# Face Analysis, Description and Recognition using Improved Local Binary Patterns in One Dimensional Space

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**Abstract:** In this study of a biometric system, Improved One Dimensional Local Binary Patterns (I1DLBP) are developed and tested for use in face analysis, description and recognition. The extraction of facial features is based on the principal that the human visual system combines local and global features to differentiate between people. The proposed method starts by decomposing the facial image into several blocks with different resolutions. Each block is then projected in one dimensional space, and the developed descriptor is applied on each projected block. Finally, Principal Component Analysis (PCA) is used to reduce the dimensionalities of the concatenated vectors from each block and to keep only the relevant information. The K-nearest neighbors (KNN) algorithm is used as a classifier. Experiments were carried out under varying conditions of occlusion, rotation, and facial expressions, using the ORL and AR databases. Results show that the developed feature extraction approach can effectively describe the micro characteristics of the human face and that it outperforms well-known and classical feature extraction descriptors.

*Keywords:* Biometrics, Face Recognition, LBP, 1DLBP, I1DLBP, PCA.

## 1. INTRODUCTION

Face recognition is a fundamental field in artificial vision and pattern recognition, due to its extensive use in several applications such as forensics, electronic elections, secure access systems, financial transactions, biometrics, or management systems (Tistarelli *et al*., 2009). The human face has several advantages compared to other biometric modalities: it has a rich structure capable of differentiating between individuals, it is a modality that is well accepted by people, the acquisition of facial images does not require the cooperation of the test subject, and images can be captured from a distance (Li and Jain, 2011).

A face recognition system can be divided into two principal activities: feature extraction and classification. In feature extraction, there are two main approaches: local and global approaches. As reviewed by (O'Toole et al., 2002), psychological and neuroscience studies have shown that the human visual system combines local and global features to recognize and differentiate between people. Global approaches are based on pixel information: all the pixels in the facial image are treated as a single vector; the vector's size is the total number of pixels in the image (Kathavarayan and Karuppasamy, 2010). Most methods with this approach use another space of representation (a subspace) to reduce the number of pixels and to eliminate redundancies. Principal Component Analysis (PCA) (Turk and Pentland, 1991), Linear Discernment Analysis (LDA) (Belhumeur et al., 1997), and Independent Component Analysis (ICA) (Bartlett et al., 2002) are the most popular methods used to reduce dimensions and to select the useful information. However, these approaches are not effective in unconstrained cases, i.e., situations where occlusion, lighting, pose, and size of the face are uncontrolled.

Recently, research has focused on local approaches, which are considered to be more robust than global approaches in unconstrained cases; in this case, the description of the human face is given by an individual description of its parts and their relationships. This model corresponds to the manner of perception by the human visual system. The methods used are based on the extraction of features from the facial image and the definition of an adequate model to represent the face (Kathavarayan and Karuppasamy, 2010). Several methods and strategies have been proposed to represent and describe faces, based on the texture, normalized distances, angles, and relations between eyes, mouth, nose, and edge of the face. Local Binary Patterns (LBP) (Ahonen et al., 2006), Local Gabor Binary Patterns (LGBP) (Nguyen et al., 2009) and Oriented Edge Magnitudes (POEM) (Vu and Caplier, 2010) are the most recent methods in this approach.

Among all the local approaches, Local Binary Pattern (LBP) is the best descriptor for encoding the texture of the human face. It is characterized by a powerful and effective tolerance against variations in rotation and illumination and by its computational simplicity. However, the main disadvantage of the LBP operator resides in the size of the descriptor; it cannot capture the global patterns which can be considered as the dominant structures in the facial image.

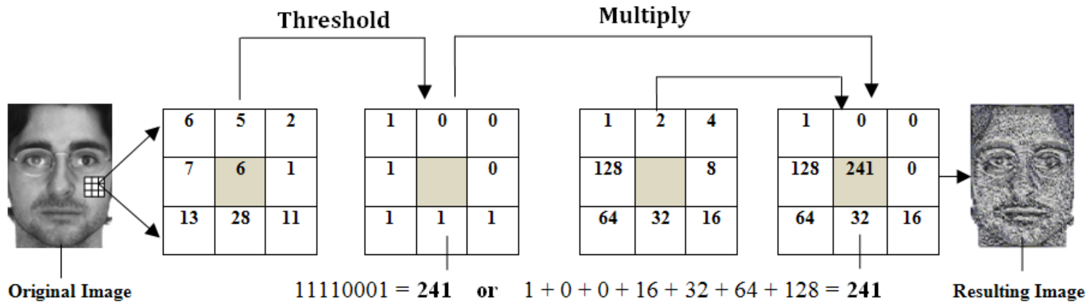


Fig. 1. Calculation of the original LBP operator.

