

# Fusion of Discriminative Robust Local Binary Pattern and Local Directional Number Pattern for Face Recognition

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**ABSTRACT:** Local texture pattern is one of the most vital scenarios in face recognition. The recently proposed Discriminative Robust Local Binary Pattern (DRLBP) represents the image with the help of directional information, and it provides promising results. This paper proposes DRLBP-based face recognition using the descriptor Local Directional Number (LDN) pattern, which is used to encode directional information of the texture patterns within the regions. In the proposed approach, the face image is divided into regions and compute its edge response using compass mask, which is used to distinguish textures with similar structural patterns. It provides the information about the entire neighbourhood. The performance analysis of the proposed method is conducted using two standard databases – FEI (Centro Universitário da Fundação Educacional Inaciana) Face Database and INRIA (Institut National de Recherche en Informatique et en Automatique). The performance is compared with the earlier techniques such as Robust Local Binary Pattern (RLBP), Robust Local Ternary Pattern (RLTP) and DRLBP. The experimental results show considerable improvement in terms of noise level and threshold values when compared with the previous works.

**KEYWORDS:** Binary Pattern; Robust, Ternary Pattern, Discriminative, Directional, Threshold

## I. INTRODUCTION

The recognition of texture is one of the most important areas of research in pattern recognition. A wide array of applications of this technique is inspecting the surfaces, categorizing the materials, remote sensing, etc. Basically, the texture is one of the most important elements in the previous works and is categorized into micro and macro patterns. The spatial definition and the visual patterns of the face images are easily extracted, identified and represented using texture measures [1,2,3,4] even with different illumination conditions, intensity variations, appearance, etc. The modelling of the texture generally followed two-dimensional gray level variation to extract the feature after the images have been segmented into objects or regions. The texture discrimination in face images in terms of statistical properties are investigated in [5]. Co-occurrence statistics and difference histograms are the types of works related to statistical texture measures. In the later stage, advanced texture modelling techniques were applied to achieve variations in illumination, robustness to scale and rotational invariance. Rotational invariance is the most important application in texture classification that can appear in the captured object because of self-rotation or camera rotation. It is classified into three categories – global image rotation, local patch rotation and discarding local orientation.

Despite the numerous investigations of DRLBP and LDN as individual techniques in image processing and pattern recognition, the underlying working mechanism still has its own pros and cons and needs more investigation considering the information about the entire neighbourhood and its magnitude information. The texture descriptor proposed in this paper is based on the fusion of DRLBP and LDN, which can be used for discriminating the information derived from textures with similar structural patterns, and it provides the information about the entire neighbourhood (Figure 1). The framework effectively distinguishes different textures with similar structural patterns, and it provides information about the entire neighbourhood aiming to improve better recognition.

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The main advantages of the proposed system are: (1) the information about the entire neighbourhood is encoded using the directional numbers instead of bit strings; (2) both magnitude information and similar patterns are taken into account; (3) with implicit use of response sign, more information is encoded in less space; (4) the amount of noise is reduced much at the reasonable level.

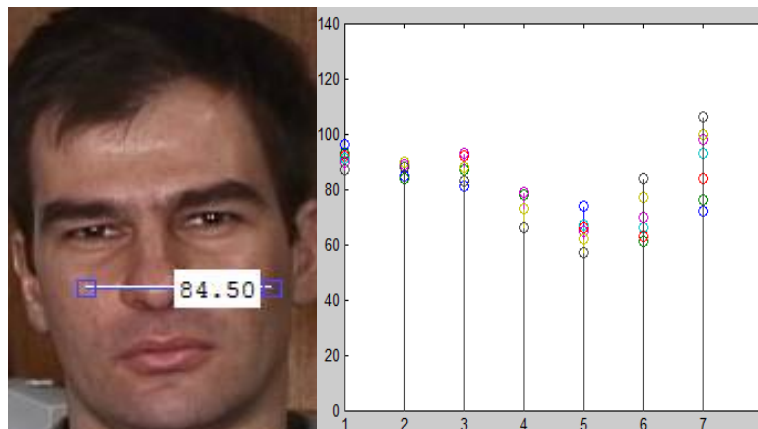


Figure 1. Module face with regions.

