Enhanced Face Recognition Approach under Illumination Variations Based on Local Binary Pattern

Anees Buzdar, Hammad Khan
anees.buzdar@iub.edu.pk, khammad88@yahoo.com
Department of Electrical & Computer Engineering,
Islamia University Bahawalpur, Pakistan

Abstract— **A new face recognition algorithm proposed by Z.Lian, M.J.Er and J.Li is implemented in this research paper. Unlike the other face recognition schemes, the proposed algorithm works efficiently in varying Illumination conditions. This paper highlights the limitation of present face recognition algorithms. Algorithms offering efficient feature extraction methods fail to differentiate between similar images under varying light conditions. Algorithms with efficient preprocessing methods give a lot of errors during distance computation. Distance measurement such as Histogram Intersection works well at global level but fails to compute pixel distance effectively. Similarly hamming distance gives better approximation of pixel distance but performs poorly at global level. A solution to the highlighted problems is presented in terms of new proposed algorithm by Z.Lian, M.J.Er and J.Li. The new algorithm is explained with the help of block diagram and experimental results. A detailed testing is done on Yale B & Extended Yale B data sets and further comparison with other existing schemes is also included to highlight the advantages of proposed method.**

Keywords— **LBP; Histogram Intersection ;Hamming Distance; Log; DoG**

I. INTRODUCTION

In recent years face recognition has received substantial attention from both research communities and the market, but still remained very challenging in real applications [3]. A face recognition system must be robust with respect to the immense variability of the human face and generalize over a wide range of conditions to capture the essential similarities for each individual [4]. The problem becomes even more challenging if Illumination conditions are varying and therefore chances of error increases.

In research paper [1] "A Novel Face Recognition Approach under Illumination Variations Based on Local Binary Pattern" Z.Lian, M.J.Er and J.Li proposes a new scheme of face recognition based on local binary pattern and a novel distance measurement approach. The proposed approach first computes logarithmic DoG of face images using suitable sigma. Local binary pattern, which is considered as one the widely used approach for recognition applications, is then computed for comparison with the stored images. A novel distance measurement scheme is then applied to compute the distance of input image with stored database. The new distance measurement considers both the differences between images on pixel level as well as on global level.

Logarithm transform is often used in image enhancement to expand the values of dark pixels [5] and [6]. Recently, more researchers focus on robust face recognition such as face recognition systems invariant to pose, expression and illumination variations. The same person can appear greatly different under varying lighting conditions [2].

Local Binary Pattern operator was introduced in 1996 [7] as a means of summarizing local gray-level structure. The operator takes a local neighborhood around each pixel, thresholds the pixels of the neighborhood at the value of the central pixel and uses the resulting binary valued image patch as a local image descriptor. It was originally defined for 3×3-neighborhoods, giving 8 bit codes based on the 8 pixels around the central one.

Z.Lian, M.J.Er and J.Li have proposed a novel distance measurement approach. The proposed scheme first computes the global distance between two LBP's using Histogram Intersection. Pixel distance is then computed between respective pixels using Hamming distance. A weighted sum of two distances is considered as the final distance. This proposed approach gives improved performance as compared to other approaches in literature.

The paper is organized as follows: Section II presents proposed algorithm, Section III presents novel distance measurement scheme that enhance the accuracy, Section IV presents the results after testing the algorithm for Yale b & extended Yale B data set [9]. Section V compares the proposed scheme with other face recognition algorithms, Section VI introduces a modification to the scheme. Section VII presents Conclusion remarks.

II. PROPOSED FACE RECOGNITION SCHEME

The proposed scheme takes two face images as input. One image is taken as primary face and second image is selected from database. The distance between primary face and face selected from database is computed. A decision is made based on the resultant distance as if two faces are similar or not. The first step is of preprocessing in which log is taken which removes brightness variations from the face. After preprocessing, Difference of Gaussian is applied on faces. Local binary pattern is then computed for DoG filtered images. The distance between two LBP's is computed using histogram intersection. Another distance measurement scheme, Hamming distance is applied directly on pixels. A weighted sum of both the distances is considered as the final distance. Figure 1 shows the operation of proposed face recognition scheme.