The specific contributions of this paper are:

- An automated biometric system using 2D facial images is developed.
- A new textural descriptor is proposed, called: Improved One Dimensional Local Binary Pattern (I1DLBP). It is based on the classical LBP, projected in one dimensional space, and improved by calculating the mean value of the summed neighbors.
- The developed approach to feature extraction, based on I1DLBP, is characterized by a combination of local and global features to analyze, describe, differentiate and recognize persons from facial information.
- The performances of the system have been improved with the introduction of Principal Component Analysis (PCA), an efficient mathematical tool to reduce dimensionality without losing information.
- K-nearest neighbors (KNN) with chi-square distance are used to classify the test images in the corresponding class.
- The experimental results applied on two well-known databases (ORL and AR) show that the proposed system provides very significant improvements in recognition rates; it outperforms well-known classical feature extraction approaches, and is effective against different external factors such as illumination, rotation, noise, and changes in facial expression.

The rest of this paper is organized as follows: Section 2 gives an overview of classical LBP and its invariants. In Section 3, the proposed algorithm of feature extraction for face recognition is presented. In Section 4, we present our experimental results by applying the proposed algorithm on the ORL and AR databases, and finally conclude the paper in Section 5.

## 2. OVERVIEW OF LOCAL BINARY PATTERNS (LBP) AND ITS INVARIANTS

### Classical LBP

The LBP operator is a very simple and efficient descriptor. It was proposed for the first time by (Ojala et al., 1996), and has been used for texture discrimination. The original LBP has shown powerful and effective results against variations in rotation and illumination. Recently, it has been widely used in various studies and applications (Houam et al., 2012; Tlioinas et al., 2011; Kim et al., 2012). The LBP operator is defined as a gray-scale invariant texture measure, derived from a general definition of texture in a local neighborhood. It is a powerful means of texture description; among its properties in real-world applications one can mention its discriminative power, computational simplicity and tolerance against monotonic gray-scale changes (Ahonen et al., 2006; Pietikainen et al., 2010; Tlioinas et al., 2011).

In the original LBP operator, the local patterns are extracted by thresholding the 3×3 neighborhood of the eight neighbors of each pixel, from the original image, with the central value. All the neighbors are assigned the value 1 if they are greater than or equal to the current element and 0 otherwise, which represents a binary code of the central element. This binary code is converted into a decimal value by multiplying it with the given corresponding weights and is summed to obtain the LBP code for the central value (Ahonen et al., 2006; Hadid et al., 2008; Hadid et al., 2011). This process is illustrated in Figure 1.

Because it is difficult to find a general parametric model for the texture distribution of the human face, the features according to this method are approximated by a two dimensional discrete pattern histogram. This is created to collect the occurrences for each pattern. The histogram, as shown in Figure 2, is used to describe the texture of the human face.

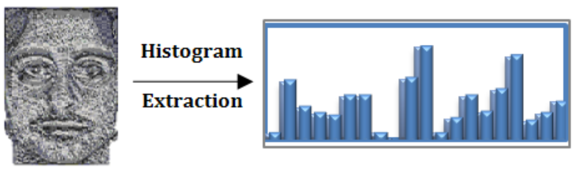


Fig. 2. Feature extraction using the histogram patterns.

However, the principal disadvantage of the original LBP operator resides in the size of the descriptor: a neighborhood of 3×3 pixels cannot capture the large-scale structures which can be considered as the dominant structures in the image. With this intention, the size of the operator has been extended by using neighborhoods of different large sizes. Using a circular neighborhood and bilinear interpolation values at non-integer pixel coordinates allows any radius and number of pixels in the neighborhood. The notation (P;R) is generally used for pixel neighborhoods to refer to P sampling points on a circle of radius R as shown in Figure 3. The LBP codes can be easily calculated in a single scan through the image. The value of the LBP code of a pixel $(x_c, y_c)$ is given by:

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

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

where $g_c$ and $g_i^{P,R}$ are respectively the values of the central element and its 2D neighbors.

