Face Recognition using Co-occurrence Matrix of Local Average Binary Pattern (CMLABP)

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***Abstract*— The local binary pattern (LBP) operator has been proved to be effective for image representation, but it is too local to be strength. In this paper, we propose Co-occurrence Matrix of Local Average Binary Pattern operator (CMLABP), and apply it to face recognition.**

In my method, calculation is performed based on average values of P-neighbor values of pixels, instead of individual pixels. In addition instead of histogram; that represents only the occurrences of the patterns without any indication about their locations, we use of Co-occurrence Matrix to extract features.The experimental results on the FERET and ORL face databases validate that the offered algorithm has better performance than or comparable performance with state-of-the-art local feature based methods.

***Index Terms*— Local Binary Pattern, Co-occurrence Matrix, Average values.**

I. INTRODUCTION

As one of the most active and visible research topics in computer vision, pattern recognition and biometrics, face recognition has been extensively studied in the past two decades [1, 2], yet it is still a challenging problem in practice due to uncontrolled environments, occlusions and variations in pose, illumination, expression and aging, etc. Various methods have been offered for face feature extraction, among which the representatives include Eigen-face [3], Fisher-face [4]; Gabor Feature based Classification (GFC) [5] and LBP methods [6], etc.

Recently, Local Binary Patterns (LBP) is introduced as a powerful local descriptor for microstructures of images [19]. The LBP operator labels the pixels of an image by thresholding the 3 × 3-neighborhood of each pixel with the center value and considering the result as a binary string or a decimal number. Recently, Ahonen et al offered a novel approach for face recognition, which takes benefit of the Local Binary Pattern (LBP) histogram [7]. After it was extended to Unicode LBP, it was used at many places because of its high efficient code way and low excellent local texture description. After this the many researches have work on LBP [7-18].Excellent results in face recognition have been achieved by using the Local Binary Pattern (LBP) method. It has been verification that "uniform" patterns play an important role in texture classification [8]. "Uniform" patterns also showed their priority in face recognition [9, 10].

However, the original LBP operator has the following drawback in its application to face recognition. It has its small spatial support region; therefore the calculations within original LBP that are performed between two single pixel values are much affected by small changes in the pattern. Moreover, original LBP use of histogram to extract features; An LBP histogram calculated over the whole face image represents only the occurrences of the patterns without any indication about their position. In this work, we offer a novel representation, called Co-occurrence Matrix of Local Average Binary Pattern (CMLABP), to overcome the restriction of LBP, and apply it to face recognition. In CMLABP, calculation is performed based on average values of P-neighbor values of pixels, instead of individual pixels. Finally, Co-occurrence Matrix is used to extract features.

The rest of this paper is organized as follows. Sequentially, in Section 2 and 3, we briefly reviewed local binary patterns (LBP) and Gray level Co-occurrence Matrix recursively. Section 4 presents the Co-occurrence Matrix of Local Average Binary Pattern (CMLABP) Method.
In Section 5, experiments on ORL and FERET face database are presented to demonstrate the effectiveness of CMLABP. Section 6 concludes this paper with a conclusion and perspective on future work.

II. LOCAL BINARY PATTERN (LBP)

The original LBP operator, introduced by Ojala *et al.* [19], is a powerful means of texture description. The operator labels the pixels of an image by thresholding the 3x3-neighbourhood of each pixel with the center value and converts the result into a binary number by using (1).

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$$LBP_{P,R(x,y)} = \sum_{p=0}^{P-1} s(g_p - g_c)2^P \quad (1)$$

$$s(x) = \begin{cases} 1 & if \quad x \geq 0 \\ 0 & if \quad x < 0 \end{cases}$$

Where gc is an intensity of central pixel and g_p is a gray level intensity of neighborhood pixel and 2p is a relevant factor for any neighborhood. S (.) is a sign function. The process is demonstrated with the Fig (1).

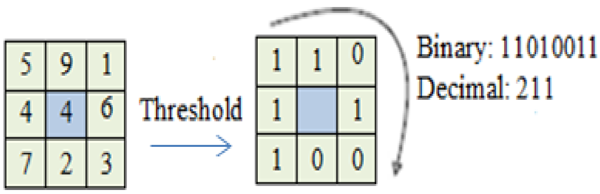

Fig (1): The basic LBP operator

Two extensions of the original operator were made in [8]. The first defined LBP's for neighborhoods of different sizes, thus making it possible to handle textures at different scales. Using circular neighborhoods and bilinearly interpolating the pixel values allow any radius and number of pixels in the neighborhood. In this extension, P sampling points on a circle of radius of R, are shown to form a (P, R).