This paper is organized as follows: In Section 1, introduction and the review of face recognition are given. Sections 2 and 3 present the texture classification using DRLBP and LDN respectively. Section 4 describes the feature selection. Experimental results of the proposed work are presented in Section 5. Section 6 presents the summary and the scope of future work.

## II. RELATED WORKS

The Local Binary Pattern (LBP) is a method for texture analysis, which uses eight neighbouring pixels and the value of the centre pixel as a threshold. The values of the threshold are multiplied with the weights given to the corresponding pixels and are summed up to give an LBP code. Although the LBP is invariant to monotonic changes of the gray scale pixels, the local contrast supplements an independent measure for it [6,7,8]. The merits of LBP are (a) ease of implementation; (b) invariance of monotonic illumination changes, and (c) low computational complexity. Local Ternary Pattern (LTP) is an extension of LBP and is a three-valued texture operator, which is used to represent multiple patterns. The ternary code is split into positive and negative codes which may lead to significant loss of information. To some extent, the histograms of these two codes are correlated, and hence a lot of redundant information may reside in those histograms [9]. RLBP is an extension of LBP, which is used to resolve discrimination in contrast information and high intra-class variation [10,11,12]. RLTP is an extension of LTP, which is used to remove intra-class variation caused by LBP due to the discrimination of bright object against and dark background and vice versa [13]. DRLBP is an extension of RLBP. The direction of each pixel is constructed by computing the reference pixel and its adjacent pixel values with different directions and distances. The ultimate aim of using this technique is to retain the contrast information and also to minimize the intra-class variations [1,14,15]. The popularity of DRLBP is based on invariance to gray scale changes retaining the contrast information, high discriminative power, minimal intra-class variation and also its computational simplicity. In spite of the aforementioned advantages, there are some limitations in this technique – (1) the precision value is not necessarily accurate because the entire face image is considered as an input; (2) instead of the magnitude information, sign value of neighbourhood pixels alone is taken into account so that limited amount of structural information is captured. LDN is a face descriptor which is used to distinguish different textures with similar structural patterns, and it provides the information about the entire neighbourhood [16,17].

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### III. TEXTURE CLASSIFICATION USING DRLBP

RLBP is sensitive to noise and small pixel value fluctuations. LTP solves this problem by using two thresholds that create three different states. It is more resistant to noise and small pixel variations. RLBP is used to solve the problem of LBP and show the difference in bright object against a dark background and vice-versa. But it is not applicable to ULBP and LLBP of LTP. DRLBP overcomes all these issues, and it retains both the edge and the texture information that is desirable to distinguish face images clearly.

$$DRLBP = \sum_{i=1}^{i=9} w(x, y) * RLBP(x, y) \dots \dots \dots (1)$$

where  $w(x,y)$  is calculated by gradient operator by finding the square root of the magnitude in  $x$  and  $y$  directions.

### IV. TEXTURE CLASSIFICATION USING LDN

LDN encodes the directional information of the face images textures in a dense way producing a more discriminative code than current methods. To figure the structure of each micro-pattern with the support of a compass mask that extracts directional information and encodes such information using the well-known direction indices and sign, which allows us to distinguish among similar structural patterns that have different intensity transitions. Then the face images is divided into several regions and take out the distribution of the LDN features from them, then concatenate these features into a feature vector and used it as a face descriptor.

The descriptor performs consistently under illumination, noise, expression, and the time lapse variations. The LDN pattern is a six-bit binary code assigned to each pixel of an input image that represents the structure of the texture and its intensity transitions. As previous research indicates, edge magnitudes are largely insensitive to lighting changes. Accordingly, the pattern is created by computing the edge response of the neighbourhood using a compass mask, and by capturing the top directional numbers are both positive and negative directions of those edge responses.

