A comparative study of Four Neighbour Binary Patterns in Face Recognition

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Abstract - **This paper proposes the novelty of Four Neighbour Binary Patterns (FNBPs) in Face Recognition. In general, various researches with various bit patterns for feature extraction in LBP were available. Four neighbours or eight neighbours or sixteen neighbours may be used for feature extraction. In the LBP each neighbour is compared with its referenced center pixel and then computes the gray level difference. It generates two bitwise transitions from 0 to 1 or vice versa. But in this paper the gray level difference is computed among the neighbours, compares with average of the neighbours and produces four bit binary pattern. Today's challenge in Face Recognition is to develop a method that should be able to increase the recognition rate, accuracy and to reduce the retrieval time. In order to improve the recognition rate suitable feature should be extracted. In this paper both gray-level images and Gabor feature images are used to evaluate the comparative performances of various four neighbour LBP. Extensive experimental results on JAFFE, ORL, YALE AND OWN databases show that the Four Neighbour Diagonal Binary Pattern consistently performs much better than traditional four neighbour LBP for both face identification and face verification under various conditions:**

Keywords — Local Binary Pattern(LBP), Four Neighbour Binary Pattern (FNBP), Histogram intersection, Micro pattern, Gabor wavelets.

I. INTRODUCTION

The face of a human being conveys a lot of information about identity and emotional state of the person. Face recognition is an interesting and challenging problem, and impacts important applications in many areas such as identification for law enforcement, surveillance, fraud investigations, biometric authentications for banking and security system access and personal identification among others.

Face recognition is a long time favourite research topic for the computer vision people. Many heuristics pattern recognitions strategies proposed to achieve an accurate solution[1]. Over the decades of research it is now getting matured and been used in real life applications under certain constrains. The face recognition problem is made difficult by the great variability in illumination, brightness and various expressions. Various methods have been proposed in order to improve the recognition rate. These sign can be used in a local or even in a global fashion. In recent times lot of work has proven the importance of local cues in recognition task. Even after so many decades of work, people are a bit opposed to use face recognition in mainstream. Hence it becomes critically important to evaluate the recognition algorithms from a real life adaptation viewing points.

The good object representation or object descriptor is one of the key issues for a well-designed face recognition system [2], [3]. Representation issues include: what representation is desirable for the recognition of a pattern and how to effectively extract the representation from the original input image. An efficient descriptor should be of high ability to discriminate between classes, can be easily computed and has low intraclass variance. Many holistic methods, such as Eigenface [4] and Fisherface [5] built on principal component analysis (PCA) and Linear Discriminant Analysis (LDA) respectively have been proved successful.

Recently, local descriptors have gained much attention in the face recognition community for their robustness in illumination and pose variations. One of the local descriptors is Local Feature Analysis (LFA) proposed by Penev et al. [6]. In LFA, a dense set of local-topological fields are developed to extract local features. To locating a description of one class objects with the derived local features, LFA is a purely second-order statistic method. Gabor wavelet is a sinusoidal plane wave with particular frequency and orientation[7]. It can characterize the spatial structure of an input object and thus is suitable for extracting local features. Elastic Bunch Graph Matching

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(EBGM) [8] represents a face by a topological graph where each node contains a group of Gabor coefficients, known as a jet. It achieves a noticeable performance in the FERET test [9]. The feasibility of the component or patch based face recognition is also investigated in [10], in which the component-based face recognition approaches clearly outperform holistic approaches.

The recently proposed Local Binary Pattern (LBP) features are originally designed for texture description [11], [12], [13]. The operator has been successfully applied to facial expression analysis [14], background modeling [15] and face recognition [16]. In face recognition, LBP achieves a much better performance than Eigenface, Bayesian and EBGM methods, providing a new way of investigating into the face representation.

This paper proposes a new Four Neighbour Binary Patterns (FNBPs). The proposed FNBPs create a micro pattern which can also be modeled by histogram.

The rest of this paper is organized as follows. Section -II explains the traditional LBP that is $LBP_{8,1}$ and $LBP_{16,2}$ methods in detail. Section-III discusses the proposed approach FNBP elaborately. Section-IV contains the histogram intersection. Extension of proposed approach by Gabor filter is explained detail in Section-V. In Section VI an extensive experiments JAFFE, ORL, YALE and OWN DATABASE databases are used to evaluate the performance of the proposed method on face recognition. Benefits and performance metrics are explained in Section VII. Finally, conclusion and future work is presented in Section -VIII with some discussions..

II. FOUR NEIGHBOUR BINARY PATTERNS (FNBPs)

The LBP method can be used for face description. This procedure uses the texture descriptor to build several local descriptions of the face and combining them into a global description.

LBP descriptions of the neighbourhood of a pixel can be derived by using binary derivatives of the pixel. The binary derivatives are used to form a short code to describe the pixel neighbourhood. The method has many interesting implementations within research areas such as Pattern Recognition and Texture analysis.