The second defined the so-called *uniform patterns*: an LBP is 'uniform' if it contains at most one 0-1 and one 1-0 transition when viewed as a circular bit string. For example, 00000000, 00011110 and 10000011 are uniform patterns. Uniformity is important because it characterizes the Pieces that include primitive structural information such as edges and corners. Ojala et al. noticed that in their experiments with texture images, uniform patterns account for a bit less than 90 % of all patterns when using the (8,1) neighborhood and for around 70 % in the (16,2) neighborhood. There are various extensions and reformations of the original LBP following its first introduction by Ojala *et al* [19]. A good source of references can be found in [18].

III. Gray-Level Co-occurrence Matrix

Histogram represents only information about distribution of intensities, but not about the relative location of pixels with respect to each other in that texture. Statistical moments of the intensity histogram of an image or region are one of the simplest findings for describing texture. The Gray Level Co-ocurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. GLCM will help to provide valuable information about the relative location of the neighbouring pixels in an image [20].GLCM express the event rate of gray values of two pixels that are located in particular Distance (d) and direction with respect to each other in image. Usually the distance between two pixels are considered equal to 1 (d = 1) and the possible angle between two pixels with 0, 45, 90 and 135 degrees are expressed [22], See figure (2).

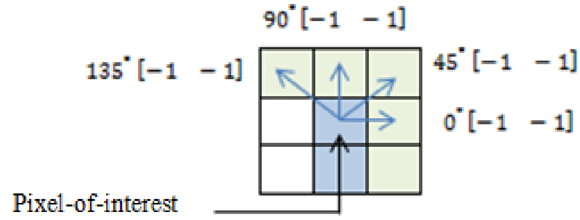

Fig (2): Expressed pixels With Distance d=1 and angles 0, 45, 90 and 135

Given an image I, of size n×m, the co-occurrence, matrix C can be defined as (2): (2)

$$C_k(i,j) = \sum_{p=1}^{n}\sum_{q=1}^{m} \begin{cases} 1, & if\ I(p,q) = i\ and\ I(p+\Delta x, q+\Delta y) = j \\ 0, & otherwise \end{cases}$$

In C_k matrix, Element (i, j) is the total events of numbers i and j that their distance from each other is (Δx, Δy).

First time, Harlyk [21] used of the co-occurrence matrix for feature extraction of image texturein order to Troubleshooting grapefruit fruit. He introduced fourteen statistical features from the GLCM and then in [23] represented that only six of the textural features; *Energy*, *Entropy*, *Contrast*, *Variance*, *Correlation and Inverse Difference Moment*, are considered to be the most relevant.Six relevant Haralick Features are defined by the following functions:

$$\text{Energy} = \sum_{i=1}^{n}\sum_{j=1}^{m} C_{ij}^2 \quad (3)$$

$$\text{Entropy} = -\sum_{i=1}^{n}\sum_{j=1}^{m} C_{ij}\log C_{ij} \quad (4)$$

$$\text{Contrast} = \sum_{i=1}^{n}\sum_{j=1}^{m} |i-j| C_{ij}^2 \quad (5)$$

$$\text{Variance} = \sum_{i=1}^{n}\sum_{j=1}^{m} (i-\mu)^2 C_{ij} \quad (6)$$

$$\text{Correlation} = \frac{\sum_{ij}(i-\mu)(j-\mu)C_{ij}}{\sqrt{var(i)var(j)}} \quad (7)$$

$$\text{Inverse Difference Moment} = \sum_{i=1}^{n}\sum_{j=1}^{m} \frac{1}{1+(i-j)^2} C_{ij} \quad (8)$$

IV. CMLABP Method for Face Recognition

A. Local Average Binary Pattern (LABP) operators

Since the calculations within original LBP are performed between two single pixel values, it is much affected by small changes in the pattern and it is too local to be strength. In order to obtain better feature representation, in my offered method, LABP operator employs a larger number of sample points. In LABP, first single pixels in original image (I), are replaced with average gray-values of P-neighbor values of pixels and capture image M. Specifically, we will use Eq. (9) to calculation average value of each pixel (Mij) in image I:

$$M_{ij} = \frac{g_{ij} + \sum_{k=0}^{p-1} g_{ijk}}{9} \quad (9)$$

Where g_{ijk} for k= {0 … 7} is P-neighbor values of pixel (i,j) in image I. Then we apply LBP operator on the image M and label each pixel of an image (M_c) by thresholding its P-neighbor values with the center value and converts the result into a binary number by using (10).