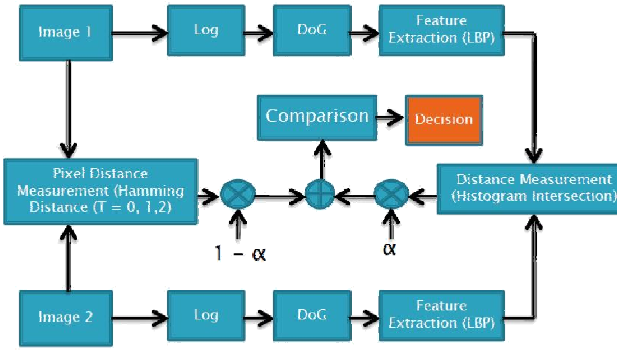

Figure 1. Architecture of Proposed Face Recognition Algorithm

A. *Pre Processing Log*

Preprocessing step involve normalization of Illumination in face images. These variation in illumination can significantly affect the accuracy of algorithm. Different approaches have been proposed in literature to nullify the brightness effect. Some researchers prefer Gamma function as pre processing step. The authors in [1] have adopted logarithmic operator. Log can be useful in the sense that it preserves low magnitudes which can be handful while implementing some edge detection scheme such as DoG in our case.

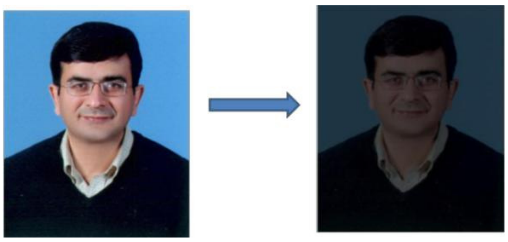

Figure 2. Face Image 1 after applying Logarithmic operator

B. *Difference of Gaussian*

Local Binary Pattern works efficiently if combined with an edge detection technique usually DoG. Most of the face recognition approaches that uses LBP for feature extraction performs DoG before LBP. The authors in [1] have also performed Difference of Gaussian of both the face images before applying feature extraction scheme. DoG works by computing a blurred version of face using σ1. A second blurred version is formed using σ2.The difference of two blurred image is the DoG filtered image. For our case we have used σ 1 = 0.5 and σ 2 = 6.

Figure 3. Blurred version of Face Image 1 using σ=0.5 & σ=6

Figure 4. DoG Filtered Image

C. *Local Binary Pattern*

LBP operator was introduced by Ojala [7] as a very effective tool for feature extraction that is used here to get the face description. It works by labeling the pixels of an image in a 3x3 neighborhood. The central pixel value is compare with its eight neighbors & for each comparison a binary no. either 1 or zero is allotted which results an eight digit binary number after every LBP operation and then the histograms are used as texture descriptor.

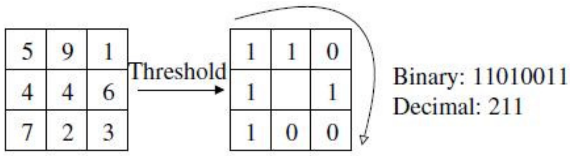

Figure 5. LBP Operation on 3 x 3 Kernel

A lot of research has been done on modifying the neighborhoods in an LBP operator with different sizes [8]. Using circular neighborhoods & bilinear interpolation of pixel values allow any radius & number of pixels in the neighborhood. In our case, we use the notation (P,R), R representing the radius & P shows sampling points on a circle. The following diagram well depicts the scenario for a (8,2) neighborhood.

