

Face Recognition using Local Patterns

Mukesh D. Rinwa

Department of Information Technology
Amrutvahini College of Engineering (AVCOE)
Sangamner, Ahmednagar Dist., India
e-mail: mukesh_rinwa@yahoo.com

Prof. Bharat S. Borkar

Department of Information Technology
Amrutvahini College of Engineering (AVCOE)
Sangamner, Ahmednagar Dist., India
e-mail: borkar.bharat@gmail.com

Abstract— Deriving an effective face representation is very essential task for automatic face recognition application. In this paper we used a feature descriptor called the Local Directional Number Pattern (LDN), which allows individual's face recognition under different lighting's, pose and expressions. Face recognition deals with different challenging problems in the field of image analysis and human computer interface. To deal with attention in our proposed work we use local patterns, a local directional number pattern (LDN) method, a six bit compact code for face recognition and understanding. By using LDN method we encode the directional information of the face images by convolving the face image with the compass mask. This compass mask extracts the edge response values in eight directions in the neighborhood. For each pixel we get the maximum and the minimum directional values which generate a LDN code i.e. generating an LDN image. Later LDN image is divided into number of blocks for each block histogram is computed and finally adds these histogram from each block to form the feature vector which acts as face descriptor to represent the face images. We perform different experiments under various illumination, pose and expression conditions.

Keywords- Biometrics, face recognition, feature extraction, feature vector, Local patterns, Local Binary Pattern, Local Directional Number Pattern.

I. INTRODUCTION

In the Recent years, automated method of recognizing a person is going to be more popular like by using biometric system. A biometric has shown an increasing interest in many fields such as surveillances, human computer interface, and security identification. Biometric recognition is an automated method of recognizing an individual by means of comparing the feature vector derived from the behavioral and the physiological distinctiveness. Previously in traditional based recognition system used Password, PIN's, Identity cards, Badges etc. There are several limitations of using traditional based system like passwords are hardly to remembered or sometimes it may be forgotten. Tokens may be forgotten, mis-placed, stolen or lost. Whereas, in biometric systems it cannot be stolen or forged. It does not require any remember of password or PIN. Various types of biometric techniques are Face recognition, Iris recognition, Palm recognition, Retina recognition, Voice recognition, Gait recognition etc. Among them face recognition system is most easily accepted by user due to the use of very few inexpensive camera's and also doesn't require active user participation [1], [2].

There are two types of approaches to recognize an individual: geometric-feature-based and appearance-based methods. In Geometric feature based method which encodes the shape and the locations information of different types of the facial components which are added to form the feature vector that represents the face images. But this method is graph based method usually requires the accurate and reliable facial feature detection and tracking system which is very difficult in different environmental conditions. And the appearance based methods used either holistic features or local features to extract the different features from the face images. To create the holistic features use image filters on the whole face and to create local features use image filters on some specific face region to extract the appearance changes in the facial images. But the performance of the

holistic approaches degrades in environmental variations [3]. There are various techniques used for the holistic approach like eigenfaces, fisherfaces etc. and the techniques used for the local approaches are Gabor features, Elastic Bunch Graph Matching (EBGM), Local Binary Pattern (LBP) etc among them LBP achieved better performance it's a 3*3 matrix which generates the LBP code by computing the referenced or centre pixel with the neighboring pixels. But this method works better in the monotonic illumination changes but however the performance degrades in the highly environmental variations like illumination, random noise etc to overcome these problems Local Ternary Pattern (LTP), Local Derivative Pattern(LDP) and Local Directional Pattern (LD_iP) was developed. The last method used directional information instead of intensity to overcome the noise and illumination variation problems. But these methods still lag to extract the discriminated information to overcome this Local Tetra pattern(LTrP) was developed which extracts the information in the (n-1)th horizontal and the vertical derivatives for efficient face recognition but this method suffers from the high redundancy problems and feature length increasing. To overcome the feature length problems in our proposed work we use Local Directional Number Pattern for efficient face recognition techniques, a six bit code which extracts the directional information by convolving compass mask with the input image and obtaining the maximum and the minimum direction values to generate the six bit micropatterns and corresponding an LDN image is generated. Generated LDN image is later divided into number of blocks to extract the histogram of the each blocks and concatenating these histogram from each block to form the feature vector which acts as the face descriptor which later used to describe the face images.