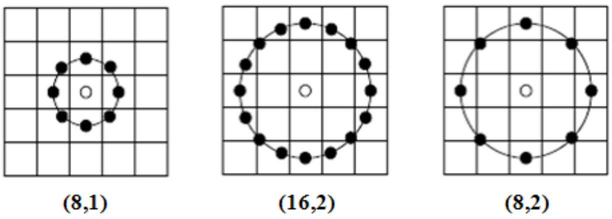


Fig. 3. Neighborhood set for different (P,R). (Hadid et al., 2008).

Recently, several variants of the LBP operator have been proposed, especially for face analysis applications. In (Nguyen et al., 2012; Nguyen and Caplier, 2012), the Elliptical Local Binary Pattern (ELBP) was proposed. In ELBP, at each pixel $(x_c, y_c)$, the authors consider that its surrounding pixels lie on an ellipse, because the eyes and mouth are the most important facial features and are elliptical in shape. The authors demonstrated that ELBP is more suitable and more efficient than LBP in feature extraction for face recognition. In (Jin et al., 2004), the Improved LBP (ILBP) was proposed. In ILBP, the local patterns were extracted by thresholding the surrounding pixels with the mean gray value. ILBP has shown better results than LBP in face detection and tracking. For spatiotemporal representation, the volume LBP (VLBP) was introduced in (Hadid et al., 2007). The idea consists in considering a face sequence as a rectangular prism (or volume) and defining the neighborhood of each pixel in three dimensional spaces. VLBP showed good results in facial dynamics for face recognition from video.

In (O'Toole et al., 2002), psychological and neuroscience studies showed that the human visual system combines local and global features to recognize and differentiate between people. In contrast, the LBP operator and its extended versions are effective at capturing the local patterns and the micro features of the human face, but they perform poorly in capturing the global patterns that can be considered as the dominant structures in the image, which is contradictory to the theory of recognition demonstrated in neuroscience and psychological sciences.

Local Binary Pattern in One dimensional Space (1DLBP) and Improved Local Binary Pattern in One Dimensional Space (I1DLBP)

The Projected Local Binary Pattern in One dimensional space (1DLBP) was introduced for the first time by (Houam et al., 2010; Houam et al., 2012; Houam et al., 2014). It has been combined with wavelets to classify X-ray bone images for bone disease diagnosis. In (Benzaoui and Boukrouche, 2013 a,b), we implemented the 1DLBP descriptor for face recognition. Our experimental results clearly demonstrated good performances and robustness against various challenges such as occlusion, rotation, lighting, and changes in facial expression.

The concept of the one dimensional LBP operator consists in a binary code describing the local agitation of a segment in the 1D signal. The local patterns are extracted by thresholding the linear neighborhood of each pixel, from the projected image, with the central value. All the neighbors are assigned the value 1 if they are greater than or equal to the current element and 0 otherwise, which represents a binary code of the central element. This binary code is converted into a decimal value by multiplying it with the given corresponding weights and is summed to obtain the 1DLBP code for the central value (Houam *et al.*, 2010; Houam *et al.*, 2012; Houam *et al.*, 2014). This process is illustrated in Figure 4; it can be recapitulated as follows:

$$1DLBP = \sum_{n=0}^{N-1} S(g_n - g_0)2^n \quad (3)$$

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

where $\boldsymbol{g_0}$ and $\boldsymbol{g_n}$ are respectively the values of the central element and its 1D neighbors. The index $\boldsymbol{n}$ increases from the left to the right in the 1D string as shown in Figure 4.c. The 1DLBP patterns are defined by the final resulting vector.