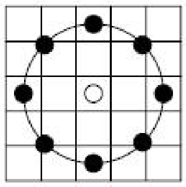

Figure 6. LBP using Radius of 8

An LBP is called uniform LBP if it contains at most twice transitions from 0 to 1 or 1 to 0 in a binary sequence. Experiment results from Ojala et al also showed that the uniform patterns account for a bit less than 90% for all patterns using (8,1) neighborhood & around 70% at (16,2). A histogram labeled image $f_i(x,y)$ can be defined as:

$H_i = \text{Sum}(x,y)\{fi(x, y) = i\}, i = 0, \ldots, n - 1 \; {}_{x,y}$

Where n is the number of different labels as the output of LBP operator and

$\{ \} = 1,$

$0,$

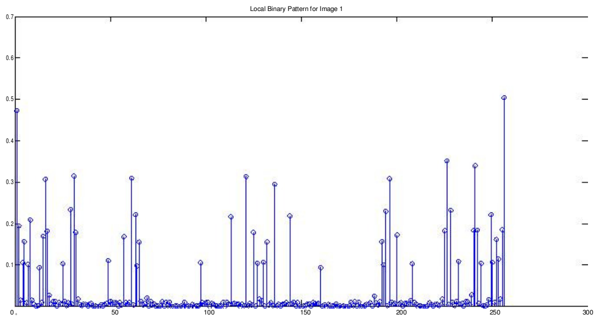

Figure 7. LBP Normalized Histogram for Face Image 1

D. Implementation of proposed algorithm on second face image

Similar steps are performed for second face image. Logarithmic operator is first used followed by DoG and LBP.

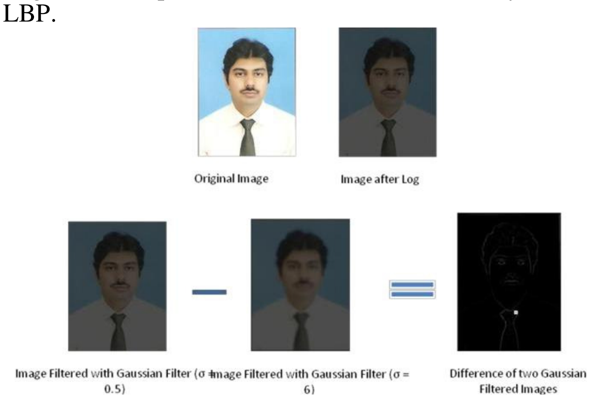

Figure 8. Preprocessing Log & DoG applied on face Image 2

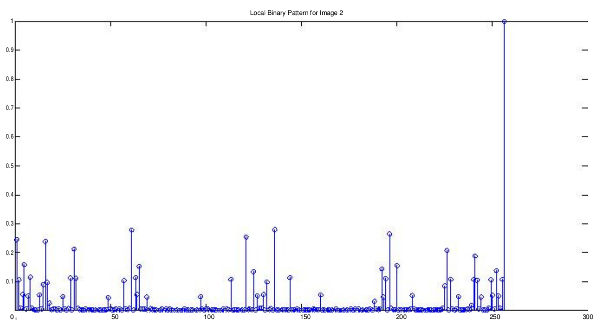

Figure 9. LBP Normalized Histogram for Face Image 2

III. NOVEL DISTANCE MEASURMENT SCHEME

A novel distance measurement scheme is introduced by authors in [1] to compute the distance between two face images. The new distance measurement scheme first considers the difference between local binary pattern of the two images. Next the distance is computed on pixel level - using Hamming Distance.

A. Histogram Intersection (Global Distance)

Distance between histograms of local binary pattern is computed using histogram intersection where the common area is calculated as min(Si,Qi)

$$D(Q,S) = \sum_{k=1}^{n} \mathrm{Min}(Qi, Si) \qquad (1)$$

Subtracting common area from total area gives the distance between two LBP's. In case of normalized histogram the common area is subtracted from 1.

