Four Neighbour Binary Pattern in Face Recognition

Geetha A[1], Jacob Vetharaj Y[2]
[1]*Research Scholar, Nesamony Memorial Christian College affiliated to Manonmaniam Sundaranar University, Abishekapatti, Tirunelneli 627012, Tamil Nadu, India*
(E-mail: geethavijayaragavan1999@gmail.com)
[2] *Associate Professor, Nesamony Memorial Christian College affiliated to Manonmaniam Sundaranar University, Abishekapatti, Tirunelneli 627012, Tamil Nadu, India*
(E-mail: jacobvetharaj@gmail.com)

Abstract— This paper proposes a novelty in Four Neighbour Binary Pattern (FNBP), in Face Recognition. Customarily, various researches with various bit patterns for feature extraction are available. In the traditional LBP, each neighbour is being compared with its referenced center pixel and then the gray level difference is being computed. LTP has a three-value code in accordance with the gray values of its neighbours. The proposed method, FNBP first computes the average of each pixel's horizontal and vertical neighbours. Then the gray level difference between the four neighbours and the computed average value is being figured up. Finally, this approach produces a four bit binary pattern. Today's challenge in Face Recognition is to improve the recognition rate and reduce the retrieval time for this suitable feature has to be extracted. In this paper, both gray-level images as well as Gabor feature images are used to evaluate the comparative performances of FNBP and eight neighbour-LBP and LTP. Extensive experimental results on JAFFE, ORL, YALE and OWN databases show that, the proposed FNBP is consistently performs much better than LBP and LTP for both face identification and face verification under various conditions.

Keywords— *Four Neighbour Binary Pattern (FNBP), Gabor Filter, Local Binary Pattern (LBP), Local Ternary Pattern (LTP).*

I. INTRODUCTION

The face of a human being conveys abundant information about the identity and emotional state of the person. Face recognition is an interesting but rather challenging problem, and has today made its feet get imprinted on 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 longtime favourite research topic for the computer vision people. Many heuristics pattern recognitions strategies have been proposed to achieve an authentic solution [1]. Over decades of research, it is now getting matured and is being used in real life applications under certain constrain. The face recognition problem is made herculean by the great variability in illumination, brightness and various expressions. Various methods have been proposed in order to improve the recognition rate. These signs can be used in a local or even in a global fashion. In the recent times, ocean of works has proven the importance of local cues in recognition task. Even after so many decades of work, people are little hesitant to use face recognition in mainstream. Hence it becomes critically important to evaluate the recognition algorithms from a real life adaptation viewing point.

A good object representation or object descriptor is one of the key issues for a well-designed face recognition system [2], [3]. Representation issues are: 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 possess high ability to discriminate between classes, so that tallying can be easily performed with a low intra class 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 lucrative.

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. 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 a particular frequency and orientation, modulated by a Gaussian envelope [7]. It can characterize the spatial structure of an input object and thus is suitable for extracting local features. Elastic Bunch Graph Matching (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 outperforming holistic approaches.

The recently proposed Local Binary Pattern (LBP) features were 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, it has actualized a much better performance than Eigenface, Bayesian and EBGM methods, providing a new way of investigating into face representation.

The Local Ternary Pattern (LTP) was acquainted to capture more detailed information than LBP. LTP is an extension of LBP. LTP is less sensitive to noise than LBP as well as a small pixel difference is encoded into a separate state. To reduce its dimensionality, the ternary code constructed by LTP is split into two binary codes: a positive LBP and a negative LBP [17]. A threshold value is added to the center pixel (u) and is subtracted from the center pixel (l) and generates a boundary [l,u]. If the neighbouring pixel is lesser than l assign -1, assign 1 if the neighbouring pixel is greater than u and assign 0 if it is lies between l and u [18]. This ternary code is now split into two. Assign 0 to -1's to construct higher bit pattern. Assign 1 to -1's to construct lower bit pattern and thereby construct higher and lower bit pattern. The LTP only encodes the texture features of an image depending on the grey level difference between center pixel and its neighbours, which are coded using two directions.

This paper proposes a new Four Neighbour Binary Pattern (FNBP). The proposed FNBP creates a micro pattern which can also be modeled by histogram.