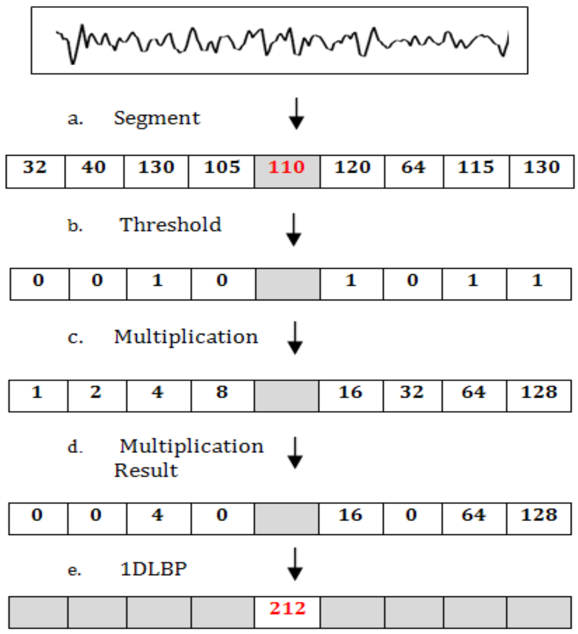


Fig. 4. Calculation of the One Dimensional Local Binary Pattern (1DLBP operator).

The concept of the I1DLBP is similar to that of the 1DLBP. While in 1DLBP the linear thresholding is applied on each pixel, from the projected image, with the central value, in I1DLBP, the local patterns are extracted by thresholding the linear neighbors of each pixel, from the projected image, with the mean value of the summed neighbors. Next, all the neighbors are assigned the value 1 if they are greater than or equal to the current element and 0 otherwise, which represents a binary code of the central element. This binary code is converted into a decimal value by multiplying it with the given corresponding weights and is summed to obtain the I1DLBP code for the central value. This process is illustrated in Figure 5; it can be recapitulated as follows:

$$I1DLBP = \sum_{n=0}^{N-1} S(g_n - \acute{g})2^n \quad (4)$$

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

where $\acute{g}$ and $\boldsymbol{g_n}$ are respectively the mean value of the linear neighborhood and the values of its 1D neighbors. The index $\boldsymbol{n}$ increases from the left to the right in the 1D string as shown in Figure 5.c. The I1DLBP patterns are defined by the final resulting vector.

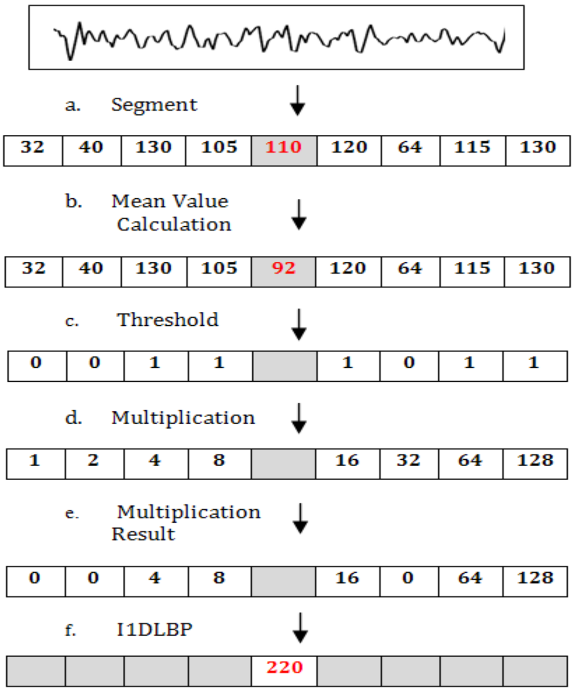

Fig. 5. Calculation of the Improved One Dimensional Local Binary Pattern (I1DLBP) operator.

## 3. PROPOSED APPROACH

The proposed biometric system requires two phases of operation. The first is a training phase: it consists in recording the facial features of each individual in order to create his own biometric template; this is then stored in the database. The second is the test phase: it consists in recording the same features and comparing them to the biometric templates stored in the database. If the recorded data match a biometric template from the database, the individual in such a case is considered identified.

The proposed algorithm used to extract information for face recognition is described in the following recapitulation:

- *Preprocessing.*
- *Multi-block decomposition of each image.*
- *Projection of each decomposed block in one dimensional space.*
- *Application of the proposed descriptor I1DLBP for each projected block.*
- *Concatenation of the resulting vectors from each block in one global vector.*

The objective of the pre-processing step is to modify the source image representation in order to facilitate the task of the following modules and to improve the recognition performances. First, the facial image is converted into a gray-scale image. Next, every gray-scale image is filtered by a median filter to suppress noise. This filtered image is then adjusted to improve the image contrast (Benzaoui and Merouani, 2012).