$$D1(Q,S) = 1 - D(Q,S) \qquad (2)$$

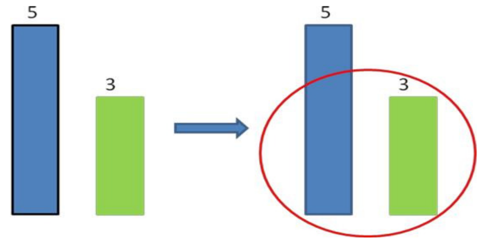

Figure 10. Histogram Operation

B. Pixel Difference using Hamming Distance

Pixel difference is computed using Hamming Distance between bits of respective pixels. The distance between images on pixel level is defined as the percentage of pixels which have different patterns in two images. Each pixel is converted to binary then hamming distance is computed using

$$D(A,B) = \sum_{i=1}^{n} \sum_{j=1}^{m} Z(A(i,j), B(i,j)) \qquad (3)$$

Z(x,y) = 0 if Hamming Distance between x & y is smaller than T

1 else

Threshold can be taken as 0, 1 or 2 where zero thresholds means that distance will be zero only if two pixels match exactly. Threshold = 1 means that distance will still be zero even if two pixels have one bit difference.

Image 1		Image 2		Hamming Distance	
Threshold, T = 0					
10101101	10011011	10101101	10011010	0	1
01110111	00101011	01110101	01001011	1	1
Threshold, T = 1					
10101101	10011011	10101101	10011010	0	0
01110111	00101011	01110101	01001011	0	1
Threshold, T = 2					
10101101	10011011	10101101	10011010	0	0
01110111	00101011	01110101	01001011	0	0

Figure 11. Hamming Distance Operation on pixels with different T

C. Final Distance

Final distance between two face images is computed by taking a weighted sum of global distance and pixel distance. α is defined as the weight factor. By varying the value of α, weight age of pixel or global distance can be varied while computing the final distance. For the two face images we have processed so far the distance comes out to be **Pixel Distance = 0.9982 (T = 0) Global Distance = 0.5011 Final Distance = 0.7497 (α = 0.5).**

IV. TESTING THE PROPOSED MODEL FOR YALE B & EXTENDED YALE B DATA SET

To verify the author's claim we have tested the model for Yale B data set and Extended Yale B data set [9]. This data set contains 64 different faces of a same person under varying illumination conditions. There are 39 subjects with 64 images of each subject under different light conditions. We have tested our model for first 10 subjects i.e. for 640 face images.

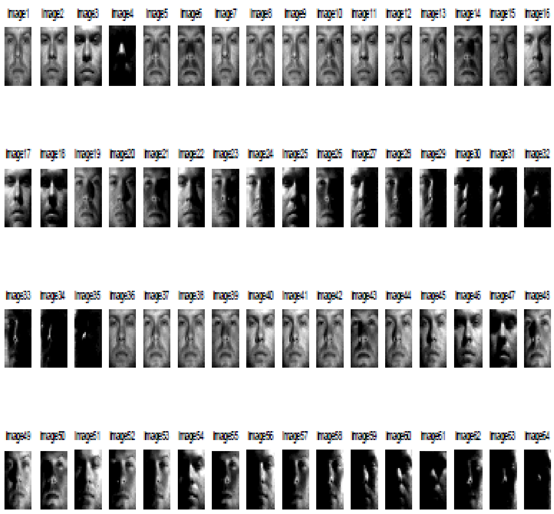

Figure 12. Extended Yale B Data Set Subject 1 Images

The proposed algorithm worked efficiently for subject 1 & subject 2. However the error rate grew higher from subject 3 onwards. For each subject we have taken the first image as primary image and then we have computed the distance of this image from the 63 other face images of same subject. On the basis of final distance, we can make a decision if the algorithm was successful.

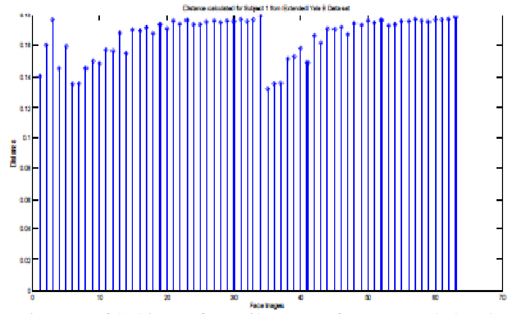

Figure 13. Distance of Subject 1 from 63 Images from Extended Yale B

On the basis of incorrect result we have calculated error rate for each subject. The rate is as low as 0 % for subject 1 and goes as high as 8% for subject 5.