The remaining paper is planned as follows. Section -II explains the traditional LBP and LTP 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 in detail in Section-V. In Section VI extensive experiments on 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. As a sequel, conclusion presented in Section -VIII with some discussions.

II. RELATED WORKS

A. Local Binary Pattern (LBP):

The LBP method can be used for face description. This procedure consists of using 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.

LBP was originally designed for texture description. For all the pixels of an image, 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 [19]. In nature, LBP is generally represented as the first-order circular derivative pattern of images.

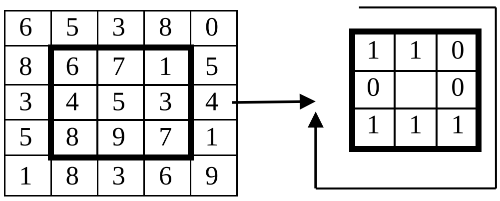
The thresholding function for $f(\cdot,\cdot)$ for the basic LBP can be represented by the following equation:

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

Where N_i(i=1,2,...8) is an eight neighbourhood point around the center pixel N_0 as shown in Fig. 1.

N_1	N_2	N_3
N_8	N_0	N_4
N_7	N_6	N_5

Fig. 1 Eight neighbourhoods around N_0



Binary number 11001110
Decimal 115

Fig. 2 Micro Pattern Obtained from the Eight Neighbour LBP

Fig. 2 shows the micro pattern generated by the concatenation of the binary gradient directions. In this example pixel N_1 value is 6 and N_0 value is 5, where the first value 6 is greater than 5 then the function will return 1 as the first bit. Likewise compare all the eight neighbours (6, 7, 1, 3, 7, 9, 8, 4) with the center pixel 5 and generate the eight bit pattern 11001110. Then the equivalent decimal value 115 is assigned to the center referenced pixel.

B. Local Ternary Pattern (LTP):

LTP is an advanced version of LBP. The LTP has three-valued code with relation to grey values of its neighbours. Not like LBP, it does not threshold the pixels into 0 and 1, but it uses a threshold constant to threshold pixels into three values

1, 0 and -1. As presented in Fig.3 considering t as the threshold constant, N_0 as the value of the center pixel and the value of the neighbouring pixels Ni, i = 1,2,..8. The outcome of the thresholding function for f(·,·) for the basic LTP can be represented in Eq.(2):

$f\,(Z(N_c), Z(N_i))$

$$= \begin{cases} 1, & if\ Z(N_i) > Z(N_c) + t \\ 0, & if\ Z(N_i) \geq Z(N_o) - t \text{ and } Z(N_i) \leq Z(N_o) + t \\ -1 & \text{if } Z(N_i) < Z(N_o) - t \end{cases} \tag{2}$$

N_4	N_3	N_2
N_5	N_0	N_1
N_6	N_7	N_8

Fig. 3 Eight neighbourhood around N_0

Assign 0 in a cell when the pixel value is between N_o - t and N_o + t, where N_o is the intensity of the center pixel. The Fig.4 shows local ternary pattern, when the threshold is set to 6.

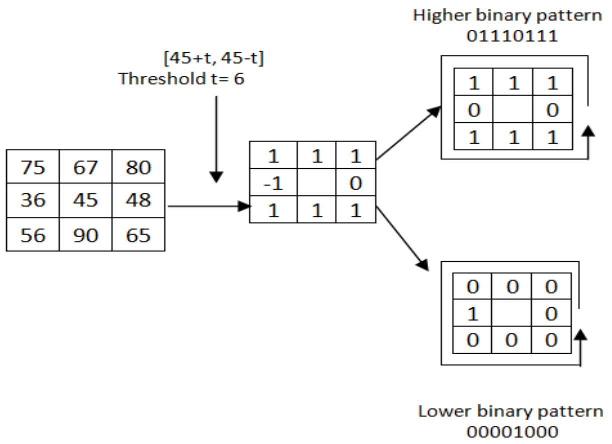


Fig. 4 To Obtain Local Ternary Pattern

The intensity of the center pixel is 45. Therefore the range is between [39, 51], where value of t is 6. Any cells that are above 51 get assigned 1 and any cells that are below 39 get assigned -1. Assign 0 to cells with intensity from 39 to 51. Once create the ternary code [13], and then split up the code into higher and lower patterns. Fundamentally, any values that get assigned a -1 get assigned 0 for higher patterns and any values that get assigned a -1 get assigned 1 for lower patterns. And also, for the lower pattern, any value of the cell that is 1 in the original window gets mapped to 0. The construction of final bit pattern starts from the second row third column, then going around anti-clockwise. Therefore, when this modification gives both lower patterns and higher patterns as output to the given image.

