Face Recognition Using 1DLBP Texture Analysis

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***Abstract*— A new algorithm for face recognition is proposed in this work; this algorithm is mainly based on Local Binary Pattern texture analysis in one dimensional space and Principal Component Analysis as a technique for dimensionalities reduction. The extraction of the face's features is inspired from the principal that the human visual system combines between local and global features to differentiate between people. Starting from this assumption, the facial image is decomposed into several blocks with different resolutions, and each decomposed block is projected in one dimensional space. Next, the proposed descriptor is applied for each projected block. Then, the resulting vectors will be concatenated in one global vector. Finally, Principal Component Analysis is used to reduce the dimensionalities of the global vectors and to keep only the pertinent information for each person. The experimental results have shown that the proposed descriptor Local Binary Pattern in one Dimensional Space combined with Principal Component Analysis have given a very significant improvement at the recognition rate and the false alarm rate compared with other methods of face recognition, and a good effectiveness against different external factors as: illumination, rotations, and noise.**

Keywords*— face recognition; local binary pattern (LBP); local binary pattern in one dimensional space (1DLBP); texture description; dimesionalitiy reduction; Principal Compenent Analysis (PCA).

I. INTRODUCTION

The automatic analysis of the human face has become recently an active research area in the artificial vision and patterns recognition domains, due to its important use in several applications such as electronic election, biometrics and video surveillance [1, 2, 3]. Face analysis includes face detection and tracking, face recognition, age and gender recognition, and emotion recognition. Human face is dynamic entity, which changes under the influence of several factors as pose, size, occlusion, background complexity, lighting and the presence of some components such as mustaches, beard, and glasses. So, the essential key for any face analysis problem is on how to find an efficient descriptor to represent and to model the face in a real context?

The crucial step in any problem of face analysis is the phase of features extraction. In this phase, there are two major approaches, local and global approaches. Global approaches are based on pixel information; all pixels of the facial image are treated as a single vector; the vector size is the total number of the image pixels [4]. Most of the methods of this approach use another space of representation (subspace) to reduce the number of pixels and to eliminate the redundancies. Principal Component Analysis (PCA) [5] and Linear Discernment Analysis (LDA) [6] are the most popular methods used to reduce the dimensions and to select the useful information. However, these approaches are not effective in the unconstrained cases, i.e., situation where occlusion, lighting, pose, and size of the face are uncontrolled.

Recently, the scientists concentrate on local approaches, which are considered as a robust approaches in the unconstrained cases compared with global approaches; in this case, the face analysis is given by the individual description of its parts and their relationships, this model corresponds to the manner of perception by the visual human system. The methods of this approach are based on the extraction of features from the facial image and the definition of an adequate model to represent the face [7]. Several methods and strategies have been proposed to model and classify faces essentially based on the texture, normalized distances, angles and relations between eyes, mouth, nose and edge of the face. Local Binary Pattern (LBP) [8], Local Gabor Binary Pattern (LGBP) [9] and Oriented Edge Magnitudes (POEM) [10] are the recent methods in this approach.

Psychological and neuroscience studies have showed that the human visual system combines between local and global features to differentiate between people [11]. LBP is the best descriptor for capturing the local features, but it is not performed in the description of the global features [8]. From these assumptions, we propose in this work a new feature extraction method based on a descriptor proposed in our laboratory in [12, 13, 14], called 1DLBP (Local Binary Pattern in One Dimensional Space), inspired from classical LBP. The proposed method, which is applied on face recognition, is characterized by the combination of the local and global features for modeling faces. The algorithm of extraction is decomposed into five principal stages; first, the input image is decomposed into several blocks with different resolutions. A vertical projection in one dimensional space is applied for each decomposed block. Next, the proposed descriptor is applied on each projected block. Then, the resulting vectors from each block are concatenated in one global vector. Finally, Principal Component Analysis is needed to regroup the global vectors, to reduce the dimensionalities and to keep only the useful information for each individual.

This paper is organized as follows: in the next section, we describe the classical LBP and histogram feature. In Section 3, the proposed algorithm of feature extraction for face recognition is presented. For this purpose, *chi-square* distance is required to measure similarities between face templates. In Section 4, we present our experimental results by applying the proposed algorithm on ORL and AR databases. Finally, a conclusion related to this work is given in Section 5.