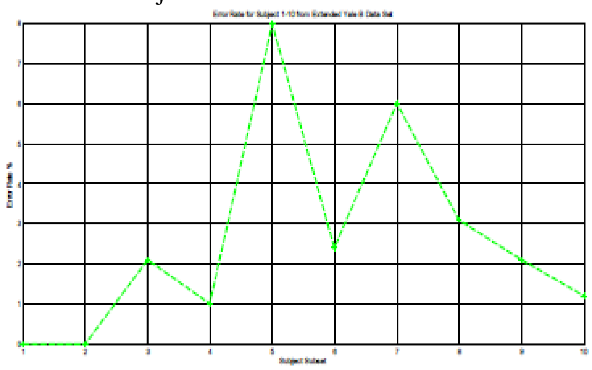

Figure 14. Error Rate % for Subjects 1-10 using proposed algorithm

Changing the weight factor α can affect the error rate. Subject 5 error rate can be reduced to 6.8% from 8 if α is taken as 0.7 but it increases error in other subjects. Therefore selection of α can be crucial in determining the final result.

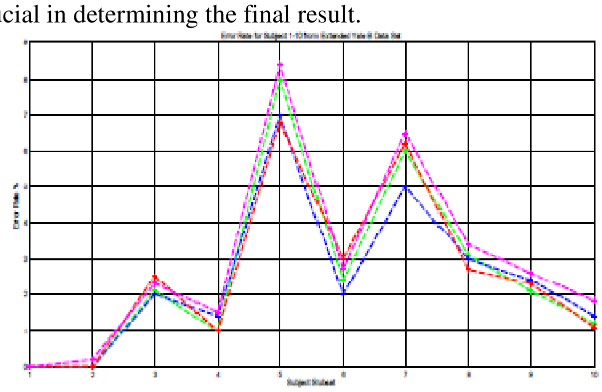

Figure 15. Error Rate % for Subjects 1-10 using proposed algorithm for α=0.4, 0.5, 0.6 & 0.7

In the same way by varying value of Threshold when computing Hamming distance between respective pixels can also result in different error rate. A threshold value of 0 gives a lot of incorrect results as only slightest of variation in pixel value will increase the overall distance. Similarly a high value of threshold will also increase error rate as pixels with a lot difference will be considered as same.

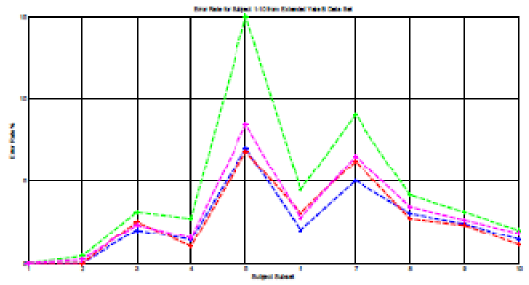

Figure 16. Error Rate % for Subjects 1-10 for T=0, 1, 2 & 3

V. COMPARISON WITH OTHER FACE RECOGNITION ALGORITHMS

To verify the authors claim we have compared the result of proposed algorithm with other face recognition schemes such as Face Recognition Scheme using DCT, LN and LBP. We have not implemented the other schemes but the error result of DCT, LN & LBP are given in [1] for subjects 2, 3, 4 & 5.

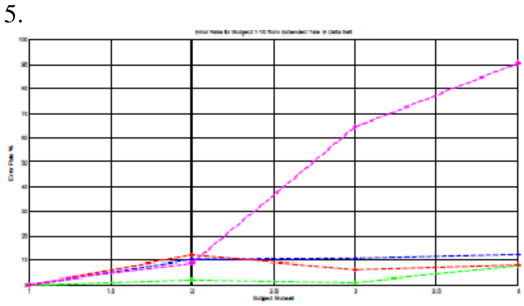

Figure 17. Error Rate % for Subjects 2-5 using DCT, LN, LBP & Proposed Scheme

VI. EXTENDING THE DESIGN BY INTRODUCING RESIZE & ROTATE OPTION

An extra step of Rotate + Resize is introduced before log to align the two faces. Though LBP hardly shows any difference for original or rotated image but pixel distance gives improved result by introducing this option.