Fig. 4 shows the higher bit pattern 01110111 and the lower bit pattern 00001000 construction by LTP.

III. PROPOSED FOUR NEIGHBOUR BINARY PATTERNS (FNBP)

The four neighbour binary patterns consider only four neighbours around the center pixel N_0. The four neighbours are N_1, N_2, N_3 and N_4. The FNBP consider only horizontal and vertical four neighbours. Not like LBP and LTP it compares the average of the four neighbours with the four neighbours. Only four bit binary is constructed by FNBP. This feature automatically reduces the time taken and storage of four bit binary pattern.

	N_2	
N_3	N_0	N_1
	N_4	

Fig. 5 Horizontal and Vertical Four Neighbours

The FNBP first compute the average of four neighbours N_1, N_2, N_3 and N_4. Next compare four neighbours with the average. If the difference is greater than or equal to zero then assign bit 1 otherwise assign 0. Finally construct a 4 bit binary pattern.

$$Z(N) = \sum_{i=1}^{4} Z(N_i) \tag{3}$$

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

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

While taking the four neighbour value 3, 7, 4, 9 from Fig.2 and substituting the values in Equation 3 the average becomes 5.75. Equation 4 compares the difference between the average 5.75 and the four neighbours 3, 7, 4, 9 and then constructs the four bit 0101

IV. HISTOGRAM INTERSECTION

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

$$H_{FNBP}(I) = \{H_{FNBP}(R_i) | i = 1,2,\ldots n\} \tag{5}$$

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.

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

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

V. 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 [20].

This paper attempts for an accurate feature extraction by the use of 2D Gabor filter, in order to overcome the local the local distortions caused by the variance of illumination, pose and expression [21]. 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 [21]. 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 [22]. The 2D Gabor filter can be represented as a complex sinusoidal signal modulated by a Gaussian function as given equation 7.

$$\Psi_{f,\theta}(x,y) = exp\left[\left(\frac{-1}{2}\right)\left\{\left(\frac{x^2}{\sigma_x^2}\right)+\left(\frac{y^2}{\sigma_y^2}\right)\right\}\right] * exp(2\pi f\,\theta_n) \quad (7)$$

$$\begin{bmatrix} a_{11} \\ a_{12} \end{bmatrix} = \begin{bmatrix} sin\theta_n & cos\theta_n \\ -cos\theta_n & sin\theta_n \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (8)$$

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:

$$\theta_n = \left(\frac{\pi}{p}\right) * (n-1); n = 1,2, \dots p \quad (9)$$

pεn 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,

$$g_{f,\theta}(x,y) = f(x,y) \otimes \Psi_{f,\theta}(x,y) \quad (10)$$

VI. EXPERIMENTS

A complete system performance investigation, which 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. In the following, 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 FNBP is compared with the LBP and LTP on both gray-level images and Gabor feature images with different parameter settings.

The comparative experiments between the FNBP and the LBP and LTP were conducted on the JAFFE, ORL, YALE and 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. Some example images on the JAFFE, ORL, YALE and OWN data set are shown in Fig. 11,12,13,14.

VII. BENEFITS AND PERFORMANCE METRICS

A. *Benefits of proposed approach*

The proposed approach proves that the comparison among the FNBP, LBP and LTP. The recognition rate, execution time and accuracy of FNBP are better than the traditional LBP and LTP. 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, Error rate and execution time to measure the performance.