II. LOCAL BINARY PATTERN (LBP)

The original LBP operator introduced by Ojala *et al.* [15], which has been used for texture discrimination, has shown a powerful and effective results against to the variations in rotation and illumination. The operator labels the pixels of an image by thresholding the 3×3 neighborhood of each pixel with the central value and considering the result as a binary code. Next, the histogram of the labels can be used as a texture descriptor (see Figure 1); for a given pixel $g_c(x_c,y_c)$ from gray image, its texture LBP is calculated by comparing g_c with its neighbors pixels P on a circle of radius R (see Figure 2 for more details on circular neighborhood). The value of LBP(g_c) is obtained as:

$$LBP^{P,R}(x_c, y_c) = \sum_{i=1}^{P} S(g_i^{P,R} - g_c)\, 2^{i-1} \tag{1}$$

S(x) is defined as: $$S(x) = \begin{cases} 1 & \text{if } x \geq 0; \\ 0 & \text{otherwise;} \end{cases} \tag{2}$$

The major disadvantage of the original LBP operator resides in the size of the descriptor, a mask of 3×3 pixels cannot capture the structures of large scale which can considered as a dominants structures in the image. Recently, the size of the operator has been extended by using a mask with different large sizes. Figures 2.a, 2.b, 2.c show three examples of the extended LBP.

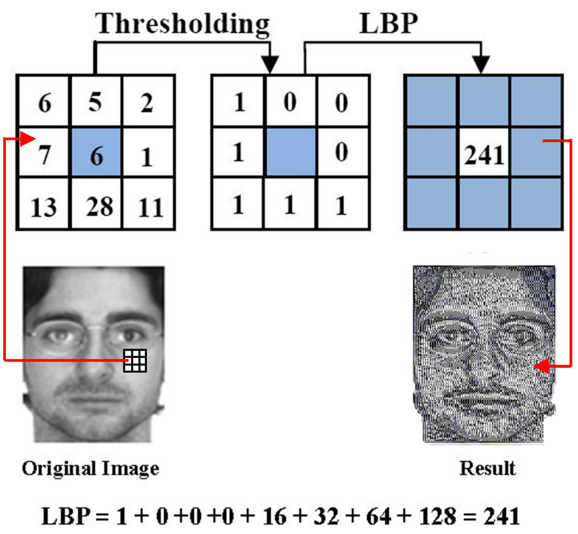
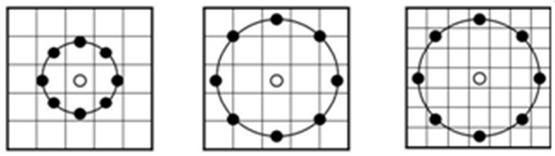
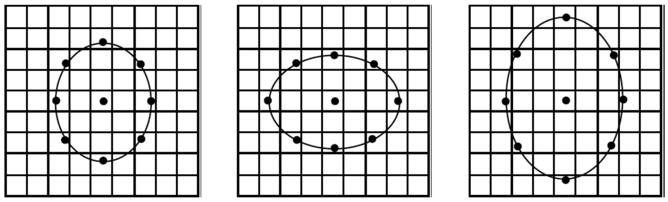


Figure 1. LBP calculation performed into 3×3 neighborhood.



(a) (b) (c)

Figure 2. Neighborhood set for different (P,R). (a) The basic LBP operator (P,R) = (8,1) (b) LBP with circular neighborhood (8,2). (c) LBP with circular neighborhood (8,3).



(8,2,3) (8,3,2) (8,3,4)

Figure 3. ELBP samples with different extention [16].

Original image LBP (8,1) LBP (8,2) ELBP (8,3,2) ELBP (8,3,4)

Figure 4. Results of LBPs application with differentd masks .