The LBP was originally designed for texture description. The LBP creates a micro pattern by thresholding the 3x3-region of each pixel with the center pixel value and considering the result as a binary number. Then the histogram of the micro patterns can be used as a texture descriptor.

The idea behind using the LBP features is that a face can be seen as a composition of micro patterns [17]. In nature LBP is generally represented as the first-order circular derivative pattern of images.

6	5	3	8	0
8	6	7	1	5
3	4	5	3	4
5	8	9	7	1
1	8	3	6	9

Fig. 1 Sample data set

The LBP operator was originally designed for texture description. The operator assigns a label to every pixel of an image by thresholding the 3x3-neighborhood of each pixel with the center pixel value and considering the result as a binary number. But in the proposed approach consider only four neighbours. The four neighbours have been taken as a horizontal or vertical. Gray level difference can be calculated among themselves or with the central pixel [18]. Among all the four neighbours the diagonal FNBP's recognition rate is better.

A. Horizontal and Vertical Four Neighbours:

Horizontally two neighbours and vertically two neighbours can be taken and their gray level difference can be calculated with center pixel. Fig. 2 shows the four neighbours of N_0.

	N_2	
N_3	N_0	N_1
	N_4	

Fig. 2 Vertical and horizontal neighbours of N_0

a. Horizontal and Vertical Center Four Neighbour Binary Patters (HVCFNBP):

Where N (i=1,2,...4) is a four neighbourhood point around the center pixel N_0. The thresholding function for $f(\cdot,\cdot)$ for this can be represented by the following equation:

$$f(Z(N_c), Z(N_i)) = \begin{cases} 0, & if\ Z(N_i) - Z(N_c) \le thresho \\ 1, & if\ Z(N_i) - Z(N_c) > thresho \end{cases} \quad .... (1)$$

Eqn.1 compares the four neighbours with the central pixel and generates four bit micro pattern. After the application of equation 1 in the data shown in Fig. 1 compares the four neighbours 3, 7, 4, 9 with the center value 5 and produce the four bit micro pattern 0101.

b. Horizontal and Vertical Four Neighbour Binary Patterns (HVFNBP):

$$f(Z(N_i), Z(N_{((i) \bmod 4)+1}))$$

$$=\begin{cases}0, & if\ Z(N_i) - Z(N_{((i) \bmod 4)+1}) < 0\\ 1, & otherwise\end{cases} \quad \text{.......... (2)}$$

Where N_i (i=1,..,4) is a four neighbours around N_0. Equation 2 computes the difference among the four neighbour itself. If the difference is greater than 0 then the value 1 otherwise assign 0. The equation 2 is executed using the data shown in Fig.1. It compares the difference among the four neighbours 3, 7, 4, 9(3-7=-4<0, returns 0, 7-4=3>0, returns 1, 4-9=-5<0, returns 0 and 9-3=6>0, returns 1) and produces the four bit micro pattern 0101.

c. Horizontal and Vertical Average Four Neighbour Binary Patterns (HVCFNBP):

$$Z(N) = \sum_{i=1}^{4} Z(N_i)\ /4 \quad \text{..............(3)}$$

$f(Z(N_i), Z(N))$

$$= \begin{cases}1, & if\ (Z(N_i) - Z(N) \geq \\ 0, & if\ Z(N_i) - Z(N) < \end{cases} \quad \text{.......... (4)}$$

Equation 3 computes the average of four neighbours. Equation 4 compares the difference between the average and four neighbours. If the difference is greater than or equal to zero then produces the bit 1 otherwise 0. Use the data in Fig.1 and apply the equation 3, it computes the average value 5.75. Then equation 4 compares the average value with four neighbours 3, 7, 4, 9 and constructs the bit pattern 0101.

B. Diagonal Four Neighbours:

Fig. 3 shows the diagonal four neighbours arrangement. Change neighbour into diagonal and use the same eqn. to find the four bit micro pattern.

N_2		N_1
	N_0	
N_3		N_4

Fig. 3. Diagonal neighbours of N_0

a. Center Four Neighbour Binary Patterns (DCFNBP):

Equation 1 compares the four neighbours with the central pixel and generates four bit micro pattern. After the application of equation 1 in the data shown in Fig. 1 compares the four neighbours 1, 6, 8, 7 with the center value 5 and produce the four bit micro pattern 0111.

b. Diagonal Four Neighbour Binary Pattern (DNFNBP):

Equation 2 computes the difference among the four neighbour itself. If the difference is greater than 0 then the value 1 otherwise assign 0. The equation 2 is executed using the data shown in Fig.1. It compares the difference among the four neighbours 1, 6, 8, 7 and produces the four bit micro pattern 0101.

c. Diagonal Average Four Neighbour Binary Patterns (DAVGFNBP):

Equation 3 calculates the average of four neighbours. Equation 4 compares the difference between the average and four neighbours. If the difference is greater than or equal to zero then produces the bit 1 otherwise 0. Use the data in Fig.1 and apply the equation3, it calculates the average value 5.5. Then equation 4 compares the average value with four neighbours 1, 6, 8, 7 and constructs the bit pattern 0111.