The rest of this paper is discusses as follows. Section II briefly discuss about what are the various local patterns used for face recognition like LBP, LDP, LTP, LD_iP, LTrP etc which describe the properties of these methods for encoding

the micropatterns. In Section III discusses about the proposed Local Directional Number Patterns (LDN) in detail. Section IV discusses about the experimental results and discussions. Finally conclusions are given in section V.

II. LITERATURE SURVEY

In the proposed work we are working on the local pattern approach for face recognition and understandings. This section gives brief idea about what are the different local pattern approaches used for face recognition like LBP, LDP, LTP, LD_iP, LTrP etc.

A. Local Binary Pattern

T. Ahonen et al and Zhang et al in [4], [5] defines LBP is a simple 3*3 matrix which having one centre pixel and eight surrounding neighbor pixels. The binary result is obtained by computation of the reference pixel with all the eight neighboring pixels. LBP is mainly used for texture analysis of the image it works better in monotonic illumination variations but however, it performance degrades with non-monotonic illuminations variations like random noise etc. and also LBP don't capture the dominant information in large scale structure due to very less number of the surrounding pixels [7], [8].

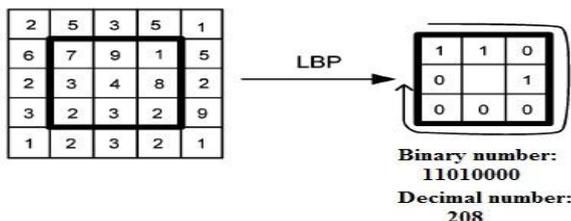


Figure 1. The basic LBP operator [6].

B. Local Derivative Pattern

LBP method is not captured the dominant information in very large scale structures due to sparse points of pixels to overcome this limitation Zhang et al. in [6] proposed a new descriptor called the Local Derivative Patterns(LDP), in which the (n-1)th order derivative direction variations based on a binary coding function, this LDP operator is 32 bit code which encodes the higher-order derivative information which contains more detailed discriminative features that the first order LBP cannot obtained from an image.

In a general formulation, the nth- order LDP is a binary string describing gradient trend changes in a local region of directional (n-1)th-order derivative images $I_{\alpha}^{n-1}(Z)$ as $LDP_{\alpha}^n(Z_0) = \{f(I_{\alpha}^{n-1}(Z_0), I_{\alpha}^{n-1}(Z_1)), \{f(I_{\alpha}^{n-1}(Z_0), I_{\alpha}^{n-1}(Z_2)), \dots, \{f(I_{\alpha}^{n-1}(Z_0), I_{\alpha}^{n-1}(Z_8))\} \}$ (1)

Where $I_{\alpha}^{n-1}(Z_0)$ is the (n-1)th- order derivative in α direction at $Z=Z_0$. $\{f(I_{\alpha}^{n-1}(Z_0), I_{\alpha}^{n-1}(Z_i))\}$ is defined as,

$$f(I_{\alpha}^{n-1}(Z_0), I_{\alpha}^{n-1}(Z_i)) = \begin{cases} 0, & \text{if } I_{\alpha}^{n-1}(Z_i) \cdot I_{\alpha}^{n-1}(Z_0) > 0 \\ 1, & \text{if } I_{\alpha}^{n-1}(Z_i) \cdot I_{\alpha}^{n-1}(Z_0) \leq 0 \end{cases}, i=1,2,\dots,8 \quad (2)$$

The nth-order LDP is a local pattern string defined as, $LDP^n(Z) = \{LDP_{\alpha}^n(Z) | \alpha=0^0, 45^0, 90^0, 135^0\}$. (3)

C. Local Ternary Pattern

LBP is sensitive to noise to overcomes this problem, Tan and Triggs introduced a generalization of LBP called Local Ternary Patterns(LTP) which is less sensitive and more

discriminative to noise in uniform regions.LTP is a 3 coded value 1,0, & -1. In LTP gray levels in a zone of width $\pm t$ around i_c are quantized to zero, one above this are quantized to +1, and one below to it quantized to -1. One problem of using this method is to set threshold t, which is not a simple [8] [9].

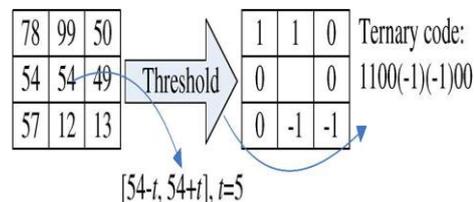


Figure 2. Illustration of basic LTP Operator [9].