The positive and negative responses give valuable information of the structure of the neighbourhood as they expose the gradient direction of bright and dark areas in the neighbourhood. Thus, this distinction between dark and bright responses allows LDN to discriminate between blocks with the positive and the negative directions swapped which is equivalent to swapping the bright and the dark areas of the neighbourhood by generating a different code for each case, while other methods may mistake the swapped regions as one. These transitions also occur repeatedly in the face image, for example, the top and the bottom edges of the eyebrows and mouth have different intensity transitions.

The code is generated using LDN, by analyzing the edge response of each mask,  $\{M_0, \dots, M_7\}$  that represents the edge significance in its respective direction and by combining the dominant directional numbers. Given that the edge responses are not equally important the presence of a high negative or positive value signals a prominent dark or bright area. Hence to encode these prominent regions, implicit use of sign information as to assign a fixed position for the top positive directional number as the three most significant bits in the code, and the three least significant bits are the top negative directional numbers.

$$LDN(x, y) = 8i_{x,y} + j_{x,y} \dots \dots \dots (2)$$

where  $(x,y)$  is the central pixel of the neighbourhood being coded,  $i_{x,y}$  is the directional number of the maximum positive response, and  $j_{x,y}$  is the directional number of the minimum negative response defined by:

$$i_{x,y} = \arg \max_i \{I_i(x, y) | 0 \leq i \leq 7\} \dots \dots \dots (3)$$

$$j_{x,y} = \arg \max_j \{I_j(x, y) | 0 \leq j \leq 7\} \dots \dots \dots (4)$$

where  $I_i$  is the convolution of the original image,  $I$ , and the  $i^{\text{th}}$  mask,  $M_i$  is defined by:

$$I_i = I * M_i \dots \dots \dots (5)$$

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To create the LDN code, a compass mask is used to compute the edge responses. The proposed code is analyzed using two different asymmetric masks: Kirsch and derivative-Gaussian. Both masks operate in the gradient space that reveals the face image structure. Gaussian smoothing is used to stabilize the code in the presence of noise by using the derivative-Gaussian mask. The Kirsch mask is rotated apart to obtain the edge response in eight different directions. This indicates the use of this mask to produce the LDN code by LDNK. Kirsch mask uses the derivative of a skewed Gaussian to create an asymmetric compass mask that is used to compute the edge response on the smoothed face. This mask is strong against noise and illumination changes while producing strong edge responses. Therefore, the Gaussian mask is defined by

$$G_{\sigma}(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \dots\dots\dots(6)$$

where  $x$  and  $y$  are location positions, and their width of the Gaussian bell; this defines the mask as:  $M_{\sigma}(x, y) = G_{\sigma}(x+k, y) * G_{\sigma}(x, y)$  where  $y$  is the derivative of  $G_{\sigma}$  with respect to  $x$ ,  $\sigma$  is the width of the Gaussian bell,  $*$  is the convolution operation, and  $k$  is the offset of the Gaussian with respect to its centre. A compass mask is generated,  $\{M_{0\sigma}, \dots, M_{7\sigma}\}$ , by rotating  $M_{\sigma}$   $45^{\circ}$  apart in eight different directions. Thus, a set of masks is obtained.

## V. FEATURE SELECTION

This section demonstrates the role and effect of similar patterns, which are generally discarded in most of the existing LBP approaches because this also contains discriminative information. In general, similar patterns are known to exhibit high discriminative patterns, and it does not generalize across different datasets because for complex images, similar patterns may not be the most frequently occurring ones [18,19]. To overcome this kind of drawback, the fusion of similar patterns of DLRBP and LDN performed and it contributes to both reducing the length of the feature vector and improving the performance of classifiers. In the proposed algorithm, the subset of discriminative patterns of each dataset from the training images is created based on most frequently occurring similar patterns and is used for classification. Let  $X_1, \dots, X_N$  represent the training images where the images are resized to  $128 \times 128$  pixels by using down-sampling method. The histograms ( $HG$ ) are computed for all the training images ( $HG_i \in \mathbb{R}^{2^f}$ ), and are bin-wise summed together to find the distribution of patterns from the training images  $HG = HG_1 + \dots + HG_N$ . The bins of the summed histogram  $HG$  are sorted in the descending order, and the patterns corresponding to the first  $K$  bins are selected. The value of  $K$  is calculated as follows:

$$K = \arg \min_N \frac{\sum_{i=1}^{N-1} HG[i]}{\sum_{i=1}^P HG[i]} > \tau \dots\dots\dots(7)$$