Mathematically, this can be stated as:

i. Recognition rate

Recognition rate is calculated by the following equation.

$$Recognition\ Rate = \left(\frac{No.of\ correctly\ identified\ images}{Total\ No.of\ images}\right) \times 100 \quad (11)$$

Fig 5, 6, 7, 8 shows the recognition rate of FNBP, LBP and LTP for the JAFFE, ORL, YALE and OWN dataset. The FNBP's recognition rate is better than traditional LBP and LTP.

Fig. 5: Recognition Rate of FNBP, LBP and LTP on the JAFFE, OR, YALE and OWN Dataset's Gray Images.

To observe how well 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 FNBP is significantly improved when the compared with LBP and LTP. Figure 6 shows that the Gabor feature based FNBP achieves much better performance than the gray image.

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

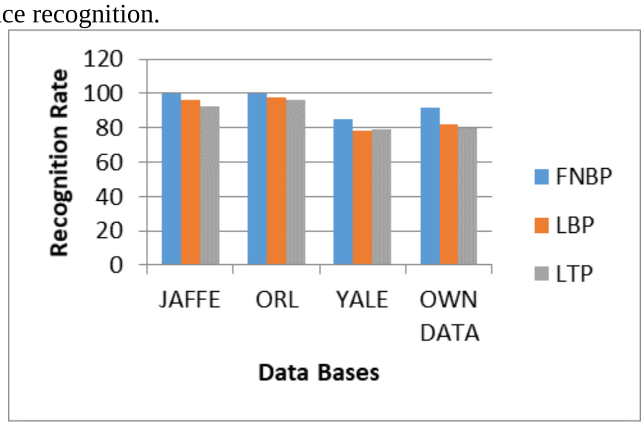


Fig. 6: Recognition Rate of FNBP, LBP and LTP on the JAFFE, ORL, YALE and OWN Dataset's Gabor Feature Images.

ii. Accuracy

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

$$Accuracy = \frac{TP}{Number\ of\ files} \tag{12}$$

Where, TP denotes true positive.

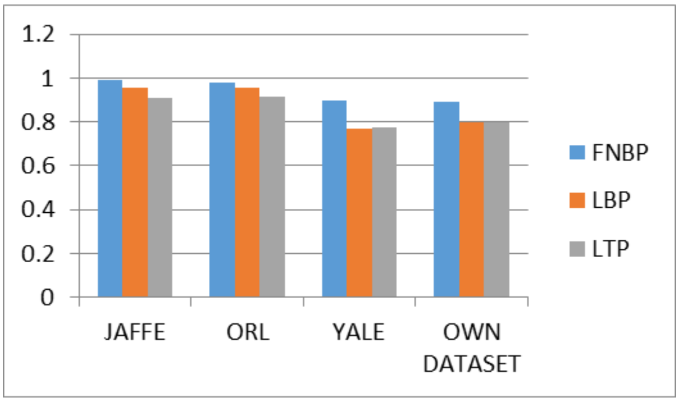


Fig. 7: Accuracy of FNBP, LBP, LTP for the Gray Images on JAFFE, OR, YALE and OWN Datasets

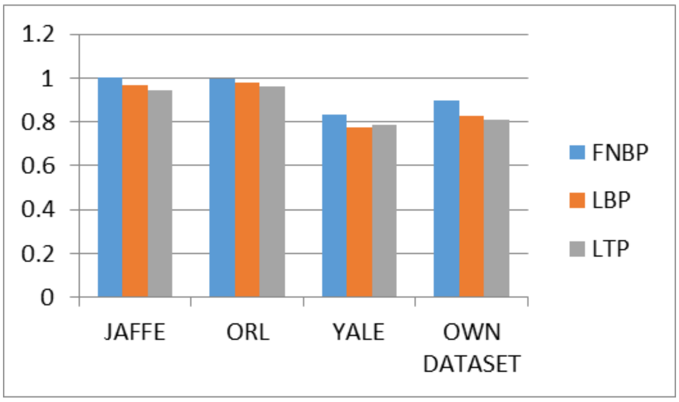


Fig. 8: Accuracy of FNBP, LBP, LTP for the Gabor Images on JAFFE, OR, YALE and OWN Datasets

The Accuracy of FNBP, LBP, LTP is shown in Fig. 7, 8. Accuracy is calculated for JAFFE, ORL, YALE and OWN DATASET for both gray and Gabor images. The accuracy of FNBP is more than LBP and LTP for all the dataset.