D. Local Directional Pattern

LD_iP descriptor considers the edge response values derived from the kirsch gradient operator in eight directions around a pixel, see Kirsch mask in fig.3. LD_iP codes are generated by setting the k most prominent directional bits to 1 and remaining bits are set to 0. This method ignores the distinction between the most prominent edge response direction and the second most prominent one [10].

E. Local Tetra Pattern

Murala et al. in [11] found that the single high order derivative direction (1D) relationship of the LDP can be extended to the two higher order derivative direction (2D) relationships in terms of the LTrP which adopts both the horizontal and vertical high order derivative directions. LTrP encodes with four distinct values by using 0⁰ and 90⁰ directions which extracts more detailed discriminative information than the LDP which only considers 1D direction with two distinct values. In order to encode the nth-order LTrP, the (n-1)th-order derivatives along 0⁰ and 90⁰ direction.

And the direction of the center pixel can be calculated as,

$$I_{Dir}^1(g_c) = \begin{cases} 1, & I_{0^0}^1(g_c) \geq 0 \text{ and } I_{90^0}^1(g_c) \geq 0 \\ 2, & I_{0^0}^1(g_c) < 0 \text{ and } I_{90^0}^1(g_c) \geq 0 \\ 3, & I_{0^0}^1(g_c) < 0 \text{ and } I_{90^0}^1(g_c) < 0 \\ 4, & I_{0^0}^1(g_c) \geq 0 \text{ and } I_{90^0}^1(g_c) < 0 \end{cases} \quad (4)$$

The second-order LTrP²(g_c) is defined as,

$$LTrP^2(g_c) = \{f_3(I_{Dir}^1(g_c), I_{Dir}^1(g_1)), f_3(I_{Dir}^1(g_c), I_{Dir}^1(g_2)), \dots, f_3(I_{Dir}^1(g_c), I_{Dir}^1(g_p))\}_{p=8} \quad (5)$$

$$f_3(I_{Dir}^1(g_c), I_{Dir}^1(g_p)) = \begin{cases} 0, & I_{Dir}^1(g_c) = I_{Dir}^1(g_p) \\ I_{Dir}^1(g_p), & \text{else} \end{cases} \quad (6)$$

Therefore, the generalized formulation for the nth-order LTrP can be defined by using (n-1)th-order derivatives in horizontal and vertical directions $I_{\theta}^{n-1}(g_p) | \theta=0^0, 90^0$ as, $LTrP^n(g_c) = \{f_3(I_{Dir}^{n-1}(g_c), I_{Dir}^{n-1}(g_1)), f_3(I_{Dir}^{n-1}(g_c), I_{Dir}^{n-1}(g_2)), \dots, f_3(I_{Dir}^{n-1}(g_c), I_{Dir}^{n-1}(g_p))\}_{p=8}$ (7) from (5) and (6), we get 8-bit tetra pattern for each center pixel. After that separate all the patterns into four parts based on the direction of center pixel. Finally, the tetra patterns for each directions are converted to three binary patterns.

$$LTrP^2|_{Direction=2,3,4} = \sum_{p=1}^P 2^{(p-1)} \times f_4(LTrP^2(g_c))|_{Direction=2,3,4} \quad (8)$$

$$f_4(LTrP^2(g_c))|_{Direction} = \phi = \begin{cases} 1, & \text{if } LTrP^2(g_c) = \phi \\ 0, & \text{else} \end{cases} \quad (9)$$

Where $\phi = 2,3,4$

Similarly, the other three tetra patterns for remaining three directions (parts) of the center pixels are converted to binary patterns. Thus, we get 12(4x3) binary patterns. Therefore, totally 4x3x8=96 bit LTrP pattern is generated which increases the feature length and high redundancy problems.

III. PROPOSED SYSTEM

In our proposed work we are going to use Local Directional Number Pattern (LDN), a six bit binary code which is assigned to each pixel of an input image which represents the structure of the texture and its intensity transitions. In the Previous work like in LBP which is very sensitive to illuminations variations and noise to overcome this problem, we create our pattern using compass mask for computing the edge response of the neighborhood by taking the top directional numbers, which are the most positive and the negative directions of the edge responses. These positive and the negative responses provide essential information of the structure of the neighborhood as they give the direction of the bright and the dark areas in the neighborhood. These most positive and the negative direction information's generates a six bit LDN code corresponding to it an LDN image is generated. The LDN image is divided into number of blocks, for each block an histogram is computed which forms the feature vector after combining these histograms for each blocks. This procedure is done both for the training image and the test image, comparing the feature vector using the chi-square distance formula the value which is minimum will gives the recognized image. This method is robust as this method gives different values for different regions of the intensity variations for example like dark and the bright regions [12].