III. HISTOGRAM INTERSECTION

Before calculating the histogram intersection the micro pattern constructed by FNBPs is divided into rectangular regions represented by R1, R2…R_n, from which spatial histograms are extracted as

$$H_{FNBP}(i)=\{H_{FNBP}(R_i)|\ i=1,2,\ldots,n\} \quad \text{……………(5)}$$

Where $H_{FNBP}(R_i)$ is the FNBP histogram feature extracted from the rectangular local region. The regions may be of any shape and size . For example, circular regions with different radii can also be used for histogram. Many similarity measures have been proposed for histogram matching. For histogram matching, this paper uses histogram intersection to measure the similarity between two histograms.

$$S(Htrn,Htst)=\sum_{i=1}^{n} \min\ (Htrn_i, Htst_i) \quad \text{………(6)}$$

Where n is the number of regions. Similarity measure finds the minimum histogram value among the testing (Htrn) and training (Htst) data set.

In this work micro pattern array constructed by FNBP for both the testing training image is divided into 36 regions (4X9). Compare regions from both training and testing images for the purpose of finding minimum value. Finally add the minimum values which are used to classify testing image.

IV. EXTENDING FOUR NEIGHBOUR BINARY PATTERN TO FEATURE IMAGES

This section investigates the feasibility and effectiveness of extending FNBP beyond spatial domain to feature domain. The basic problem definition is to recognize the image of a person from a set of testing images using a stored set of dataset. Image degradation affects the process of feature extraction. Thus image de-noise has to be carried out which requires the prominent features in an image such as edges to be preserved and restored. Once the edges are preserved it is very important to detect those significant edges, since edges play an important role in feature extraction [19].

This paper attempts for an accurate feature extraction by the use of 2D Gabor filter, in order to overcome the local the

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local distortions caused by the variance of illumination, pose and expression. The relevant frequency spectrum in all directions is captured in order to extract features aligned at specified angles by Gabor filtering.

Gabor filter is a linear filter used for edge detection named after named Dennis Gabor [20]. The Gabor filtered images are capable of capturing relevant frequency spectrum in order to extract features aligned at specified orientations to recognize a region of interest. The 2D Gabor filter can be represented as a complex sinusoidal signal modulated by a Gaussian function as given equation 7.

$$\psi_{f,\theta}(x,y) = \exp[(-1/2)\{(x^2/\sigma_x^2)+(y^2/\sigma_y^2)\}]*\exp(2\pi f\theta_n)$$
$$\begin{pmatrix} a_{11} \\ a_{12} \end{pmatrix} = \begin{pmatrix} \sin\theta_n & \cos\theta_n \\ -\cos\theta_n & \sin\theta_n \end{pmatrix}\begin{pmatrix} x \\ y \end{pmatrix} \qquad \text{……(7)}$$

σ_x and σ_y are the standard deviation of the Gaussion envelop along the x and y dimensions, f is the central frequency of the sinusoidal plane wave and θ is defined by:

$$\theta_n = (\pi / p) * (n-1); n = 1,2,3,...p \qquad \text{……..(8)}$$

$p\varepsilon n$ where p denotes the number of orientation. Let f(x,y) be the intensity at the coordinate (x,y) in a gray scale face image, its convolution with a Gabor filter in order to extract features accurately is defined as,

$$g_{f,0}(x, y) = f(x, y) \otimes \Psi_{f,0}(x, y) \qquad \text{……….(9)}$$

V. EXPERIMENTS

The following system investigates throuly covers, various conditions of face recognition including lighting, accessory, pose, expression and aging variations, has been conducted. An extensive set of publicly available face databases JAFFE, ORL, YALE and OWN databases, were used to evaluate the proposed approach. In the experiments, the facial portion of each original image was normalized and cropped based on the locations of the two eyes. Experiment A conducts comparative performance evaluations on all the four subsets of the JAFFE database (all 215 people) with expression, lighting and aging variations. Experiment B reports the experimental results on a subset (the first 400 people) of the ORL database with varying accessory, expression and lighting conditions. Experiment C reports the experimental results on the YALE database (all 300 faces) with pose and illumination variations. Experiment D reports the experimental results on the OWN database (all 20 people) with severe illumination and expression variations. In all these experiments, the proposed diagonal FNBP is compared with the vertical and horizontal FNBP on both gray-level images and Gabor feature images with different parameter settings.

A. Experimental Comparisons on the JAFFE Database

The comparative experiments between vertical and horizontal FNBP and diagonal FNBP were conducted on the JAFFE face database, which is widely used to evaluate face recognition algorithms [20]. All the images were normalized and cropped to 256 x 256 pixels.

To observe how well diagonal four neighbour binary patterns perform under different conditions, the experiment is conducted on the JAFFE dataset. Experimental results in Fig. 5 demonstrate that the recognition rate of DFNBP is significantly improved when the comparison is only among the diagonal neighbours rather than center and vertical and horizontal. Gabor feature based DFNBP achieves much better performance than the gray image.