The total number of patterns ( $K$ ) selected by the algorithm depend on the threshold parameter ( $\tau$ ) and the training data. Hence the dimensionality of the feature is not constant, but varies across different datasets. Here, the threshold value ( $\tau$ ) plays an important role in authentication system to identify whether a person is genuine or an imposter. Its value is obtained by summing up the distance between each image of the same face and by dividing with the number of images being compared [20]. The result of the mean image is used as a threshold. The threshold is chosen as  $\tau=2, 5, 8, 10, 13$  and  $16$ . The maximum value of the  $\tau$  is restricted to  $16$  because of dimensionality issues, and the computational complications arise in higher values. It affects the improvement in performance substantially. The False Acceptance Rate (FAR) is the error calculation when the system rejects the face that is stored in the database. False Rejection Rate (FRR) is the error calculation when the system is receiving or identifying a face which is not registered [21]. The formulas for FAR and FRR and the accuracy of the authentication system are provided below:

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$$FAR = \frac{\text{Wrongly accepted faces}}{\text{Total number of correct matching}} \dots\dots\dots(8)$$

$$FRR = \frac{\text{Wrongly rejected faces}}{\text{Total number of correct matching}} \dots\dots\dots(9)$$

$$Accuracy(\%) = (100 - (FAR(\%) + FRR(\%)) / 2)$$

Gaussian noise is a general kind of noise that arises due to illumination, environmental circumstances, and so on. It really affects the quality and visualization of an image. For better recognition, noise needs to be removed from the face image and its probability density function is given by the expression:

$$P(G) = \frac{e^{-(G-\mu)^2/2V}}{\sqrt{2\pi\sigma}} \dots\dots\dots(10)$$

where  $G$  = gray level;  $\mu$  = mean of average value of  $G$ ;  $\sigma$  = standard deviation, and  $V$  = variance. The distortion level represented by noise variance is uniformly sampled on a log-scale between 0.1, 0.15 and 0.2 [22,23].

## VI. EXPERIMENTAL RESULTS

An empirical study is done extensively to evaluate the existing approaches and the proposed techniques with various variables and conditions. The proposed method is tested on two different texture datasets – FEI Face Database and INRIA Database. The major findings of this study are that texture features can often be characterized as noise level and threshold values that make us impart the human expressions in a better way.

- (1) *FEI Face Database*: The dataset consists of 2800 images from 14 different texture classes under different lighting conditions, rotations, and pose variations. The testing set consists of 2380 images, and the training set consists of  $(14 \times 30) = 420$  images. It can be observed that the modifications in the proposed descriptors have achieved highest accuracy, 89.6%, 92.99% and 95.90% at the threshold values 10, 16 and 16 respectively for RLBP+LDN, RLTP+LDN and DRLBP+LDN. The highest recognition rate for the noise level is 98.99% at  $P(G)=0.1$ . The results of this experiment are shown in Figures 2 and 4, and Tables 1 and 2 respectively.