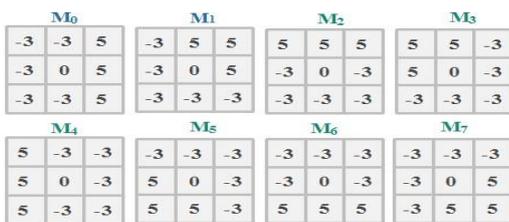


Figure 3 . Kirsch's Template in eight directions [12].

In the our proposed work we use Kirsch compass mask and the Sobel operator which extracts the edge response of the face image as well as smoothing the face image from noise and illumination variation to produce a robust code.

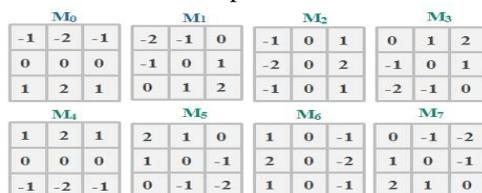


Figure 4. Sobel Template in eight directions.

Our Proposed System is divided into following modules:
Image Sensor: The Image sensor (i.e. Camera) is used to capture the face image. As we are using the standard face database as a gallery and probe images, the block 'Image sensor' is shown here only for the completion of the system diagram.

Face Alignment: Pre-processing the data before extracting the features from the data, its function is to eliminate the noise from the data, and to resize the data so that all the data to be compared should have same dimensions. The images in the PIE database are cropped and resized using MATLAB- Image Processing Toolbox.

Feature Extraction: Before extracting the features from the face image. It is preprocessed using the Kirsch and then Sobel compass masks separately. After convolving with each mask a high pass filtered image is obtained. This image contains most of the information related with edges. The edge contains prominent information for the discrimination between the objects. From this eight images, taking into the directional information in the positive (max value) and negative (min value) a LDN code for each pixel is generated. Repeating this procedure for all pixels finally we get an LDN image. This LDN image is then divided into 4x4 regions. The histogram of each region is calculated. Hence we have 16 histograms for a LDN image. These histograms represents feature vector for the given face image. This face features are termed as face descriptor. Each Object (Face) has its own face descriptor.

Classification: To recognize/classify the object, its face descriptor is compared with the face descriptor of all objects in the database. For this we are using Chi-Square dissimilarity measure (distance formula) between the two face descriptors. The object (face) which has smallest (value) difference after comparison with the gallery images (training database) is treated as recognized object. Such algorithm is termed as Nearest Neighbor (NN) algorithm.

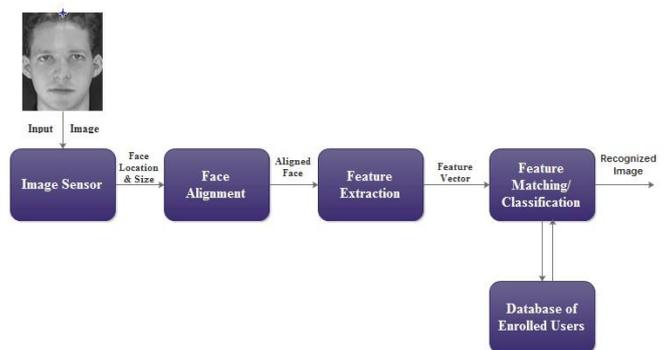


Figure 5. Proposed Face Recognition Architecture Using LDN.

Algorithm:

Input: Query image; Output: recognized image

1. Load the image, and convert it into grayscale image.
2. Apply the compass mask with the original face image to get the directional information.
3. Select the maximum and the minimum position direction from the neighborhood of the face image.

4. Concatenate the maximum and the minimum position direction to form the LDN code, and corresponding LDN image is generated.
5. Divide the LDN image into number of blocks, for each block calculates their histogram.
6. Concatenate the histograms from each block to form the feature vector.
7. Similarly, calculate the histogram for training image to form the feature matrix (this step requires only once at the first time when the application is initialized.)
8. Compare the feature vector of the query image with the feature vector of training image using Chi-Square dissimilarity measure.
9. The value which is minimum indicates the recognized image.