Another type of the extended operators of LBP called: Elliptical Local Binary Patterns (ELBP) [16]. In ELBP, at each pixel $g_c(x_c,y_c)$, we consider its surrounding pixels that lie on an ellipse (see Figure 3) with (x_c,y_c) is the center. ELBP of (x_c, y_c) with P neighboring pixels at (R1, R2) distances is computed as:

$$ELBP^{P,R1,R2}(x_c, y_c) = \sum_{i=1}^{P} S(g_i^{P,R1,R2} - g_c)\, 2^{i-1} \tag{3}$$

S(x) function is defined as (2).

In details, the coordinates of the i th neighboring pixel of (x_c,y_c) are calculated using the formulas:

$$\text{angle-step} = 2 * \pi / P \tag{4}$$

$$x_i = x_c + R1 * \cos((i-1) * \text{angle-step}) \tag{5}$$

$$y_i = y_c + R2 * \sin((i-1) * \text{angle-step}) \tag{6}$$

However, the extend versions of LBP operators and the Elliptical LBPs present a good results by capturing the local and global patterns but they are not performed for capturing the micro characteristics (fine details) of the human face. Figure 4 shows the rsults of LBP and ELBP applications using different masks.

III. PROPOSED APPROACH

The proposed algorithm used to extract information for face recognition is described in the following recapitulation; next, we present each step in details. We consider that we have a gallery θ of biometric samples with P persons, S biometric sample (image) per person, N training images for each person

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P_i and M testing images (example θ=400, P=40, S=10, N=5, M=5, with ORL database, θ=2600, P=100, S=26, N=13, M=13 with AR database). The process of features extraction is composed of six principal stages for each person:

- Preprocessing of the N images.
- Decomposition of each image N_i into several blocks with different resolution.
- Projection of each block decomposed in one dimensional space.
- Application of the proposed descriptor 1DLBP for each projected block.
- Concatenation of the resulting vectors of an image N_i in one global vector V_i.
- Dimensionalities reduction of the V grouped global vectors using PCA.

A. *Preprocessing*

The objective of the preprocessing is the modification of the source's image representation to facilitate the task of the following steps and to improve the rate of recognition. First, the facial image is converted into grayscale image. Next, every grayscale image is filtered by median filter to suppress noise. Lastly, the noise suppression image is then adjusted to improve the contrast of the image.

B. *Image decomposition*

Most LBP operators characterize the face texture distribution of each pixel with its neighborhood only. But, the differences between two faces can be demonstrated not only by the texture distribution of each pixel with its neighborhood, but also by the relative connection with other pixels. With this intention, we have decomposed the original image into several sub-images (see Figure 5) to characterize better the details and the relationships between all the image pixels. Next, the extracted histograms will be concatenated in one global vector in the next stages. With this technique, we can obtain the fine details and the relative connections between all pixels.

C. *1D vertical projection*

The 1D projection of rows or columns of each level provides an effective mean to describe better the local and global patterns. Figure 6 presents an example of vertical projection. The objective of the projection is to validate the descriptor LBP in one dimensional space to find another mean for describing and analyzing better the human face's texture.

Figure 5. Image decomposition in differents blocks.

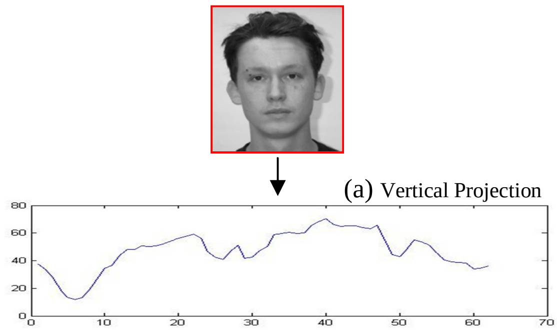
D. *1DLBP application*

The concept of the 1DLBP method consists in a binary code describing the local agitation of a segment in 1D signal. It is calculated by thresholding of the neighborhood values with the central value. All neighbors get the value 1 if they are greater or equal to the current element and 0 otherwise. Then, each element of the resulting vector is multiplied by a weight according to its position (see Figure 6.c). Finally, the current element is replaced by the sum of the resulting vector. This can be recapitulated as follows:

$$1DLBP = \sum_{n=0}^{N-1} S(g_n - g_0).2^n \quad (7)$$

S(x) function is defined as (2).

g_0 and g_n are respectively the values of the central element and its 1D neighbors. The index n increases from the left to the right in the 1D string as shown in Figure 6.c. The 1DLBP descriptor is defined by the histogram of the 1D patterns.