$$LABP_{P,R(x,y)} = \sum_{p=0}^{P-1} s(M_p - M_c)2^P \qquad (10)$$

Where Mc define the gray values of the center pixel and Mp are gray values of P equally spaced pixels on the circumference of a 3 3 window in image M. And s(x) is a sign function (11).

$$s(x) = \begin{cases} 1 & if \quad x \geq \theta \\ 0 & if \quad x < \theta \end{cases} \qquad (11)$$

In [8] is shown that using the "uniform" subset of LBP code improves the performance of LBP based methods. Finally, to extract representative features; we consider only uniform patterns of LABP.

B. Co-occurrence Matrix of LABP (CMLABP)

Original LBP use of histogram to extract features; An LBP histogram calculated over the entire face image represents only the occurrences of the patterns without any indication about their positions. Gray Level Co-occurrence Matrix (GLCM) displays the distributions of the intensities and the information about relative positions of neighboring pixels of an image. In offered method, we use of co-occurrence matrix to extracted features. Given an LABP image of size N×M, the co-occurrence, matrix GLCM can be defined as:

$$GLCM_{p,r}(i,j) = \sum_{i=1}^{N} \sum_{j=1}^{M} B\left(LABP_{p,r}(x,y)\right) \qquad (12)$$

Where in that i,j is a is a number of code that capture with LABP operator.

$$i,j \in [0{,}255], \quad r \in [1, R]$$

Function B (I) is defined as:

$$B(I) = \begin{cases} 1, & \text{if } I(x,y) = i \text{ and } I(x+\Delta_x, y+\Delta_y) = j \\ 0, & \text{otherwise} \end{cases} \qquad (13)$$

My method idea is simple and straight forward. For each LABP image, four co-occurrence matrices are calculated for the offsets {[0 1], [-1 1], [-1 0], [-1 -1]} that are determined as one neighboring pixel in the possible four direction. Then for each occurrence matrices, the most relevant Haralick features containing 6 statistical features are calculated. The achieved feature vector in this way is shown in (14):

$$\begin{aligned} &\text{Feature} = \\ &[GLCM_1(:), GLCM_2(:), GLCM_3(:), GLCM_4(:), \\ &\text{Variance}(1:4), \text{Contrast}(1:4), \text{Entropy}(1:4), \\ &\text{Energy}(1:4), \text{Inverse Difference Moment}(1:4), \\ &\text{Correlation}(1:4)\ ] \end{aligned} \qquad (14)$$

Where $GLCM_i$ is a Co-occurrence matrixes in direction i (i= [1 4]) that converting to a vector. And Energy, Entropy, Contrast, Variance, Correlation and Inverse Difference Moment are six relevant Haralick Features (Contrast (1:4) is a contrast in four Co-occurrence matrixes).

C. Face recognition by CMALBP

There are four steps to display the face using Co-occurrence Matrix of LABP feature from raw face image. First, the LBP operator is applied on the average gray-values of pixels that capture from original pixels, to get LABP feature. It should be noted that, threshold is based on standard deviation value of each pixel. Second, Co-occurrence Matrix is extracted from "uniform" LABP in four orientations. Third, all Co-occurrence Matrix and six relevant Haralic feature are concatenated into one feature vector to build the representation. Finally, nearest neighborhood classifier are used for classification.

V. Experimental Results

My system is implemented and compared with existing Local Binary Pattern face recognition systems [6, 11] and LDA [4], Gabor systems [5] on the FERET and ORL face databases. All experiments were run randomly 20 times, after which results were averaged. The scaling factor α is set to 0.1 in the experiments.