iii. Precision Rate

The Precision is use to retrieve instances that are relevant to the find.

$$Precision = TP\ /\ (TP + FP) \tag{13}$$

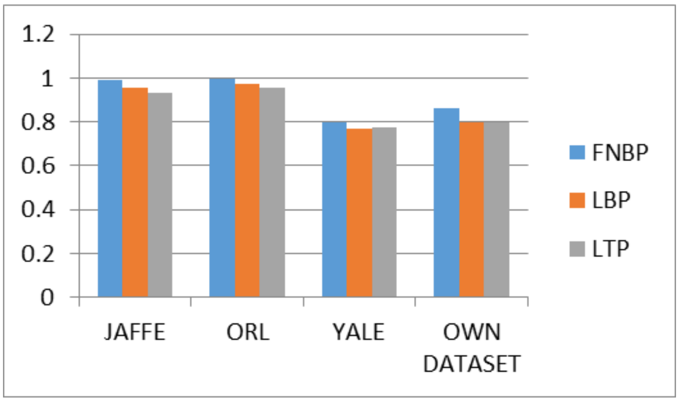


Fig. 9: Precision Rate of FNBP, LBP,LTP for the Gabor Images on JAFFE, OR, YALE and OWN Datasets

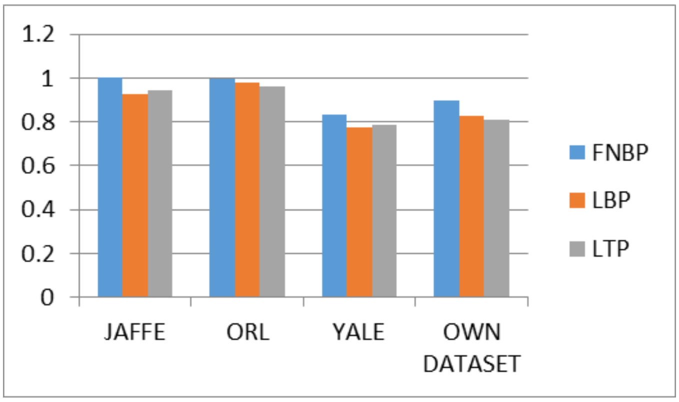


Fig. 10 Precision Rate of FNBP, LBP, LTP for the Gabor Images on JAFFE, OR, YALE and OWN Datasets

Figure 9 and 10 shows the precision rate of FNBP is higher for all the data sets than the LBP and LTP.

iv. Error 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.

$$Error\ rate = 1 - TP \quad (14)$$

Table I and II compares the error rate of FNBP, LBP and LTP for both the gray and Gabor images.

Table I. Error Rate of FNBP, LBP, LTP for the Gray Images on the JAFFE, ORL, YALE and OWN Datasets

DATABASE	**FNBP**	**LBP**	**LTP**
JAFFE	0.009	0.047	0.070
ORL	0.005	0.025	0.043
YALE	0.200	0.233	0.223
OWN DATASET	0.140	0.200	0.200

Table II. Error Rate of FNBP, LBP, LTP for the Gabor Images on the JAFFE, ORL, YALE and OWN Datasets

DATABASE	FNBP	LBP	LTP
JAFFE	0.000	0.033	0.056
ORL	0.003	0.020	0.038
YALE	0.167	0.223	0.217
OWN DATASET	0.100	0.175	0.190

v. Execution time

Execution time of FNBP, LBP and LTP is compared in table III and table IV for the JAFFE, ORL, YALE and OWN datasets.

Table III. Execution Time of FNBP, LBP, LTP for the Gray Image on the JAFFE, ORL, YALE and OWN Datasets

DATABASE	FNBP	LBP	LTP
JAFFE	4.677032	5.100702	11.211999
ORL	36.23320	39.66957	49.096536
YALE	7.912625	9.302521	11.056012
OWN DATASET	12.00612	17.35432	19.588387

Table IV. Execution Time of FNBP, LBP, LTP for the Gabor Image on the JAFFE, ORL, YALE and OWN Datasets

DATABASE	FNBP	LBP	LTP
JAFFE	5.641563	6.076832	9.508596
ORL	37.62437	44.06206	68.45078
YALE	9.751405	11.30161	15.32074
OWN DATASET	13.01674	19.95921	23.95031

Table III and IV clearly proves the execution time of FNBP is less for both gray and Gabor images.

