the LDENP code and other methods in the Extended YALE-B database

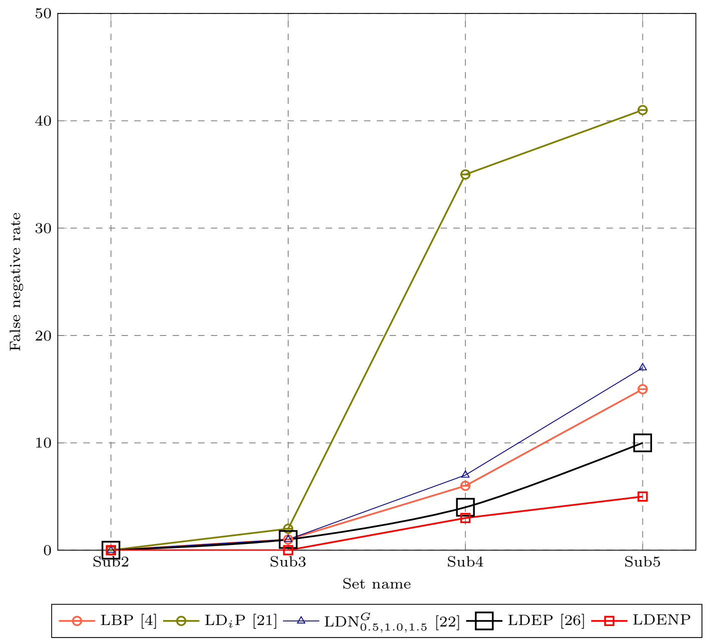

Figure 12: Graphical comparison of false negative rate of the LDENP code and other methods in the Extended YALE-B database

Figure 13: Sample images from ORL database

3.3. Performance Analysis on ORL Database

Additionally, the performance of LDENP feature descriptor was evaluated on the ORL database which contains 10 different images of 40 subjects in different light conditions, different expressions (open or closed eyes, smiling or non-smiling), and facial details (glasses or no-glasses). Further, all the images have changes in orientation and poses which have full frontal exposures. Moreover, from each subject, 2 images were selected randomly to be considered as gallery images, and the remaining images were used as probe images [30].

Fig. 13 shows the sample images of ORL database. The difficulty level of ORL database increases due to varying face expressions such as eyes open, eyes closed, smiling, non-smiling, glasses, no-glasses, changes in poses and orientation. Table 3 shows the result of LDENP compared with other methods: PCA [34], LDA [10], GLCM [36], Gabor wavelets [33], LBP [4], LDP [21], LDN [22], GLCM + LDP [21], LDEP [26]. The results are obtained without pre-processing the input image. PCA method attained the 82.26% recognition rate. Similarly, LDA, GLCM, Gabor wavelets, LBP, LDP, LDN, GLCM + LDP, LDEP methods obtained 86.67%, 80.50%, 87.56%, 87.80%, 88.50%, 89.15%, 92.70%, 93.40% recognition rates respectively. The LDENP earned a 94.60% recognition rate which indicates that the LDENP can work with different facial expressions. Further, the accuracy rate and false negative rate of the LDENP and other methods are shown in the Table 4 and Table 5 respectively.

Table 3: Comparison of recognition rate of the LDENP code and other methods in the ORL database

Method	Recognition rate
PCA [34]	82.26
LDA [10]	86.67
GLCM [36]	80.50
Gabor wavelets [33]	87.56
LBP [4]	87.80
LDP [21]	88.50
LDN [22]	89.15
GLCM + LDP [21]	92.70
LDEP [26]	93.40
LDENP	**94.60**

Table 4: Comparison of accuracy of the LDENP code and other methods in the ORL database

Method	Accuracy
LBP [4]	87.15
LD_iP [21]	88.8
LDN [22]	89.67
LDEP [26]	90.6
LDENP	**91.25**

Table 5: Comparison of false negative rate of the LDENP code and other methods in the ORL database