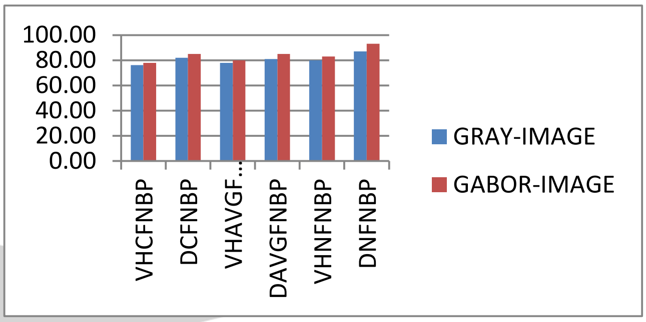

Fig. 4. Face recognition rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for JAFFE dataset

The results on the large-scale database also show that the detailed information contained in the DNFNBP can significantly improves the performance of local pattern representation in face recognition.

B. Experimental Comparisons on the ORL Database:

The comparative experiments between vertical and horizontal FNBP and diagonal FNBP were conducted on the ORL face database, which is widely used to evaluate face recognition algorithms [20]. All the images were normalized and cropped to 256 x 256 pixels.

To observe how well diagonal four neighbour binary patterns perform under different conditions, the experiment is conducted on the ORL dataset. Experimental results in Fig. 6 demonstrate that the recognition rate of DNFNBP is significantly improved when the comparison is only among the diagonal neighbours rather than center and vertical and horizontal. Gabor feature based DFNBP achieves better performance than the gray image.

The results on the large-scale database also show that the detailed information contained in the DNFNBP can significantly improves the performance of local pattern representation in face recognition.

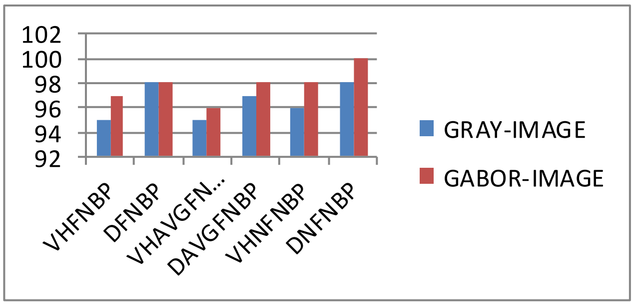

Fig. 5. Face recognition rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for ORL dataset

C. Experimental Comparisons on the YALE Database:

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The comparative experiments between vertical and horizontal FNBP and diagonal FNBP were conducted on the YALE face database, which is widely used to evaluate face recognition algorithms [20]. All the images were normalized and cropped to 256 x 256 pixels.

To observe how well diagonal four neighbour binary patterns perform under different conditions, the experiment is conducted on the YALE dataset. Experimental results in Fig. 5 demonstrate that the recognition rate of DFNBP is significantly improved when the comparison is only among the diagonal neighbours rather than center and vertical and horizontal. Gabor feature based DFNBP achieved much better performance than the gray image.

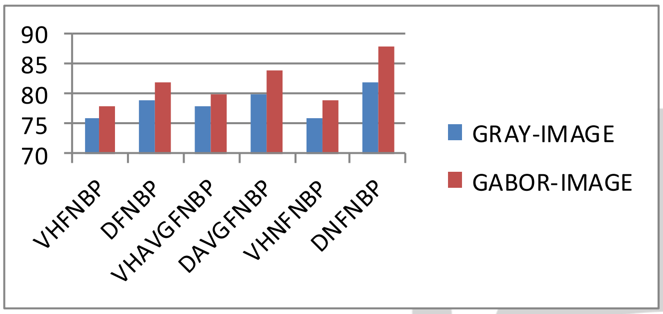

Fig. 6. Face recognition rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for YALE dataset

The results on the large-scale database also show that the detailed information contained in the DNFNBP can significantly improves the performance of local pattern representation in face recognition.

D. Experimental Comparisons on the OWN Database:

The comparative experiments between vertical and horizontal FNBP and diagonal FNBP were conducted on the OWN face database, which is widely used to evaluate face recognition algorithms [20]. All the images were normalized and cropped to 256 x 256 pixels.

To observe how well diagonal four neighbour binary pattern performs under different conditions, the experiment is conducted on the OWN dataset. Experimental results in Fig. 5 demonstrate that the recognition rate of DFNBP is significantly improved when the comparison is only among the diagonal neighbours rather than center and vertical and horizontal. Gabor feature based DFNBP achieved much better performance than the gray image.