**Table 1. Noise level with recognition rate – FEI database.**

FEI	Different Noise Level ( $P$ ) with Recognition Rate		
	$P(G)=0.1$	$P(G)=0.15$	$P(G)=0.2$
RLBP	94.78	80.89	73.56
RLTP	92.34	90.67	89.55
DRLBP	93.65	94.45	91.45
LDN	95.41	93.89	93.21
RLBP+LDN	96.23	95.76	94.27
RLTP+LDN	96.89	95.29	93.78
DRLBP+LDN	98.97	97.26	95.91

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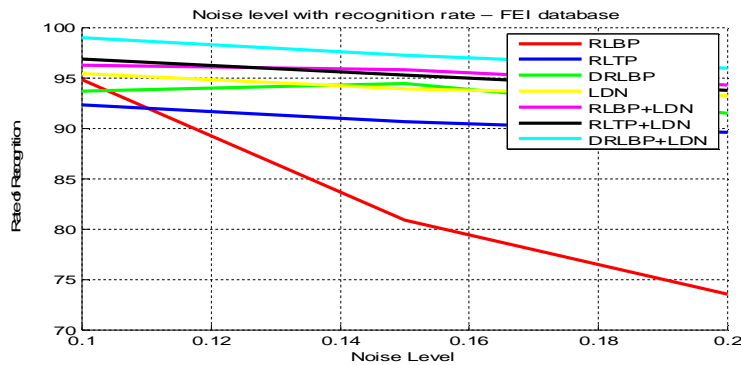


Figure 2. Noise level with recognition rate – FEI database.

Table 2. Threshold values with recognition rate – FEI database [15].

	$T$	FAR	FRR	Accuracy
RLBP	2	18	20	81
	5	17.5	16.9	82.8
	8	16.9	17.2	82.95
	10	17	16	83.5
	13	15.7	14.3	85
	16	14.7	15.9	84.7
RLTP	2	15.5	17.4	83.55
	5	16.2	17.5	83.15
	8	15.9	16.7	83.75
	10	16.3	14.3	84.7
	13	15.5	14.6	84.95
	16	14.5	12.9	86.3
DRLBP	2	11.5	14.6	86.95
	5	10.7	9.6	89.9
	8	8.5	9.5	91
	10	7	9	92
	13	6.5	8.5	92.5
	16	7	7.5	92.75
LDN	2	12	13.6	87.2
	5	10	8.8	90.6
	8	8.5	10.8	90.35
	10	8.8	9.7	90.75
	13	7	8.9	92.05
	16	7.2	7	92.9
RLBP+LDN	2	14	15.9	85.5
	5	14	14.98	85.51
	8	8.4	14	88.8
	10	9	11.8	89.6
	13	10.3	12.7	88.5
	16	11.7	15.9	86.2
RLTP+LDN	2	14.5	15.4	85.05
	5	11.2	17.5	85.65
	8	12	17.3	85.35



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	10	9.56	12.3	89.7
	13	8.5	11.6	89.95
	16	5.23	8.78	92.99
<b>DRLBP+LDN</b>	2	8.67	11.34	89.99
	5	3.5	5.5	95.5
	8	6.2	9.3	92.25
	10	4.2	5.8	95
	13	4.3	5.8	94.95
	16	4	4.23	95.89

(2) *INRIA Database*: As for the dataset, 12,180 windows are sampled randomly from 1218 negative training photos under different lighting conditions, rotations, and pose variations. Then, the images are rotated at nine different angles (0°, 5°, 10°, 15°, 30°, 45°, 60°, 75° and 90°). The testing set consists of 11,630 images and the training set consists of 550 images. The results of this experiment are shown in Figures 3 and 5, and Tables 3 and 4 respectively. It can be observed that the modifications in the proposed descriptors have achieved highest accuracy, 90.05%, 93% and 95.89% at the threshold values 10, 16 and 16 for RLBP+LDN, RLTP+LDN and DRLBP+LDN. The highest recognition rate for the noise level is 98.89% at  $P(G)=0.1$ .

