A Low Complexity Face Recognition Scheme Based on Down Sampled Local Binary Patterns

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Abstract: *The accurate description of face images under variable illumination, pose and face expression conditions is a topic that has attracted the attention of researchers in recent years, resulting in the proposal of several efficient algorithms. Among these algorithms, Local Binary Pattern (LBP)-based schemes appear to be promising approaches, although the computational complexity of LPB-based approaches may limit their implementation in devices with limited computational power. Hence, this paper presents a face recognition algorithm, based on the LBP feature extraction method, with a lower computational complexity than the conventional LBP-based scheme and similar recognition performance. The proposed scheme, called Decimated Image Window Binary Pattern (DI-WBP), firstly, the face image is down sampled and then the LBP is applied to characterize the size reduced image using non overlaping blocks of 3x3 pixels. The DI-WBP does not require any dimensionality reduction scheme because the size of the resulting feature matrix is much smaller than the original image size. Finally, the resulting feature vectors are applied to a given classification method to perform the recognition task. Evaluation results using the Aleix-Robert (AR) and Yale face databases demonstrate that the proposed scheme provides a recognition performance similar to those provided by the conventional LBP-based scheme and other recently proposed approaches, with lower computational complexity.*

Keywords: *Local binary patterns, DI-WBP, face recognition, identity verification, bicubic interpolation*.

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1. Introduction

Face recognition is a widely used, non-intrusive, biometric recognition method in which the data acquisition can be performed, with or without the cooperation of the person under analysis, by taking a picture. This together with the fact that the face is one of the most common features used by the people to recognize to each other, have increased the acceptance of face recognition, among the users of biometric recognition methods [6, 23, 26].

The face recognition systems basically performs two tasks: identity verification in which the system must to determine if the person under analysis corresponds to the person he claims to be; and identification task in which the system must determine the identity of the person under analysis by comparing the face characteristics stored in a database with the face characteristics of the person under analysis. Thus, usually recognition is developed to perform both tasks, i.e., person identification and identity verification [10].

Variable illumination, pose, facial expressions, and occlusions are important problems that must be considered in the development of face recognition systems because these factors alter the perception of face images, significantly decreasing the accuracy of face recognition performance [6, 32]. Among these factors, changes in lighting conditions are very important because they occur not only due to the differences on illumination conditions between indoor and outdoor environments but also within any of them due to the 3D shape of the face, which produces shadows depending on the direction of illumination. This issue has received significant attention [32]. Accordingly, different schemes have been proposed during the last decade to reduce the variable illumination problems [32]. These approaches can be divided in two groups. The first group processes the input image to reduce the illumination changes and improve the quality of the input face image; examples include illumination plane subtraction with histogram equalization [32], and Contrast-Limited Adaptive Histogram Equalization (CLAHE) [8].

A second approach to address variable illumination conditions is the development of face recognition algorithms that can provide robust performance under such conditions because, the performance of most faces recognition algorithms depend the accuracy of the feature extraction method. Thus, several methods have been proposed that intend to simultaneously provide small intra-person and significant interpersonal variability under varying illumination conditions. One example is the eigenphase approach, which uses the phase spectrum together with Principal Component Analysis (PCA) and the Support Vector Machine (SVM) [8, 9, 24, 30]. Under certain conditions, this algorithm provides recognition rates of over 95%. Feature extraction methods based on other frequency transforms, such as the discrete cosine transform [4, 11, 12], discrete Gabor transform [1, 17, 31, 35], discrete wavelet transform [14, 19, 20], and discrete Haar transform [13], have been proposed. These approaches, under controlled conditions, achieve recognition rates of over 90%. Additional methods proposed in the literature include the eigenfaces approach [8, 22, 29], which uses PCA [18, 20, 34], modular PCA-based face recognition methods [15], the Fisherfaces approach [7], which uses the Linear Discriminant Analysis (LDA) method, and the Laplacianfaces [16], which uses locally preserving projections. Several other approaches have been recently proposed to solve the problems related to changes in illumination conditions and partial occlusion using genetic algorithms [21], image processing filters [5], SVMs [8, 24, 30],artificial immunity networks [33], sparse representation-based classification [27], and linear regression-based classification [26, 28].