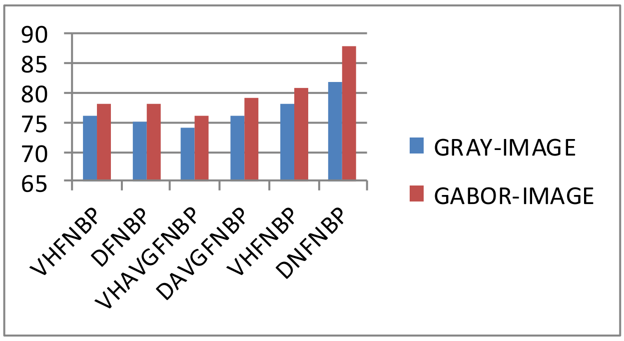

Fig. 7. Face recognition rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for OWN dataset

The results on the large-scale database also show that the detailed information contained in DNFNBP can significantly improves the performance of local pattern representation in face recognition.

VI. BENEFITS AND PERFORMANCE METRICS

A. Benefits of proposed approach

The proposed approach proves that the comparison among the diagonal neighbours recognition rate is better than the vertical and horizontal neighbourhood. Clearly shows that the gabor feature's performance is better than the gray image.

B. Performance metrics

The performance can be evaluated by several performance metrics which are available. This paper utilizes the Recognition Rate, Accuracy, Precision, Recall, F-measure and Error rate to measure the performance.

Mathematically, this can be stated as:

1) Recognition rate

Recognition rate is calculated by the following equation.

$$Recognition\ Rate = \left(\frac{No.of\ correctly\ identified\ images}{Total\ No.of\ images}\right) \times 1 \quad ......(10)$$

Fig 5, 6, 7, 8 shows the recognition rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for the data sets JAFFE, ORL, YALE and OWN DATASET. The DNFNBP's recognition rate is better than traditional FNBP.

2) Accuracy

The accuracy of a test is its ability to differentiate the match and mismatch correctly. To estimate the accuracy of a test, it is calculated as shown below

$$Accuracy = \frac{TP}{Number\ of\ files} \quad .... (11)$$

Where, TP denotes true positive.

The Accuracy of FNBPs is shown in Fig. 8, 9, 10, 11. Accuracy is calculated for JAFFE, ORL, YALE and OWN DATASET. The accuracy of DNFNBP is more than the other FNBPs for all the dataset.

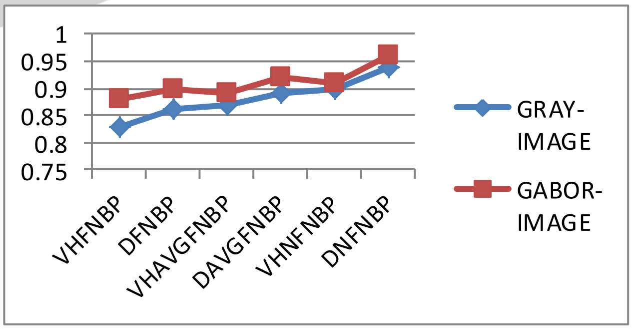

Fig. 8. The Accuracy of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for JAFFE dataset

Experimental results in Fig. 9, 10, 11, 12 demonstrate that the accuracy is improved from VHFNBP TO DNFNBP on both gray-level images and Gabor feature images. These results further indicate that the diagonal neighbour four neighbour binary patterns is more accurate than the other four neighbour binary patters in both gray gabor images.

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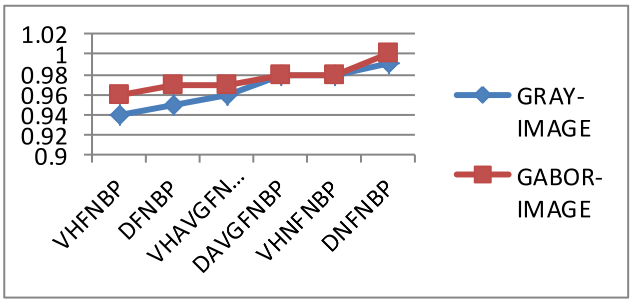

Fig. 9. The Accuracy of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for ORL dataset

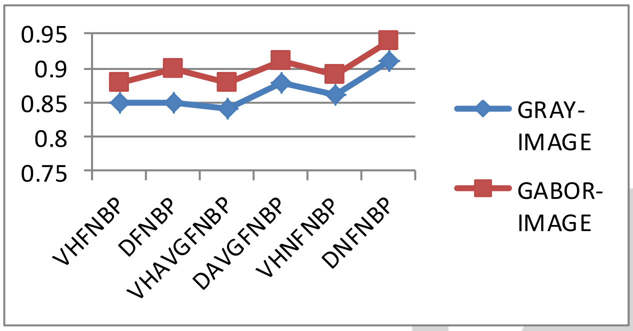

Fig. 10. The Accuracy of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for YALE dataset

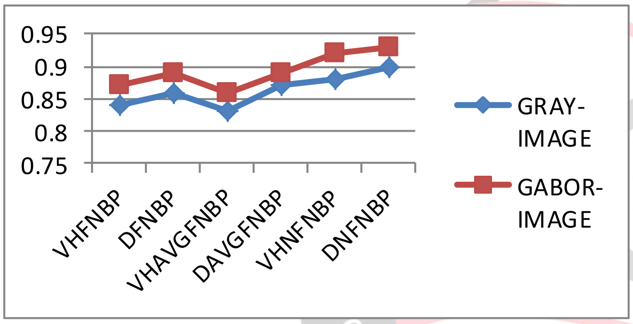

Fig. 11. The Accuracy of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for OWN dataset

3)E rror Rate

To calculate the error rate, there is need to compare an estimate to an exact value. Error is calculated by finding the difference between the approximate and exact values as a percentage of the exact value.

$$Error\ rate = 1 - TP \qquad \text{..............(12)}$$

Table I, II, III, IV shows that the DNFNBP's error rate is less than all other FNBPs in both gray and in Gabor image.