VIII. CONCLUSION

This paper compares the accuracy, error rate, recognition rate and execution time of LBP, LTP and FNBP used 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 FNBP achieves better recognition, less error rate and less execution time than LBP and LTP. It is clear that the Gabor filter improves the performance of FNBP. The proposed four bit FNBP focuses on the higher accuracy rather than the traditional eight bit LBP and LTP.

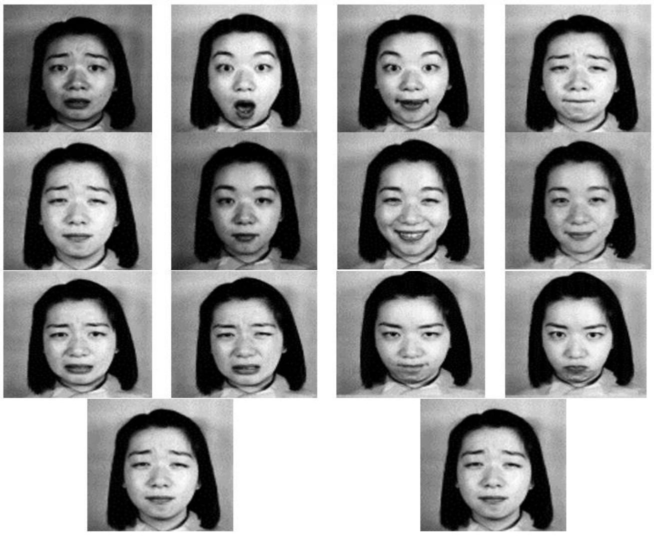


Fig. 11 Sample Images of JAFFE Data Set

Fig. 12 Sample Images of ORL Data Set

Fig. 13 Sample Images of YALE Data Set

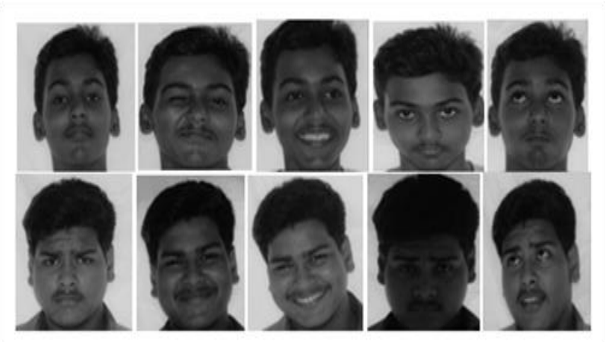


Fig. 14 Sample Images of OWN Data Set

REFERENCES

[1] C.Tsio1sions, M. Petrou, "On the choice of the parameters for Anisotropic Diffusion in Image Processing", *Pattern Recognition,* 46(5):1369-1381, May2013.

[2] R. Chellappa, C. L. Wilson, and S. Sirohey, "Human and machine recognition of faces: A survey,"Proc.IEEE,vol.83,no.5,pp.705–740, May 1995.

[3] W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, "Face recognition: A literature survey," ACM Comput. Surv., vol. 35, no. 4, pp. 399–459, 2003.

[4] M. Turk and A. Pentland, "Eigenfaces for recognition," J. Cogn. Neurosci., vol. 3, no. 1, pp. 71–86, 1991.

[5] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection," IEEE Trans. Pattern Anal. Mach. Intell., vol. 19, no. 7, pp. 711–720, Jul. 1997.

[6]P.S.PenevandJ.J.Atick,"Localfeatureanalysis:Ageneralstatistical theory for object representation," Network: Comput. Neural Syst., vol. 7, no. 3, pp. 477–500, 1996.

[7] D.Gabor, "Theoryofcommunication,"J.Inst. Elect. Eng.,vol. 93,no. 26, pp. 429–457, 1946.