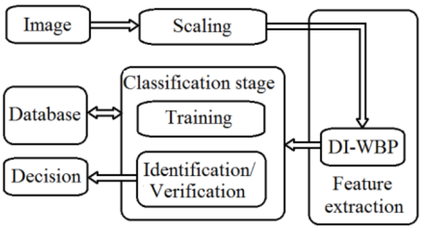
Face recognition methods using the Local Binary Pattern (LBP) operator [2, 3], which is among the most accurate texture characterization methods, have recently been proposed in several applications. Some advantages of these methods are their computational efficiency and their robustness to monotonic gray-level changes, which makes them suitable for several image characterization and pattern recognition tasks [2, 28, 37]. The main reason for using the LBP for face characterization is that face images can be consider as composed by several micro patterns, which can be accurately characterized using the LBP [3]. Several LBP-based schemes have been proposed during the last several years; among them the Holistic LBP Histogram (hLBPH) which was introduced for texture description [3], where the occurrences of the LBP are collected into a histogram for classification using either histogram intersection or chi-square. However, the hLBPH is not well suited for face recognition because its performance degrades when preprocessing is not used to compensate for variations in the illumination conditions [32]. The spatially Enhanced LBP Histogram (eLBPH), which is the first face recognition technique based on the LBP operator, divides the full image into sub-images. Then, a regional LBP is extracted from each sub-image, whose histograms are concatenated, for face recognition, into a single histogram. The sub-image division and concatenation of the local histograms play a key role in improving the performance of eLBPH, doing it more effective than the hLBPH for face and facial expression recognition [5, 32]. Another approach is the hLBPI, which has not been widely used in face recognition compared to the eLBPH despite its interesting properties [32]; for example, the hLBPI coefficients have local robustness and high discrimination properties, besides that the hLBPI maintains the spatial relation among the image pixels and then the intrinsic appearance of face images. Additionally, the computational complexity of the hLBPI is lower than that of the eLBPH, and the feature vector size is the same as that of the face image. These properties have attracted the attention of some researchers, and several variations of the hLBPI have been proposed in recent years, including a LBP-based kernel sparse representation face recognition algorithm [24, 27], which provides high enough recognition rates for several practical applications.

There has been increasing interest in the development of face recognition schemes that are suitable for implementation in mobile devices, such as smartphones, which generally have low computational power. Because these systems must operate in environments with varying illumination, it is advantageous to maintain minimal computational complexity, which corresponds to a face recognition scheme belonging to the second approach, i.e., one that does not require a preprocessing stage to improve the image quality. Hence, this paper proposes a modification of the LBP-based face recognition method called the Decimated Image Window Binary Pattern (DI-WBP), in which the face image is first decimated by a factor of 9 to reduce the image size. Then the reduced image is divided in sub-blocks of 3×3 pixels, which are characterized by the LBP coefficient corresponding to the central pixel of each sub-block. This approach reduces the feature vector size by approximately 81-fold relative to that of the conventional LBP-based methods. Finally, some classification method, such as the SVM or the K-Means (KM) algorithm using the Euclidean distance and cosine distance, are used to perform recognition. The proposed methods are evaluated with several illumination and facial expression conditions, relying on the Aleix-Robert (AR) and Yale face databases. Although the interest in developing unconstrained face recognition schemes has been growing during the last several years, face recognition systems operating in controlled environments still can be found in a large number of practical applications.

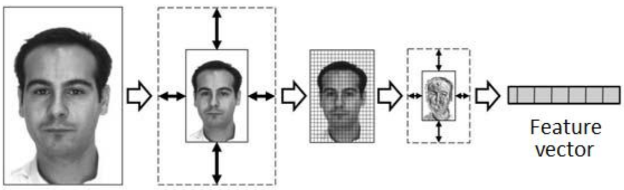
The remaining of this paper is organized as follows: section 2 presents the description of the proposed scheme. Section 3 presents and analysis of the evaluation results. Finally, section 4 provides the conclusions of this research.