Table I

Error Rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for JAFFE dataset

FNLBPs	GRAY-IMAGE	GABOR-IMAGE
VHFNBP	0.1674	0.1163
DFNBP	0.1395	0.0977
VHAVGFNBP	0.1256	0.1070
DAVGFNBP	0.1070	0.0837
VHNFNBP	0.1023	0.0884
DNFNBP	0.0558	0.0372

Table II Error Rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for ORL dataset

FNLBPs	GRAY-IMAGE	GABOR-IMAGE
VHFNBP	0.0575	0.0450
DFNBP	0.0500	0.0275
VHAVGFNBP	0.0425	0.0350
DAVGFNBP	0.0250	0.0175
VHNFNBP	0.0250	0.0200
DNFNBP	0.0125	0.0025

Table III Error Rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for YALE dataset

FNLBPs	GRAY-IMAGE	GABOR-IMAGE
VHFNBP	0.1500	0.1167
DFNBP	0.1467	0.1033
VHAVGFNBP	0.1567	0.1233
DAVGFNBP	0.1200	0.0867
VHNFNBP	0.1400	0.1067
DNFNBP	0.0900	0.0567

Table IV Error Rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for OWN dataset

FNLBPs	GRAY-IMAGE	GABOR-IMAGE
VHFNBP	0.1650	0.1300
DFNBP	0.1450	0.1100
VHAVGFNBP	0.1750	0.1400
DAVGFNBP	0.1350	0.1100
VHNFNBP	0.1200	0.0850
DNFNBP	0.1000	0.0700

4) Precision Rate

The Precision is the fraction of retrieved instances that are relevant to the find.

$$Precision = TP / (TP + FP) \qquad \text{...(13)}$$

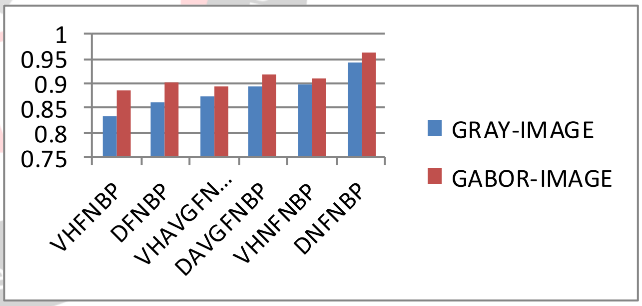

Fig. 12. The Precision Rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for JAFFE dataset

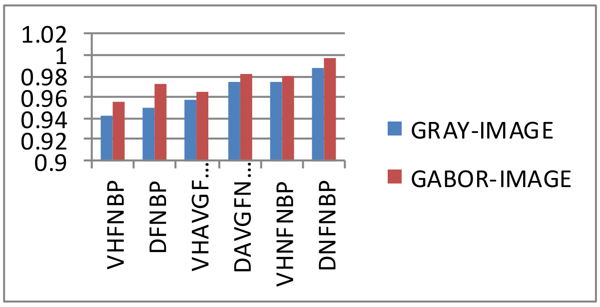

Fig. 13. The Precision Rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for ORL dataset

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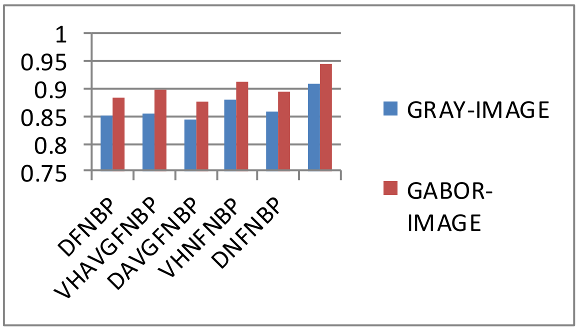

Fig. 14. The Precision Rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for YALE dataset

Figure 12, 13, 14, 15 shows the precision rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, and DNFNBP. In all the charts the Gabor image created by the diagonal neighbours is having higher precision rate than all other LBPs. Hence the difference among diagonal four neighbours is better for face recognition rather than vertical and horizontal four neighbours.