Mathematical Modeling

$f(x,y)$ denotes the input image of an object, where x & y represents the coordinates of an image and $f(x,y)$ represents intensity or gray level of an image. The input image may be color or monochrome. If it is color image it is converted into gray image first and then processed. Here in the proposed work we use two different compass masks to generate the LDN code which convolve with input image in 8 directions to obtain the directional information.

The input image $f(x,y)$ is processed with masks to get the LDN code

$$LDN(x,y) = 8i_{x,y} + j_{x,y} \quad (10)$$

Where (x,y) is the central pixel of the neighborhood 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.

The directional number for maximum & minimum response is calculated by

$$i_{x,y} = \arg \max_i \{\pi^i(x,y) \mid 0 \leq i \leq 7\} \quad (11)$$

$$j_{x,y} = \arg \max_j \{\pi^j(x,y) \mid 0 \leq j \leq 7\} \quad (12)$$

Where, Π^i is the convolution of the original image I .

The convolution is done by

$$\Pi^i = I * M^i \quad (13)$$

Where I is the original image and M^i is i^{th} mask.

The Kirsch compass mask used is as shown in figure 3. In addition to it we are using Sobel mask which is calculated as gradient space as per the equations given below.

The sobel mask is calculated by,

$$g_x = df/dx = (z7+2z8+z9) - (z1+2z2+z3) \quad (14)$$

and,

$$g_y = df/dy = (z3+2z6+z9) - (z1+2z4+z7) \quad (15)$$

The magnitude of the gradient is approximated by

$$M(x,y) = |g_x| + |g_y| \quad (16)$$

Finally, a histogram is calculated for each block of the LDN image.

$$LH = \prod_{i=1}^N H^i \quad (17)$$

Where, π is the concatenation operation, and N is the number of regions of the divided face.

The histogram obtained such represent the feature vector for that individual face. Hence for all faces in the database we have this feature vector. These are then compared with Chi-Square dissimilarity measure. The value which is minimum indicates the recognized image.

$$\chi^2(F_1, F_2) = \sum_{i=1}^N \frac{(F_1(i) - F_2(i))^2}{F_1(i) + F_2(i)} \quad (18)$$

Where F_1 and F_2 are two feature vectors.

Similar steps are taken with Sobel Operator.

IV. RESULT ANALYSIS AND DISCUSSIONS

In the Proposed work we use LDN method for face recognition by using Kirsch and the Sobel operator as the compass mask. Here we perform different operations for face recognition under different Illumination, Pose & Expression conditions. In the previous system work is done by using Matlab here we are doing by using Java by using JAI(Java Advance Imaging) as API.

The various experiments are conducted on the different databases as given in the tables I, II, & III.

As the number of objects taken are different from the different database, the graph is shown separately for each database.

Table No I. Performance Analysis of ORL Database

Experiment	Gallery Images (Training)		Probe Images (Testing)	Correctly recognized Images using		Recognition Rate = No. of images recognized correctly/Total no. of images in the Probe set * 100 (%)	
	No. of Objects	No. of face image/object		Kirsch Compass Mask	Sobel Operator	Kirsch Compass Mask	Sobel Operator
1	10	3	20	19	18	95	90
2	20	4	40	37	35	92.5	87.5
3	40	5	80	75	72	93.7	90

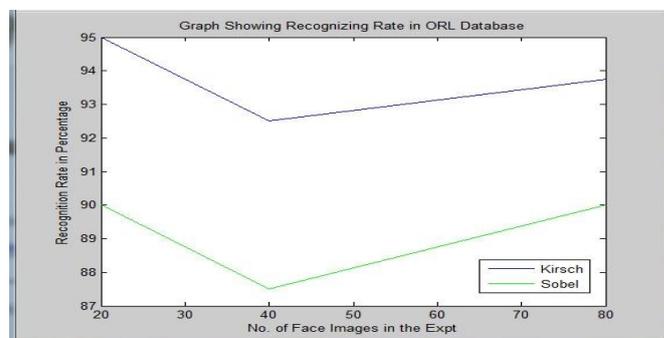


Figure 6. Graph showing Recognition Rate in ORL Database

Table No II. Performance Analysis of YALE Database

Experiment	Gallery Images (Training)		Probe Images (Testing)	Correctly recognized Images using		Recognition Rate = No. of images recognized correctly/Total no. of images in the Probe set * 100 (%)	
	No. of Objects	No. of face image/object		Kirsch Compass Mask	Sobel Operator	Kirsch Compass Mask	Sobel Operator
1	5	3	10	9	10	90	100
2	10	4	20	17	19	85	95
3	15	5	30	25	26	83.3	86.6