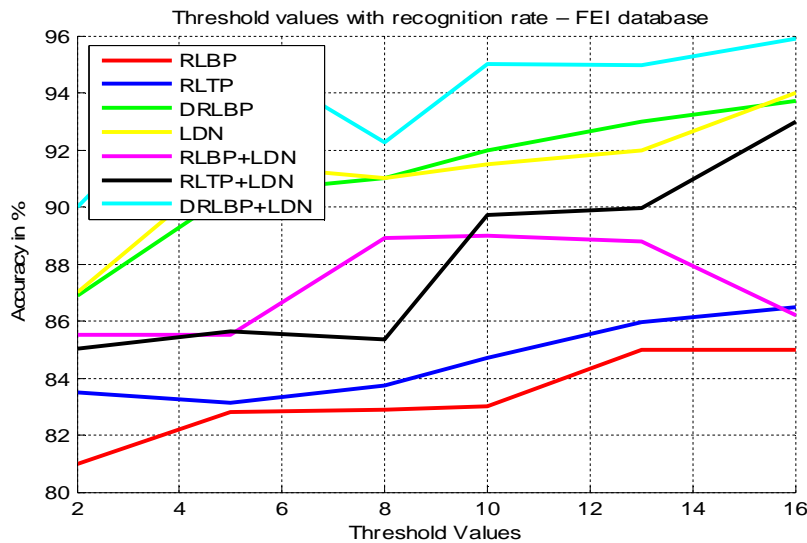


Figure 4. Threshold values with recognition rate – FEI database.

Table 3. Noise level with recognition rate – INRIA database.

INRIA Methods	Different Noise Level ( $P$ ) with Recognition Rate		
	$P(G)=0.1$	$P(G)=0.15$	$P(G)=0.2$
<b>RLBP</b>	93.25	87.25	90.1
<b>RLTP</b>	91.23	90.29	86.55
<b>DRLBP</b>	92.49	95.34	92.21
<b>LDN</b>	96	92.41	91.3
<b>RLBP+LDN</b>	94.29	94.37	93.33
<b>RLTP+LDN</b>	96.45	95	94.19
<b>DRLBP+LDN</b>	98.99	97	96

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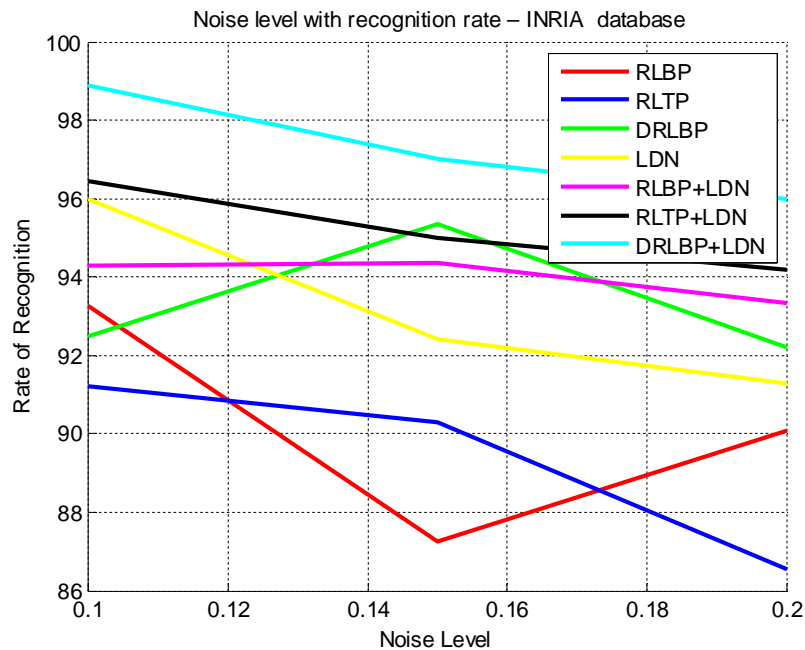


Figure 3. Noise level with recognition rate – INRIA database.

Table 4. Threshold values with recognition rate – INRIA database [15].