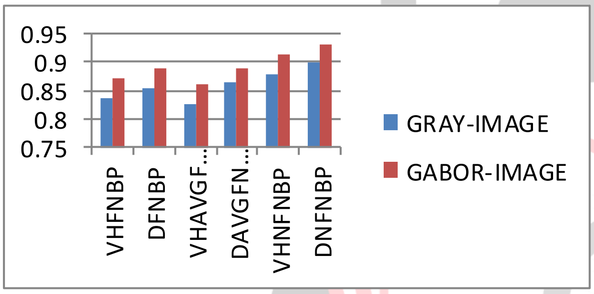

Fig. 15. The Precision Rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for OWN dataset

5) Recall Rate

The Recall is the fraction of relevant instances that are retrieved according to the query.

$$Recall = TP / (TP + FN) \quad \ldots(14)$$

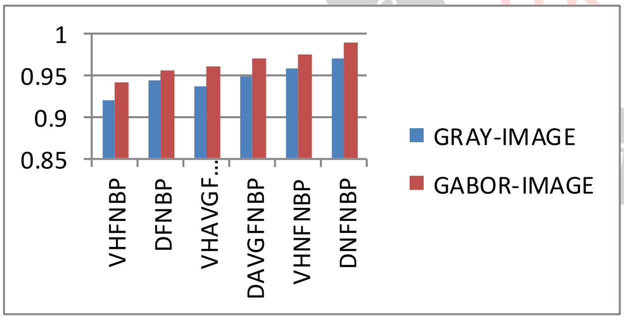

Fig. 16. The Recall Rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for JAFFE dataset

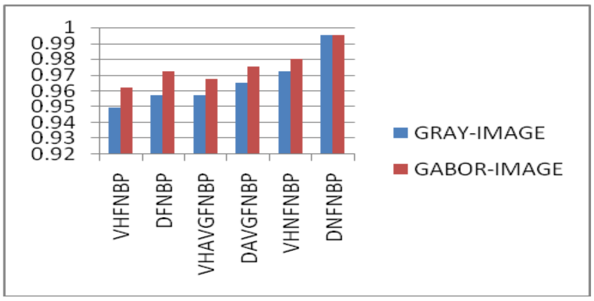

Fig. 17. The Recall Rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for ORL dataset

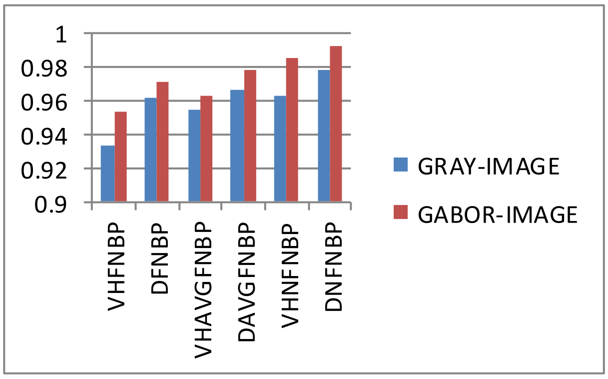

Fig. 18. The Recall Rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for YALE dataset

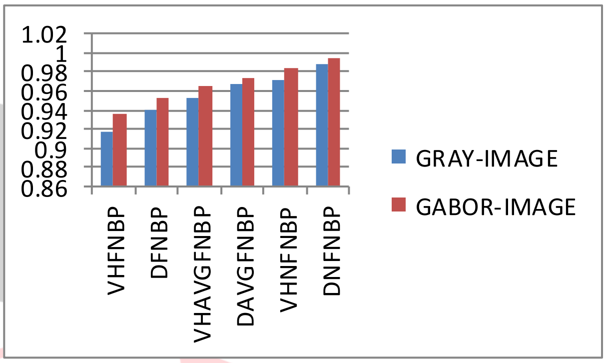

Fig. 19. The Recall Rate of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for OWN dataset

6) F measure

F-measure is the ratio of product of precision and recall to the sum of precision and recall. The f-measure can be calculated as,

$$F_{measure} = (P_{rate} \times R_{rate}) / (P_{rate} + R_{rate}) \quad \ldots(15)$$

Figure 20, 21, 22, 23 shows the F-Measure all FNBP. Figure shows that the F-Measure of Gabor image is better than the gray image.

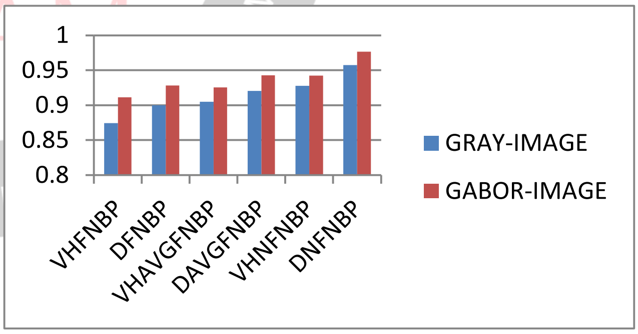

Fig. 20. The F-Measure of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for JAFFE dataset