32	40	130	105	110	120	64	115	130

(b) Threshold

0	0	1	0		1	0	1	1

(c) Multiplication

1	2	4	8		16	32	64	128

(d) Multiplication Result

0	0	4	0		16	0	64	128

(e) 1DLBP

				212				

Figure 6. Example of vertical projection in 1D space + 1DLBP application.

E. Concatenation of the resulting vectors

The proposed descriptor 1DLBP is applied on all blocks of the decomposed image with the different resolution presented in Figure 5. The extracted histograms from each block are concatenated in one global histogram (vector) representing one face image V_i. A problem of information redundancies is appeared due to the important size of each global vector. To resolve this problem, we have used the Principal Component Analysis (PCA) as a technique of dimensionalities reduction, to regroup all the global vectors of each person Xi in one global matrix and to select the useful information needed to modeling each person.

F. Dimensionalities reduction with PCA

The principal idea of PCA is to represent a group of images (vectors) of a same person X in another space of lower dimension; this space is constructed from a set of training images. PCA begins with a set of 1D training vectors of the same class; each vector Γ_i represents a training image I_i (I = 1...N), and construct $O_i = \Gamma_i - \acute{\Gamma}$ where $\acute{\Gamma}$ represents the mean vector of all Γ_i vectors. Then, determinate the eigenvectors μ_i of the covariance matrix $C= \sum_i O_i \times O_i^T$. The first K "Principal axis" corresponds to the K largest eigenvalues (the value of K is chosen in the same that the sum of the first axis K provides a large proportion of the total eigenvalues sum).

Now, given a new image ξ considered as a test example. First, we built its 1D representation using the extraction method proposed in this work (stages: 1-5), and we subtract the average face as follows: $\theta = \xi_{1D} - \acute{\Gamma}$. Next, we project the image in the principal axis elaborated as: $\theta_p= \sum_{i=1,K} \mu_i^T (\theta - \mu_i)$. Finlay, we calculate the chi-Square distance to classify the image ξ in the nearest class corresponding to a degree of similarities that exceeds a fixed threshold.

$$\text{Dist}_{\text{chi-square}}\,(X, Y) = \sum_{i=0}^{M} \frac{(xi-yi)2}{xi+yi} \qquad (8)$$

IV. EXPERIMENTAL RESULTS

To evaluate the performances of the proposed algorithm, we have carried out several tests on ORL and AR databases; we randomly selected half of samples for training set and the remaining samples for testing set. In all our experiments, we considered the average recognition rates of several random permutations (50 permutation with ORL database and 100 permutations with AR database), and we compared the obtained results (identification and false alarm rates) with other methods using the same testing protocols. Our experiments are implemented with *Matlab* 2010a, *Windows* 7, HP Core 2 Duo, 3 Ghz CPU with 2 Gb Ram.

A. ORL database

The ORL database contains 400 frontal images in different facial expression, conditions of illumination, hairstyles with or without beard, moustaches and glasses for 40 persons, 10 images for each person. Each sample is a 92×112 gray image, with tolerance for some tilting and rotation of up to 20° (see Figure 7).

B. AR database

The AR database was collected at the Computer Vision Center in Barcelona, Spain in 1998 [17]. It contains images of 116 individuals (63 men and 53 women). The imaging and recording conditions (camera parameters, illumination setting, and camera distance) were carefully controlled and constantly recalibrated to ensure that settings are identical across subjects. The resulting RGB color images are 768×576 pixels in size. The subjects were recorded twice at a 2–week interval. During each session 13 conditions with varying facial expressions, illumination and occlusion were captured (see Figure 8).

First, we applied the methods inspired from the LBP texture analysis in the two databases (classical LBP, extended LBP, Elliptical LBP, and the one dimensional projected LBP). The performances of these methods are shown in Table 1.

Figure 7. Some images from ORL database.

Figure 8. Some images from AR database [17].

TABLE I. COMPARATIVE RECOGNITION RESULTS OF THE ISPIRED LBP METHODS ON ORL AND AR DATABASES

RR: Recognition Rate %.
FAR: False Alarm Rate %.