A. Experiments on the FERET database

The FERET database [17, 18] is the most comprehensive publically available database and contains a large number of subjects captured under different expression, pose, illumination and aging. The most common FERET protocol defines evaluation strategy by giving standard training and test sets, mainly used in frontal face recognition scenarios in different illumination, expression and aging effects. The frontal view imagery of the FERET database is divided into 5 categories: *Fa*, *Fb*, *Fc*, *Dup*1, and *Dup*2, containing 1,196, 1,195, 194, 722, and 234 faces, respectively. Both *Fa* and *Fb* are taken in the same day with the same illumination condition but with different facial expressions. *Fc* is taken at the same day as *Fa* but with different illumination condition. *Dup*1 is acquired on different days from *Fa*. *Dup*2 is acquired at least one year apart from *Fa*. Following the FERET protocol, *Fa* is always the gallery and *Fb*, *Fc*, *Dup*1, and *Dup*2 are used as probe sets. *Gallery* is a set of labeled images of individuals. An image of an unknown face presented to the recognition algorithm is called a *probe.* The algorithm compares the probe to each of the gallery samples and labels the probe as the most similar gallery sample. Fig .3 shows some sample images from the FERET database.

Fig .3 some sample images from the FERET dataset

The recognition results by different methods, on the FERET are shown in Table.1.

Table .1 recognition rate by different methods on the FERET probe sets

Methods	FERET probe sets			
	Fb	Fc	DupI	DupII
LDA	91.32	73.25	55.34	31.45
Gabor	94.57	74.78	68.69	53.25
LGBPH	98.34	95.85	74.37	71.27
LBP	97.15	79.23	66.45	64.25
CMLABP	98.78	97.52	80.89	76.21

In our experiment, the facial portion of each original image is cropped automatically based on the location of eyes and normalized to 100×100 pixels. Our representation yields improved facial recognition rates relative to other methods on FERET database. We achieved More than 88% accuracy for FERET test sets.

B. Experiments on the ORL database

In ORL database [24, 25] exist ten distinctive images of 40 separate subjects in up-right, frontal position with tolerance for some slanting and rotation of up to 20 degrees. Furthermore, the most variation of some image scale is approximately 10%. Hence, it is expected that this is a more difficult database to work with. Fig.4 shows some sample images from the ORL database.

Figure .4 some sample images from the ORL dataset

The recognition results by different methods, on the ORL are shown in Table 2.

All experiments were run randomly 20 times, after which results were averaged. The scaling factor α is set to 0.1 in the experiment. In this experiment, training set has been formed by using *n* deferent samples of each individual (n varies from 2 to 9). The remaining images are used for testing. For each *n*, we independently run the system 20 times. The average recognition rate of each method is shown in table 2. We can see again that the proposed CMLABP approaches have better performance than other methods and when the training sample number is small, the performance of CMLABP is better than other methods. We achieved More than 97% accuracy for ORL database.

Table2. Performance of different methods on ORL Database

#Train	**Methods**				
	CMLABP	LBP[6]	LDA[4]	Gabor[5]	LGBPH[12]
2	89.47	81.33	76.33	79.03	83.87
3	94.33	88.10	86.67	86.80	91.13
4	97.31	93.43	92.86	93.76	96.35
5	98.83	95.67	95.47	96.21	98.37
6	99.62	97.43	96.67	97.12	98.75
7	100	98.64	97.10	97.75	99.43
8	100	99.65	97.33	98.67	100
9	100	100	98.56	99.60	100

Compared with LBP face recognition systems, the proposed method could get more than 5% improvement on FERET database and 2% improvement on ORL database. Also, against LGBPHS, that has significantly more time and space complexities than LBP (because use of Gabor filtering for feature enhancement) in my method feature extraction can be very fast: it only acquires a little more cost than the original LBP operator.

VI. CONCLUSIONS

To deal with main defect of the original LBP operator, in this paper, we offered novel Local Binary Pattern (LBP) operator namely Co-occurrence of Local Average Based Pattern operator (CMLABP). In my method, the calculations are performing based on average values of P-neighbor values of pixels. In addition, to extract features, we use of Co-occurrence Matrix.

Since my offered operator employs a larger number of sample points, it obtains better feature representation that is not much affected by small changes in the pattern. My offered method with lower time and space complexity, it keeps the advantage of computational simplicity from the original LBP operator.

REFERENCES

[1] W.Y. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, "Face recognition: A literature survey," ACM Computing Surveys, vol. 34, no. 4, pp. 399–485, 2003.

[2] A. K. Jain, R. Ross, and S. Prabhakar, "An introduction to biometric recognition", IEEE Transaction on Circuits and Systems for Video Technology, 2004, vol. 14, No. 1, pp. 84-92.H. Poor, *An Introduction to Signal Detection and Estimation*. New York: Springer-Verlag, 1985, ch. 4.