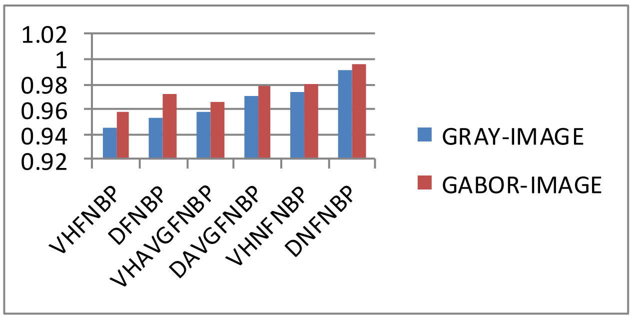

Fig. 21. The F-Measure of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for ORL dataset

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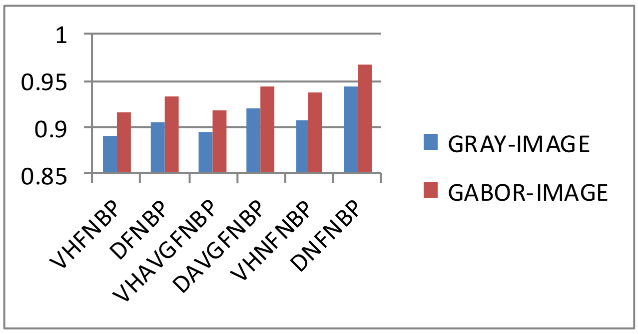

Fig. 22. The F-Measure of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for YALE dataset

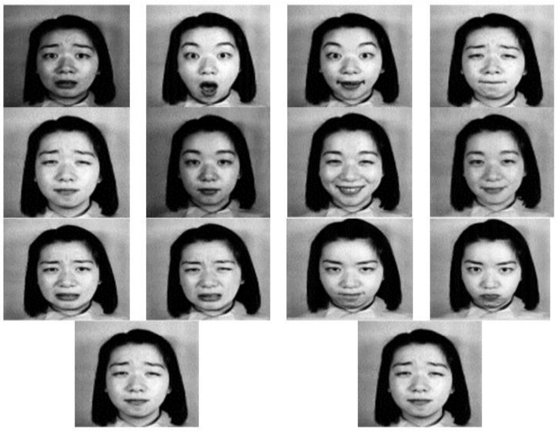

Fig. 24.Sample Images of JAFFE Data Set

Fig. 25. Sample Images of ORL Data Set

Fig. 26. Sample Images of YALE Data Set

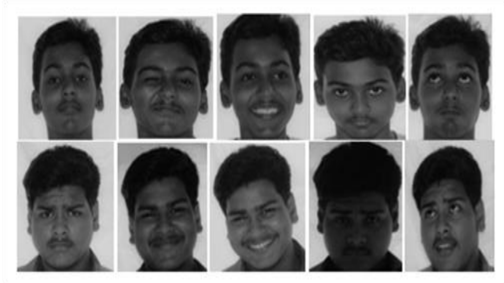

Fig. 27.Sample Images of OWN Data Set

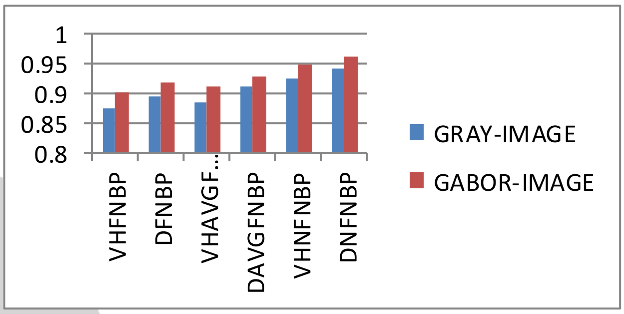

Fig. 23. The F-Measure of VHCFNBP, DCFNBP, VHAVGFNBP, DAVGFNBP, VHNFNBP, DNFNBP for OWN dataset

F-Measure diagonal four neighbour binary patterns are more than the others. After the application of Gabor filter F-Measure is increased for all FNBPs.

The performance of the proposed system is computed by using the test images in the database. This approach uses four databases for testing purpose. The first database is the standard database JAFFE database with 13 faces for 15 categories. Second one is a standard database ORL with 40 categories, which contains 10 faces per category. Third database YALE is a standard database with 30 categories. Each category consists of 10 faces with different expressions. Last data base, OWN DATABASE consists are 200 faces in twenty categories. Fig. 24, 25, 26, and 27 expresses the sample test images that are used in this paper for the categories JAFFE, ORL, YALE, and OWN DATABASE.

VII. CONCLUSION

This paper presents the accuracy, error rate and recognition rate of using FNBPs for face recognition. To model the distribution of micro patterns, the histogram intersection is used as similarity measurement. The experiments conducted on the database JAFFE, ORL, YALE and OWN-DATASET demonstrate that the proposed approach DNFNBP achieves better recognition and less error rate than all other four neighbour binary patterns. Compare with all other FNBPs the DNFNBP improves its recognition rate into 6.5% for the gray scale images and for the Gabor images which is improved into 8.32%. This paper concludes, among the entire four neighbour binary patterns the diagonal four neighbor binary pattern produces better recognition rate.

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