	ORL **RR %**	**AR** **RR %**	**Average** **RR %**	**Average** **FAR %**
LBP (8,1)	85,2	87,5	86,4	3,62
LBP (8,1) PCA	91,4	93	92,2	1,92
LBP (8,2)	86	89,4	87,7	3,1
ELBP (8,3,2)	84,3	88,1	86,2	2,97
ELBP (8,3,4)	83,8	86,9	85,4	3,03
1DLBP	92	92,6	92,3	2.36
1DLBP PCA	95,8	97,9	**96,9**	**1.44**

TABLE II. COMPARAISON WITH OTHER STATE OF THE ART APPROACHS

	ORL RR %	AR RR %	Average RR %	Average FAR %
LBP (8,1) PCA	91,4	93	92,2	1,92
1DLBP PCA	95,8	97,9	**96,9**	**1.44**
Local Gabor Binary Pattern (LGBP)	94,1	96,2	95,2	1,87
POEM	90,9	89,4	90,2	2,6
PCA	85	81,2	83,1	5,12
LDA	82,4	84,7	83,6	5,36

The results of the experiments clearly showed that the projected Local Binary Pattern with dimensionalities reduction using PCA enhances the recognition performance in all configurations and presents a very good improvement and significant results in recognition rate, false alarm rate against other variants of LBP.

We also conducted tests comparing our method against recent and classical state-of-the-art approaches using the similar protocols under more challenges and scenarios. The results, shown in Table 2, indicate clearly the effectiveness of our approach which outperforms all other methods.

The facial images are taken with ORL database which is considered as a stable database in the unconstrained cases, and the AR database which presents a very good variation, in lighting, occlusion and facial expression, to measure the performances of the approach in the difficult situations. The comparison results presented in Table 2 shows that our proposed approach presents very good results with AR database which indicates that this approach has an important effectiveness against to the variations in different factors like: occlusion, lighting, rotation, and noise.

Another conclusion we can make from Table 1 and Table 2 is that 1DLBP + PCA is much better than 1DLBP only; the association of the PCA as a robust technique in the dimensionalities reduction is very interesting to improve the performances of the proposed approach.

V. CONCLUSION AND FUTURE WORK

Facial image can be considered as a composition of local and global features. Starting from this assumption, we have successfully developed a new algorithm for texture face discrimination, this algorithm is primary based on Local Binary Patterns but projected in one dimensional space; it combines between local and global features, capable of recognizing faces in different situations. Each facial image is decomposed on multi blocks with different resolution and each decomposed block will be vertically projected in one dimensional space. Next, the proposed descriptor is applied on each projected block. Then, the extracted vectors from each block will be concatenated in one global vector. Finally, Principal Component Analysis is applied on the regrouped vectors to reduce the dimensionalities of the concatenated vectors and to extract the useful information. The experimental results applied on ORL and AR database have showed that the proposed approach has given a very significant improvement at the recognition rate, false alarm rate and a good effectiveness against different external factors as: occlusion, illumination, rotations, and noise.

As a prospect of this work, we hope to apply the proposed descriptor in other application of face analysis, like age, or gender recognition, to apply the same descriptor with other modalities of biometric system, like the use of the human ear in identity recognition.

REFERENCES

[1] M. Khasawneh, M. Malkawi, O. Al-Jarrah, T.S. Hayajneh, and M.S. Ebaid, “A Biometric-Secure e-Voting System for Election Processes,” Proc. IEEE Sym. on Mechatronics and its Applications (ISMA 8), Amman, Jordan, May 2008, pp. 371-376. doi: 10.1109/ISMA.2008.4648818

[2] A. Hadid, J.L. Dugelay, and M. Pietikainen, “On the use of Dynamic Features in Face Biometrics: Recent Advances and Challenges,” Signal, Image and Video Processing (Springer), vol. 5, no. 4, Nov 2011, pp. 495-506. doi: 10.1007/s11760-011-0247-3

[3] L. Ding and A.M. Martinez, “Features versus Context: An approach for precise and detailed detection and delineation of faces and facial features,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 32, no. 11, Nov 2010, pp. 2022-2038. doi: 10.1109/TPAMI.2010.28

[4] R.S. Kathavarayan and M. Karuppasamy, “Identification of Untrained Facial Image in Combined Global and Local Preserving Feature Space,” International Journal of Biometrics and Bioinformatics (IJBB), vol. 4, no. 1, Mar 2010, pp. 1-12.