[3] M. Turk and A. Pentland. Eigenfaces for recognition. Journal of Cognitive Neuroscience, 13(1):71-86, 1991.
[4] P. Belhumeur, J. Hespanha, and D. Kriegman. Egienfaces vs. fisherfaces: Recognition using class specific linear projection. *IEEE TPAMI*, 19(7):711-720, 1997.
[5] C. Liu and H. Wechsler. Gabor feature based classification using the enhanced Fisher linear discriminant model for face recognition. *IEEE TPAMI*, 11(4):467-476, 2002.
[6] A. Timo, H. Abdenour, and P. Matti. Face recognition with Local Binary Patterns. In *Proc. ECCV*, pages 469- 481, 2004.
[7] T. Ahonen, A. Hadid, M. Pietikainen, "Face Recognition with Local Binary Patterns", Computer Vision Proceedings, ECCV 2004, Lecture Notes in Computer Science 3021, Springer, 469-481.
[8] T. Ojala, M. Pietikäinen, and T. Mäenpää, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 7, pp. 971-987, 2002.
[9] G. Zhang, Z. Huang, and S. Z. Li, "Boosting local binary pattern (LBP)-based face recognition," SinoBiometrics, pp. 179- 186, 2004.
[10] T. Ahonen, A. Hadid, and M. Pietikäinen, "Face description with local binary patterns: application to face recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 12, pp.2037-2041, 2006.
[11] Zhang, W., S. Shan, W. Gao, X. Chen, and H. Zhang, "Local Gabor binary pattern histogram sequence (LGBPHS): A novel non-statistical model for face representation and recognition," in Proc. 10th IEEE Int. Conf. Computer Vision, pp. 786–791, 2005.
[12] A. Hazrati, A. M. Eftekhari Moghadam, "Face Recognition System Using a hybrid Approach of Co-occurrence Matrix and Local Binary Pattern"the Fifth Data Mining Conference, IDMC2011, Tehran, Iran, Dec 13-14, 2011 .
[13] Chan, C.H., "Multi-scale local binary pattern histogram for face recognition", Centre for Vision, Speech and Signal Processing School of Electronics and Physical Sciences University of Surrey Guildford, Surrey, U.K, Submitted for the Degree of Doctor of Philosophy from the University of Surrey, September 2008.
[14] Bhuiyan A.-A. And C. H. Liu, "On face recognition using Gabor filters", in World Academy of Science, Engineering and Technology 28, 2007.
[15] Mehta, R., Yuan, J., Egiazarian, K., "Local Polynomial Approximation-Local Binary Pattern (LPA-LBP) based Face Classification", Proc. SPIE 7881, 78810N, 2011.
[16] Shelton, J., Dozier, G., Bryant, K.., Popplewell, K., Abegaz, T., Purington, K.., Woodard, L., Ricanek, K., "Genetic Based LBP Feature Extraction and Selection for Facial Recognition", Proceedings of ACM Southeast Conference, Kennesaw, GA, March 24-26, 2011.
[17] P. J. Phillips, H. M. Syed, A. Rizvi, and P. J. Rauss. The FERET evaluation methodology for face-recognition algorithms. *IEEE TPAMI*, 22(10):1090-1104, 2000.
[18] http://www.ee.oulu.fi/mvg/page/lbp_bibliography.
[19] 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.
[20] R. C. Gonzalez, R. E. Woods, *Digital Image Processing*, 3*rd* Ed. Prentice Hall, 2008.
[21] R. Haralick, K. Shanmugam, I. Dinstein, "***Textural features for image classification,***" Transactions on Systems, Man and Cybernetics, Vol. 3, No. 6, pp. 610-621, 1973.
[22] Nissim, K., Harel, E., "***A Texture based approach to defect analysis of grapefruits***", Proceeding IPDPS '05 Proceedings of the 19th IEEE International Parallel and Distributed Processing Symposium (IPDPS'05) - Vol 01, 1997.
[23] N. Otsu, "A Threshold Selection Method from Gray- Level Histogram", *IEEE Trans. on System Man Cybernetics,* vol. 9(I), pp. 62-66, 1979.
[24] 'The Olivetti Research Laboratory (ORL) database,' Cambridge, U.K., 1994, Available: http://www.uk.research.att.com/pub/data/att_faces.zip.
[25] *The Olivetti Database: http://www.cam-orl.co.uk/facedatabase.html*.