Most LBP operators characterize the face texture distribution of each pixel with its neighborhood only. However, 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 decomposed the original image into several sub-images, as shown in Figure 6, to better characterize the details and the relationships between all the pixels in the image. In the following stages, the vectors extracted from each block are concatenated in one global vector. With this technique, we can obtain the fine details and relative connections, i.e. the correlation between most of the pixels in the image. The level of decomposition and the size of blocks will be discussed in the next section.


Fig. 6. Image Decomposition into Several Blocks.

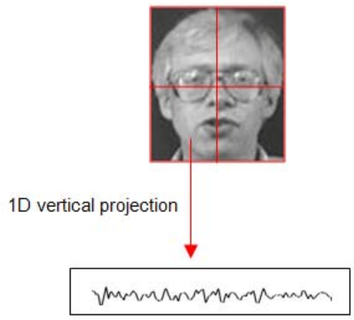

Fig. 7. Example of Vertical Projection of a block in One Dimensional Space.

The 1D projection of columns from each level, as shown in Figure 7, provides an effective way of better describing the local and global patterns. We can represent each column by one value which stands for the gravity of the column. To project a block from two dimensional representations (matrix) in one dimensional space (vector), the average values of all the pixels from each column are calculated to create the projected vector. The proposed descriptor I1DLBP is applied on all the projected blocks of the decomposed image with different resolutions, as presented in Figure 6. Then, the vectors extracted from each decomposed block are concatenated in one global vector representing the face template.

### *3.1 Dimensionality Reduction using PCA*

A problem of redundant information was encountered because of the large size of the templates; to make the classification task easier, the templates should contain only essential information. For that purpose, we used Principal Component Analysis (PCA), a robust mathematical tool in dimensionality reduction without losing information, to combine all the global vectors in one global matrix and to reduce the space of representation to a lower dimensional space (a subspace). This can be viewed as: given a $p$-dimensional random vectors $Y = (y_1, y_2, \dots, y_p)$, the objective is to find a representation in the lower dimension $Z = (z_1, z_2, \dots, z_q)$, where $q < p$ which preserves the content of the original data as much as possible (Turk and Pentland, 1991; Belhumeur et al., 1997). The idea is to represent a group of images (vectors) in another space of lower dimension constructed from a set of the training images.

In PCA, we begin with a set of 1D training vectors; each vector $\Gamma_i$ represents a training image $I_i$ $(I = 1 \dots N)$, and we construct the normalized matrix $O_i$:

$$O_i = \Gamma_i - \acute{\Gamma} \tag{5}$$

where $\acute{\Gamma}$ represents the mean vector of all the $\Gamma_i$ vectors. Then, the eigenvectors $U_i$ will be determined from the covariance matrix $C$:

$$C = \sum_i O_i \times O_i^T \tag{6}$$

The first $K$ “Principal axis” corresponds to the $K$ largest Eigen-values (the K value is chosen such that the sum of the first axis K provides a large proportion of the total sum of Eigen-values) (Turk and Pentland, 1991; Belhumeur et al., 1997).

### *3.2 Template Matching*

Matching is carried out after training the system. The aim of matching is to assess the similarity between the tested image and all the stored templates, giving a new image $\xi$ considered as a test example. First, we build its 1D representation using the feature extraction method proposed in this work, followed by the subtraction of the average face as follows:

$$\theta = \xi_{1D} - \acute{\Gamma} \tag{7}$$

Next, we project the image in the principal axis developed as:

$$\theta_p = \sum_{i=1,k} U_i^T \cdot (\theta - U_i) \tag{8}$$

Finally, we calculate the similarity measure to classify the input image $\xi$ in the nearest neighbor class corresponding to a degree of similarity that exceeds a fixed threshold. Three distances of similarity are compared: Euclidean, Hamming and Chi-square distance:

- Euclidean distance between two vectors $X$ and $Y$:

$$ED(X,Y) = \sqrt{\sum_{i=1}^{M} (x_i - y_i)^2} \tag{9}$$

- Hamming distance between two vectors $X$ and $Y$:

$$HD = \frac{1}{M} \sum_{i=1}^{M} x_i \; (XOR) \; y_i \tag{10}$$

- Chi-square distance between two vectors $X$ and $Y$:

$$Dist_{Chi-Square} = \sum_{i=1}^{M} \frac{(x_i - y_i)^2}{x_i + y_i} \tag{11}$$

$x_i$ and $y_i$ are the two bit-wise codes to be compared.