[5] M.A. Turk and M.P. Pentland, “Eigenfaces for recognition,” Journal of Cognitive Neuroscience, vol. 3, no. 1, 1991, pp. 71-86. doi: 10.1162/jocn.1991.3.1.71

[6] N. Belhumeur, J.P Hespanha, and D.J. Kriegman, “Eigenfaces vs Fisherfaces: Recognition using class specific linear projection,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 7, Jul 1997, pp. 711-720. doi: 10.1109/34.598228.

[7] T. Cootes, C. Taylor, H. Kang, and V. Petrovié, “Handbook of Face Recognition”. Chapter.3: “Modeling Facial Shape and Appearance”. Springer, 1st Edition, 2005, pp. 40. doi: 10.1007/b138828

[8] T. Ahonen, A. Hadid, and M. Pietikainen, “Face Recognition with Local Binary Pattern,” Proc. Springer. European Conference on Computer Vision (ECCV 8), Prague, Czech, May 2004, pp. 469-481. doi: 10.1007/978-3-540-24670-1_36

[9] N. Nguyen, L. Bai, and L. Shen, “Local Gabor Binary Pattern whitened PCA: A novel approach for face recognition from single image per person,” Proc. IEEE / Springer Conf. On Biometrics (ICB 3), Alghero, Italy, Jun 2009, pp. 269-278. doi: 10.1007/978-3-642-01793-3_28.

[10] N.S. Vu and A. Caplier, “Face recognition with patterns of oriented edge magnitudes,” Proc. Springer. European Conference on Computer Vision. (ECCV 11), Heraklion Crete, Greece, Sep 2010, pp. 313-326. doi: 10.1007/978-3-642-15549-9_23.

[11] A.J O'Toole, D.A Roark, and H. Abdi, “Recognizing moving faces: A psychological and neural synthesis,” Trends in Cognitive Science, vol. 6, no. 6, Mar 2010, pp. 261-266.

[12] L. Houam, A. Hafiane, R. Jennane, A. Boukrouche, and E. Lespessailes, “Trabecular Bone Anisotropy Characterisation Using 1D Local Binary Patterns,” Proc. Springer Conf. Advanced Concepts for Intelligent Vision Systems (ACIVS 12), Sydney, Australia, Dec 2010, pp. 105-113, doi: 10.1007/978-3-642-17688-3_11

[13] L. Houam, A. Hafiane, R. Jennane, A. Boukrouche, and E. Lespessailes. "Trabecular Bone Texture Classification Using 1D LBP and Wavelets Coefficients in High-pass Bands," Proc. Conf. Signal, Image, Vision and their Application (SIVA), Guelma, Algeria, Nov 2011, pp. 116-121.

[14] L. Houam, A. Hafiane, R. Jennane, A. Boukrouche, and E. Lespessailes, "Texture characterization using Local Binary Pattern and Wavelets. Application to Bone Radiograph," Proc. IEEE Conf. Image Processing, Theory, Tools and Applications (IPTA 3), Istanbul, Turkey, Oct 2012, pp. 371-376. doi: 10.1109/IPTA.2012.6469546

[15] T. Ojala, M. Pietikainen, and D. Harwood, "A comparative study of texture measures with classification based on featured distribution," Pattern Recognition, vol. 29, no. 6, 1996, pp. 51-59. doi: 10.1016/0031-3203(95)00067-4

[16] H.T. Nguyen, N.S. Vu, and A. Caplier, "How far we can improve micro features based face recognition systems?," Proc. IEEE Conf. Image Processing, Theory, Tools and Applications (IPTA 3), Istanbul, Turkey, Oct 2012, pp. 350-353. doi: 10.1109/IPTA.2012.6469533

[17] A.M. Martinez and R. Benavente, "The AR face database", CVC Technical Report, 24, 1998.

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