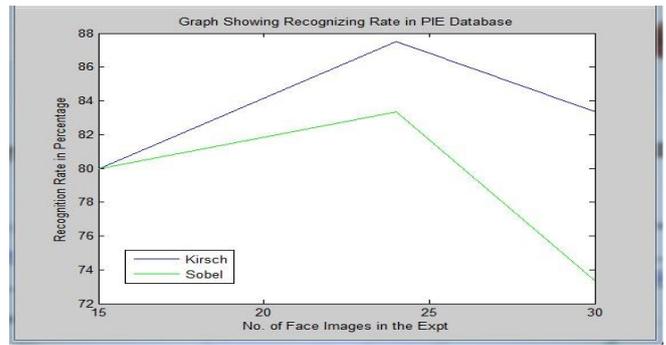


Figure 8. Graph showing Recognition Rate in PIE Database

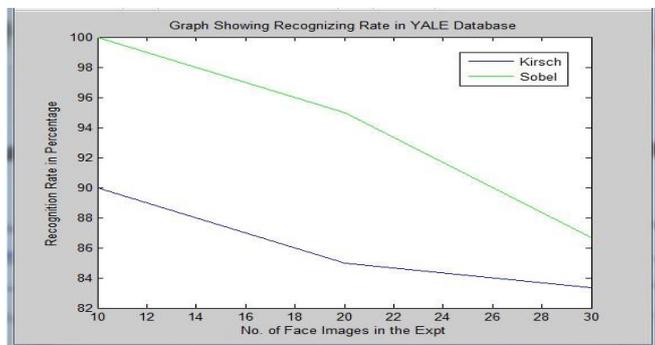


Figure 7. Graph showing Recognition Rate in YALE Database

Table No III. Performance Analysis of PIE Database

Experiment	Gallery Images (Training)		Probe Images (Testing)	Correctly recognized Images using		Recognition Rate = No. of images recognized correctly/Total no. of images in the Probe set * 100 (%)	
	No. of Objects	No. of face image/object		Kirsch Compass Mask	Sobel Operator	Kirsch Compass Mask	Sobel Operator
1	5	5	15	12	12	80	80
2	8	5	24	21	20	87.5	83.3
3	10	5	30	25	22	83.3	73.3

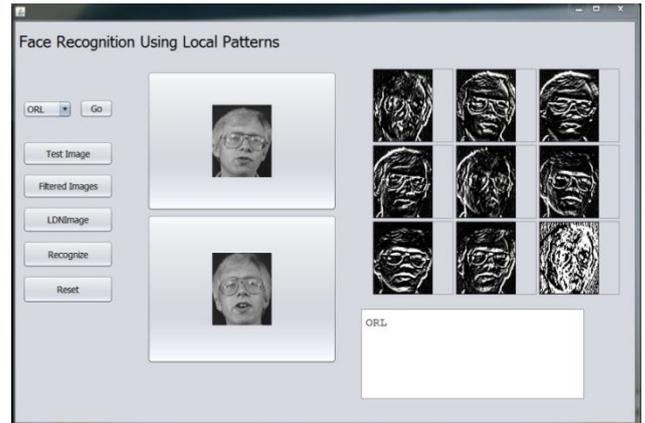


Figure 9. GUI Shows Face is recognized under different Pose and Expression Conditions.

V. CONCLUSION

Biometric technique is very useful compared to other traditional techniques like remembering of Password and PIN's for individual's identity. In Biometric, Face recognition system is more useful for individual's identity due to the using of very few inexpensive cameras and doesn't require user active participation or any health risks.

In the proposed system we use LDN method, which is six bit binary code obtain by Convoluting the kirsch's as filter along with Sobel operator with input image. This six bit LDN code is compact as compared to other method like LBP which is eight bit binary code. This coding scheme is based on the directional information, instead of small piece strings, which encodes the information of the neighborhood in a more effective way.

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