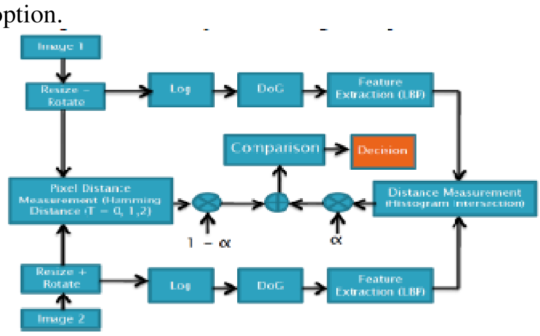

Figure 18. Modified Algorithm with Introduction of Rotate + Resize

VII. CONCLUSION

A new face recognition approach is implemented in this paper. This approach involves a novel distance measurement scheme which combines histogram intersection and hamming distance. Experimental results show that this scheme works better than most of the other face recognition schemes especially for the case where illumination conditions are varying. Proposed scheme is tested for Yale b and extended Yale b data set to verify its performance. This technique is easy to implement as it does not differ a lot from the existing face recognition approaches.

ACKNOWLEDGMENT

We would like to thank our family for all the prayers and support they gave us throughout. A very special thank to Sir Dr. Faisal Mufti and our TA Zakirullah for all the motivation and support. A special thank to Dr. Rauf Baig as his presence even a couple years back made a big difference today.

REFERENCES

[1] Z.Lian, M.J.Er and J.Li, ―A Novel Face Recognition Approach under Illumination Variations Based on Local Binary Pattern,‖ in Proc. 14th International Conference on Computer Analysis of Images and Patterns, CAIP 2011 Seville, Spain, August 2011

[2] Weilong Chen, Meng Joo Er, " Illumination Compensation and Normalization for Robust Face Recognition Using Discrete Cosine Transform in Logarithm Domain," IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS—PART B: CYBERNETICS, VOL. 36, NO. 2, APRIL 2006

[3] Ehsan Fazl Ersi, John S. Zelek, ―Local Feature Matching For Face Recognition,‖ in Proc. 3rd Canadian Conference on Computer and Robot Vision, CRV'06, 2006

[4] A. Jonathan Howell, Hilary BuxtonK, ―Towards Unconstrained Face Recognition from Image Sequences,‖ in Proc. Second International Conference on Automatic Face and Gesture Recognition, October 1996, Killington, Vermont

[5] Y. Adini, Y. Moses, and S. Ullman, ―Face recognition: the problem of compensating for changes in illumination direction,‖ IEEE Trans. Pattern Anal. Mach. Intell., vol. 19, no. 7, pp. 721–732, Jul. 1997.Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, ―Electron spectroscopy studies on magneto-optical media and plastic substrate interface,‖ IEEE Transl. J. Magn. Japan, vol. 2, pp. 740–741, August 1987 [Digests 9th Annual Conf. Magnetics Japan, p. 301, 1982].

[6] R. C. Gonzalez and R. E.Woods, Digital Image Processing. Reading, MA: Addison-Wesley, 1992.

[7] Ojala, T., Pietik ainen, M., Harwood, "A comparative study of texture measures with classification based on feature distributions," Pattern Recognition 29 (1996)

[8] Ojala, T., Pietik ainen, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," IEEE Transactions on Pattern Analysis and Machine Intelligence 24 (2002) 971–98

[9] Athinodoros Georghiades, Peter Belhumeur, and David Kriegman's paper, "From Few to Many: Illumination Cone Models for Face Recognition under Variable Lighting and Pose", PAMI, 2001.