$M$ is the size of the vector representing the template.

## 4. EXPERIMENTAL RESULTS

To evaluate the I1DLBP descriptor in face recognition, we experimentally tested and compared the proposed approach of feature extraction on two well-known image datasets: the ORL and AR databases. We used the notation I1DLBP (h) for horizontal projection in 1D space and I1DLBP (v) for vertical projection. We also compared the recognition accuracy of three similarity measures and we tested the effect of dimensionality reduction using PCA. Our experiments were implemented with *Matlab* 2010a, *Windows* 7, HP Core 2 Duo, 3 Ghz CPU with 2 GB Ram.

### *4.1 Experiments on the ORL database*

The ORL database contains 400 frontal images in different facial expressions, 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°, as shown in Figure 8. Half of the samples (200 images, 05 for each person) were randomly selected to create the training and gallery set and the remaining samples were used as the probe set. In all our experiments, we considered the average recognition rates of several random permutations (50 permutations). The images of the ORL database were normalized to a size of 72×84 pixels to accelerate the recognition process.

Fig. 8. Some images from ORL database.

The performances of the proposed feature extraction approach, based on the I1DLBP descriptor, were also compared to some widely-used facial feature representations, namely Classical Local Binary Pattern (LBP), Extended Local Binary Pattern, Improved Local Binary Pattern (ILBP), Elliptical Local Binary Pattern (ELBP), and the Projected Local Binary Pattern (1DLBP). For the first four approaches, images were divided into 7×7 sub regions to get the best results. The best performances of each descriptor are given with the configuration of $LBP^{8,2}$, $ILBP^{8,2}$, and $ELBP^{8,3,2}$. However, for the 1DLBP and I1DLBP descriptors, images are decomposed into several blocks with different resolutions, as shown in Figure 6; 1 block (72×84), 4 blocks

(36×42) and 16 blocks (18×21). To get the best results, the level of decomposition and the size of blocks were chosen after several tests and experiments.

Table 1 compares the top recognition rates on the ORL database using several descriptors under three measures of distances. Among the three distance measures tested, the Chi-Square distance gives the best recognition rates. The feature extraction approach proposed in this paper achieves higher recognition rates compared to the other approaches. Vertical, horizontal, or vertical + horizontal projections give the same results. There are no differences between the types of projection.

**Table 1. Recognition rates for the ORL database using different feature descriptors**

| Method | Euclidean % | Hamming % | Chi-Square % |
|---|---|---|---|
| **LBP** | 80.1 | 80.5 | 85.2 |
| **Extended LBP** | 81 | 81.3 | 86 |
| **ELBP** | 80.4 | 86.1 | 84.3 |
| **ILBP** | 85 | 85 | 88.1 |
| **1DLBP** | 87.9 | 88.7 | 92 |
| **I1DLBP (h)** | 89.5 | 90 | 93.4 |
| **I1DLBP (v)** | 89.5 | 90.2 | 93.5 |
| **I1DLBP (h+v)** | 89.5 | 90 | 93.2 |

To improve the recognition rates, all the templates must be projected onto a lower dimension subspace defined by the significant principal components using PCA, as discussed in the previous section. The new subspace is constructed from the training images and the dimension of the vectors, in the new space, will be reduced to preserve the content of the original data as far as possible. The problem that remains to be solved is the choice of the $K$ value, i.e., the optimal number of principal components.