[8] L. Wiskott, J. M. Fellous, N. Krüger, and C. von der Malsburg, "Face recognition by elastic bunch graph matching," IEEE Trans. Pattern Anal. Mach. Intell., vol. 19, no. 7, pp. 775–779, Jul. 1997.

[9] P. J. Phillips, H. Moon, S. A. Rizvi, and P. J. Rauss, "The FERET evaluationmethodologyforface-recognitionalgorithms," IEEE Trans. Pattern Anal. Mach. Intell., vol. 22, no. 10, pp. 1090–1104, Oct. 2000.

[10] B. Heisele, T. Serre, and T. Poggio, "A component-based framework for face detection and identification," Int. J. Comput. Vis., vol. 74, no. 2, pp. 167–181, 2007.

[11]T.Ojala,M.Pietikäinen,andD.Harwood,"Acomparativestudyoftext ure measures with classification based on feature distributions," Pattern Recognit., vol. 29, no. 1, pp. 51–59, 1996

[12] T. Ojala, M. Pietikäinen, and T. Mäenpää, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 7, pp. 971–987, Jul. 2002

[13] M. Pietikäinen, T. Ojala, and Z. Xu, "Rotation-invariant texture classification using feature distributions," Pattern Recognit., vol. 33, no. 1, pp. 43–52, 2000.

[14] G. Zhao and M. Pietikäinen, "Dynamic texture recognition using local binary patterns with an application to facial expressions," IEEE Trans. Pattern Anal. Mach. Intell., vol. 29, no. 6, pp. 915–928, Jun. 2007.

[15] M.Heikkilä and M.Pietikäinen, "Atexture-based method for modeling the background and detecting moving objects," IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 4, pp. 657–662, Apr. 2006.

[16] T.Ahonen,A. Hadid, and M. Pietikäinen,"Face description with local binary patterns: Application to face recognition," IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 12, pp. 2037–2041, Dec. 2006.

[17] T. Ojala, M. Pietikainen and D. Harwood, "A Comparative Study of Texture Measures with Classification based on Feature Distributions", Pattern Recognition, Vol. 29, No. 1, pp. 51-59, 1996.

[18] Wen-Hung Liao and Ting-Jung Young, "Texture Classification using Uniform Extended Local Ternary Patterns", Proceedings of IEEE International Symposium on Multimedia, pp. 191-195, 2010.

[19] Suman Kumar Bhattacharyya & Kumar Rahul. s, "Face Recognition by Linear Discriminant Analysis" , International Journal of Communication Network Security, ISSN: 2231 – 1882, Volume-2, Issue-2, 2013.

[20] Sebastien Marcel, Yann Rodriguez and Guillaume Heusch. "On the Recent Use of Local Binary Patterns for Face Authentication", International Journal of Image and Video Processing, special issue on Facial Image Processing, Manuscript received May 1, 2006; revised October 20, 2006; accepted May 25, 2007.

[21] N. Oliver, A. Pentland, and F. Berard, "A real-time face and lips tracker with facial expression recognition". IEEE Trans. on Pattern Recognition, 2000, 33:1369–1382.

[22] Z. Chai, Z. Sun, H. Mendez-Vazquez, R. He and T. Tan, "Gabor Ordinal, measures for face recognition‖", IEEE Trans. on Information Forensic and Security, 2014, vol. 9, no. 1, pp. 1-26.

A.Geetha is an Associate Professor, Department of Computer Applications in Nesamony Memorial Christian College, India. She is doing research under the guidance of Dr. Y.Jacob Vetha Raj an Associate Professor, Department of Computer Science in Nesamony Memorial Christian College, India. She received B.Sc degree in computer science from Manonmaiam Sundarnar University, Tirunelveli, India, M.Sc degree in computer Science from Avinashilingam Deemed University, Coimbatore also M.Phil degree in computer Science from Mother Tersea University. Her area of interest is image processing.

Dr. Y.Jacob Vetha Raj an Associate Professor, Department of Computer Science in Nesamony Memorial Christian College, India. He received B.E degree in computer science from National Engineering College, Kovilpatti, India and also he received M.Tech and Ph.d degrees from M.S University, Thirunelveli, India. His area of interest is image processing. He has developed somany application software. He has published many national and international level research papers.