Method	False negative rate
LBP [4]	12.20
LD$_i$P [21]	11.50
LDN [22]	10.85
LDEP [26]	6.20
LDENP	**4.25**

3.4. Performance Analysis on LFW-a Database

To evaluate the robustness of the LDENP feature descriptor, a highly challenging database called labelled Faces in the wild (LFW) database has been used. The challenges are in-terms of pose, misalignment, large variations of illumination, occlusion and quality of image. The LFW database comprises a collection of labelled faces captured from web. LFW contains 13,233 images of 5,749 subjects. In this paper, an aligned version of LFW called LFW-a images are used. From the database, we have selected 158 subjects, each of which have not less than 10 face images [31]. For each subject, five images were randomly chosen for gallery, and the other images were used for probe.

Fig. 14 shows the sample images taken from LFW-a database. Table 6 shows the recognition rate results from the proposed LDENP and other methods: LBP [4], ATLP [37], Fisherface [38], Bitplane LBP [39], and LDEP [26] respectively. LBP, ATLP, Fisherface, Bitplane LBP and LDEP attained 24.90%, 29.90%, 24.30%, 55.80% and 56.67% recognition rate respectively, Whereas, the LDENP obtained 58.55% recognition rate which was higher than the other methods. Table 7 and Table 8 shows the accuracy and false negative rate results of the LDENP with the other methods LBP [4], LD$_i$P [21], LDN [22] and LDEP [26]. The accuracy is as follows: 87.15%, 88.80%, 89.67%, 90.60% and 91.25% for LBP, LD$_i$P, LDN, LDEP and LDENP. The false negative rate is as

Figure 14: Sample images of LFW-a database

Table 6: Comparison of recognition rate of the LDENP code and other methods in the LFW-a database

Method	Recognition rate
LBP [4]	24.90
ATLP [37]	29.90
Fisherface [38]	24.30
Bitplane LBP [39]	55.80
LDEP [26]	56.67
LDENP	**58.55**

follows: From the results, it is evident that the LDENP works better than the other methods.

4. Conclusion

In this paper, a novel LDENP feature descriptor has been proposed for face recognition. The proposed descriptor effectively could avoid the problem of increasing feature length. The efficiency and robustness of the proposed LDENP feature descriptor was tested against various illumination, pose, expression and

Table 7: Comparison of accuracy of the LDENP code and other methods in the LFW-a database

Method	Accuracy
LBP [4]	69.45
LD$_i$P [21]	71.32
LDN [22]	71.32
LDEP [26]	72.35
LDENP	**73.02**

Table 8: Comparison of false negative rate of the LDENP code and other methods in the LFW-a database

Method	False negative rate
LBP [4]	12.15
LD$_i$P [21]	11.32
LDN [22]	10.50
LDEP [26]	4.35
LDENP	**3.02**

lighting conditions captured in databases such as FERET, Extended YALE-B, ORL and LFA-a in face recognition. From the experimental results, it was evident that the LDENP descriptor outperforms other existing methods in terms of recognition rate, false negative rate and accuracy when tested on standard databases such as FERET, Extended YALE-B, ORL, and LFW-a. The LDENP descriptor produced the following results for recognition rate on FERET database: 97.75%, 92.90%, 82.95% and 86.84% for fb, fc, *dup I* and *dup II* sets respectively. Similarly, recognition rate resulted on Extended YALE-B are 100%, 100%, 96% and 96% for $Sub1, Sub2, Sub3$ and $Sub4$ sets respectively. For ORL and LFW-a database, recognition rates of 94.6% and 58.55% were obtained respectively. Hence, the LDENP descriptor could be used for efficient face recognition to solve problems under different conditions such as illumination, lighting condition, expression, varying pose and the presence of noise. For all the databases, the proposed LDENP provided better recognition rate and accuracy result and also could reduce the feature length when compared with existing methods.

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