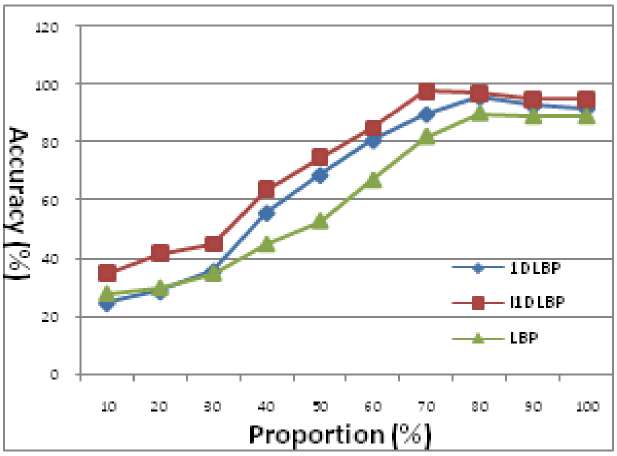


Fig. 9. Proportion of Principal Components to find the optimal value $K$.

Figure 9 plots the recognition rates of different feature extraction approaches, using the Chi-Square distance, for different proportions of principal components. The plot shows that 70% of elements from the projected vector, which is equivalent to 235 principal components, achieve the highest recognition of 98%, using our proposed approach. So, for this experiment using the ORL database, the optimal value, K=235 elements, instead of the original 336 dimensional feature vector, provides the best recognition rate.

*4.2 Experiments on the AR database*

The AR database was collected at the Computer Vision Center in Barcelona, Spain in 1998 (Martinez and Benavente, 1998). 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 were identical for all subjects. The resulting RGB colored images are 120×165 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, which increases the difficulty of recognition, as shown in Figure 10.

In this work, 2600 images (100 people, 26 images for each person) from the AR database were chosen to test the performances of the proposed approach, especially in facial expression changes and occlusion circumstances. The images of the AR database were normalized to a size of 120×164 pixels; the images were decomposed into several blocks with different resolutions; 1 block (120×164), 4 blocks (60×82), 16 blocks (30×41), and 64 blocks (15x20). The level of decomposition and the size of blocks were chosen after several tests and experiments to obtain the best results. The performance of the proposed approach of feature extraction was also compared with some well-known facial feature representations. The best performance of each approach is given with the configuration of $LBP^{8,2}$, $ILBP^{8,2}$, and $ELBP^{8,3,2}$. In the decision step, the Chi-Square distance proved more efficient than other distances in classifying each image in the nearest neighbor class. PCA is needed to improve the recognition rates. In our experiments, the best results were obtained by selecting 65% of elements from the original vectors with projected descriptors, and 72% from the original vectors with two dimensional descriptors.

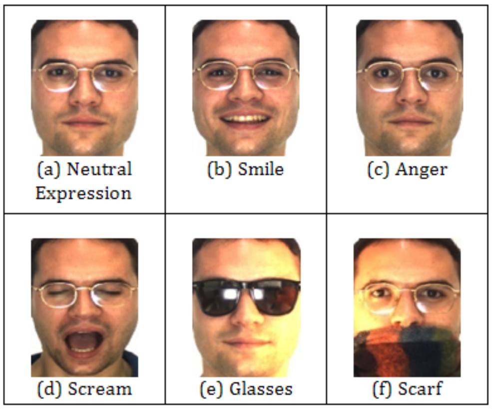


Fig.10 Some images from the AR database (Martinez et al., 1998)

In the first test, neutral expressions (see Figure 10 (a)) from each person were used to create the training and gallery set and all the remaining images with different facial expressions and occlusions (smile, anger, scream, with glasses, and scarf; see Figure 10 (b-f)) were used as the test set. The best recognition performances are recorded in Table 2.

In the second test, the first 14 images from each person (neutral, smile, anger, and scream images) were used as a gallery set and the last 12 occluded images (glasses and scarf images) were used as the test set. The best recognition performances are recorded in Table 3.

In the last test, half of the samples (1300 images, 13 for each person) were randomly selected to create the training and gallery set, the remaining samples were used as the test set. The average recognition rates of several random permutations (80 permutations) were taken into consideration. The best recognition performances are recorded in Table 4.