	$T$	FAR	FRR	Accuracy
<b>RLBP</b>	2	17	19	82
	5	16.5	17	83.25
	8	16	17	83.5
	10	16	15	84.5
	13	15	14.3	85.35
	16	14.7	15.9	84.7
<b>RLTP</b>	2	15	16	84.5
	5	15.5	17	83.75
	8	17	14	83.5
	10	16.5	14	84.75
	13	15	16.6	84.2
	16	14	13.5	86.25
<b>DRLBP</b>	2	11.5	14	87.25
	5	11	12	88.5
	8	8	9.5	91.25
	10	8	9	91.5
	13	7	8.5	92.25
	16	8	7	92.5
<b>LDN</b>	2	12.5	13	87.25
	5	10	8	91
	8	9	10.8	90.1
	10	8.5	10	90.75
	13	7	8.5	92.25
	16	6	7	93.5



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<b>RLBP+LDN</b>	2	14	15.9	85.05
	5	13	14	86.5
	8	8	14.9	88.55
	10	8	11.9	90.05
	13	9.3	13.7	88.5
	16	11.9	17.9	85.1
<b>RLTP+LDN</b>	2	14.5	15.4	85.05
	5	11	17.9	85.5
	8	12	17.8	85.1
	10	9.5	16.9	86.8
	13	8	12.6	89.7
	16	5	9	93
<b>DRLBP+LDN</b>	2	8	12.9	89.55
	5	3	5.5	95.75
	8	6	10.6	91.7
	10	4	6	95
	13	4.1	5.97	94.96
	16	4	4.23	95.89

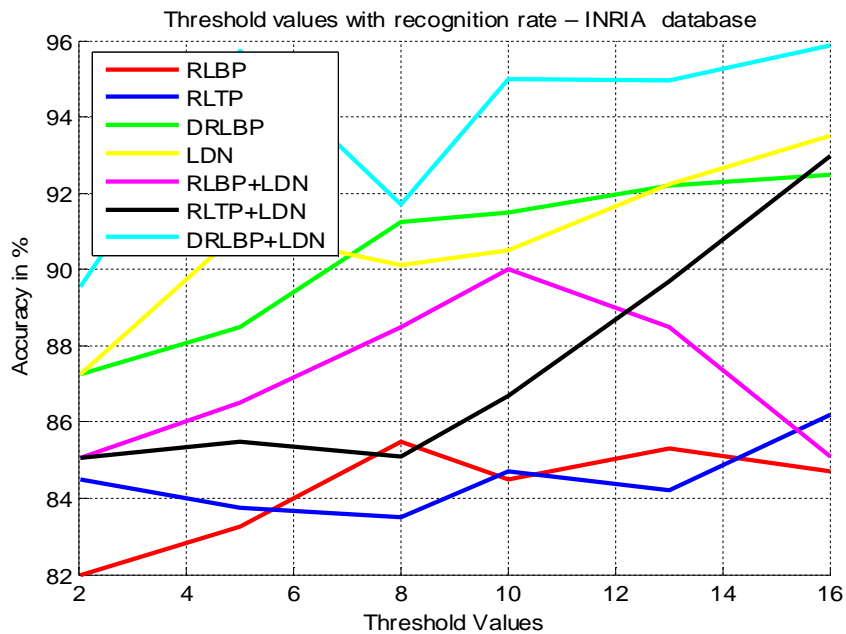


Figure 5. Threshold values with recognition rate – INRIA database.

## VII. CONCLUSION

The fusion of DLRBP with LDN is analysed as a descriptor for texture classification. The issues of uniform patterns are specifically addressed and the selection that effectively distinguishes textures with similar structural patterns, and it provides the information about the entire neighbourhood. Extensive experiments have been conducted on two standard datasets. The obtained results demonstrate that the proposed descriptor gives better performance at the noise level  $P(G)=0.1$  and the rate of recognition is 98.99% for FEI Database and 98.89% for INRIA Database,

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respectively. The implementation of the proposed framework may be extended to a group of persons, which involves counting the number of face images, gender identification and also image compression and transmission. The classification of gender can be identified using either geometric-based or appearance-based feature extraction by detecting the portion of the face image and removing the background regions. The vital features in this technique are hair, forehead, brows, eyes, nose, mouth and clothes.

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