**Table 2. Recognition and comparison rates for the AR database using PCA and Chi-Square distance with different feature descriptors to test the effect of occlusion and changes in facial expression**

| Method | Smile (%) | Anger (%) | Scream (%) | Glasses (%) | Scarf (%) |
|---|---|---|---|---|---|
| **LBP** | 92.3 | 92.1 | 76.3 | 72.7 | 74.2 |
| **Extended LBP** | 92.6 | 92.3 | 77.2 | 78.6 | 79.7 |
| **ELBP** | 95 | 95 | 82.3 | 83.3 | 85.1 |
| **ILBP** | 98.2 | 98 | 79.4 | 76.1 | 78.5 |
| **1DLBP** | 100 | 99.4 | 88.8 | 85.1 | 87 |
| **I1DLBP (h)** | 100 | 100 | 90.4 | 87.3 | 89.2 |
| **I1DLBP (v)** | 100 | 100 | 90.4 | 87.4 | 89.2 |
| **I1DLBP (v+h)** | 100 | 100 | 90.2 | 87.3 | 89.2 |

**Table 3. Recognition and comparison rates for the AR database using PCA and Chi-Square distance with different feature descriptors to test the effect of occlusion**

| Method | Recognition Rate (%) |
|---|---|
| **LBP** | 79.2 |
| **Extended LBP** | 83.7 |
| **ELBP** | 86.4 |
| **ILBP** | 83 |
| **1DLBP** | 87.2 |
| **I1DLBP (h)** | 91.4 |
| **I1DLBP (v)** | 91.4 |
| **I1DLBP (v+h)** | 91.3 |

Tables 2, 3, and 4 show the best recognition rates on the AR database of several feature descriptors for face recognition, using different configurations (facial expression + occlusion, occlusion only, and general model). We can see from Tables 2, 3, and 4 that horizontal, vertical, or horizontal + vertical projections give the same results; there are no differences between the three types of projections in recognition rates. Also, we can see that projected descriptors in one dimensional space are more efficient than two dimensional descriptors, and that the introduction of the improvement technique, by calculating the mean value, as in ILBP and I1DLBP, gives better results than unimproved descriptors such as LBP and 1DLBP respectively. In addition, the recognition performance achieved by our proposed approach, in all configurations, outperforms all the other feature extraction approaches.

**Table 4. Recognition and Comparison rates for the AR database using PCA and Chi-Square distance with different feature descriptors to test the performances of the proposed approach**

| Method | Recognition Rate (%) |
|---|---|
| **LBP** | 86.3 |
| **Extended LBP** | 89.2 |
| **ELBP** | 91 |
| **ILBP** | 88.1 |
| **1DLBP** | 95.8 |
| **I1DLBP (h)** | 98.3 |
| **I1DLBP (v)** | 98.3 |
| **I1DLBP (v+h)** | 98.3 |

It can be seen in Table 2 that our proposed approach achieves a recognition rate of 100% with smile and anger expressions because they are very similar to neutral expression, and that the performance of the proposed approach automatically decreases with scream expression and in the presence of some objects that mask part of the human face, but in comparison with other feature descriptors, the results of our approach are significantly better.

Table 3 shows that the performances of all the feature descriptors are not good but they are acceptable with projected descriptors, because natural images are used for training sets and the images used to test the system are masked by glasses or scarf (occulted images). However, the performances are very significant in Table 4 where the training set and the test set were created from mixed images (occluded + different facial expression).

## 5. CONCLUSIONS

In our investigation, we have successfully developed a new feature extraction approach for face recognition based on the proposed descriptor I1DLBP. This approach is characterized by the combination of local and global features to differentiate between people as proved in neuroscience and psychology studies. For feature extraction, each image is normalized and decomposed into several blocks with different resolutions. Next, each block is projected in one dimensional space. Then, the proposed descriptor I1DLBP is applied on each projected block. Finally, the resulting vectors from each block are concatenated in one global vector. A series of experimental evaluations on the ORL and AR databases show that the projected descriptors in one dimensional space are more efficient than two dimensional descriptors and that the improved descriptors such as ILBP and I1DLBP give better results than unimproved descriptors such as LBP and 1DLBP respectively. Furthermore, the introduction of PCA as a robust technique for dimensionality reduction achieves a higher recognition rate with a lower computational cost. In addition, the proposed approach has shown powerful performances and effectiveness against several challenges such as occlusion, rotation, and changes in facial expression. As a perspective of this work, we plan to evaluate the performances of the proposed approach in order to recognize faces in a video surveillance context.

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