2. Proposed Algorithm

Figure 1 shows the block diagram of proposed face recognition system. Here, firstly the system receives the face image under analysis, which is fed into an interpolation stage to reduce the original image size by a factor of 9. Next, the down sampled image is divided in MN/81 non-overlapped blocks, where M×N is the original image size, which is characterized using the LBP scheme. Finally the feature matrix is re-arranged in a vector of size MN/81 that is fed into the classification stage. The following subsections describe with detail each stage of proposed face recognition system.

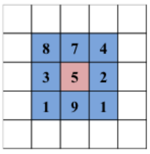


a) Block diagram.

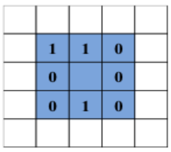


b) Feature extraction stage.

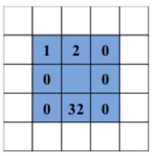
Figure 1. Proposed face recognition system.



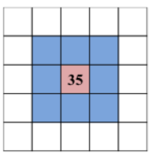
a) Second order neighborhood pattern around center pixel 5.



b) Comparison of the central pixel with the remainig pixels.



c) Representation of each pixel in the neighborhood.



d) Representation of the central pixel in the neighborhood using the LBP.

Figure 2. Representation of the central pixel of a neighbourhood using the local binary patterns approach.

2.1. Scaling Stage

To reduce the computational complexity of proposed scheme, without much performance degradation, the image size is down sampled by a factor of nine using the bi-cubic interpolation method, which is given as follows:

$$p(x,y)=\sum_{i=0}^{3}\sum_{j=0}^{3} a_{ij} I(3x+i,3y+j), \quad (1)$$

where $p(x,y)$ denotes the (x,y)-th pixel of the input image, $I(r,q)$, $r=3x+i$, $q=3y+j$; r=0, 1, 2; q=0, 1, 2; j=0,1,..(M/9-1); k=0, $1,\ldots$(N/9-1). Here a_{ij}, i=[0,3] and j=[0,3] are the interpolation filter weights, which are determined solving simultaneously sixteen equations with sixteen unknown values [23]. Any other method, including bilinear, low-pass filtering, or Discrete Wavelet Transform (DWT) methods, can also be used for the down sampling task.

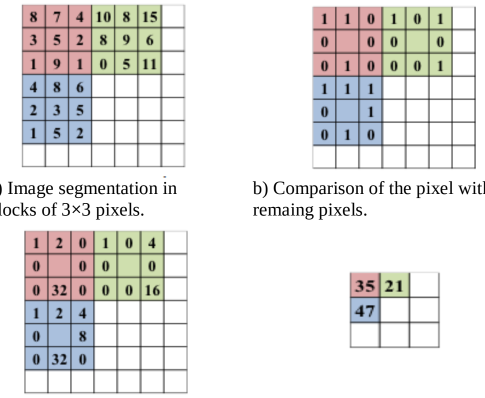
2.2. Feature Extraction Stage

To understand the proposed scheme, it is necessary to describe the original LBP method. The LBP algorithm introduced by Ojala *et al*. [28] is one of the most efficient methods for describing texture. The original LBP method, that is, the hLBPH, uses masks of 3 x 3 pixels, called the "texture spectrum", to represent a second order neighbourhood around a central pixel, as shown in Figure 2, where the values of the neighbouring pixels are compared with the central pixel, taking that pixel value as the threshold. Pixels are labelled as 0 if their values are smaller than the threshold; otherwise, they are labelled as 1, as shown in Figure 2-b. Next, the pixel labels are multiplied by 2p, where $0\leq p\leq 7$ is the position of each pixel in the neighbourhood, as shown in Figure 2-c. Finally, the resulting values are added to obtain the label of the central pixel in that neighbourhood, yielding Figure 2d. This method produces 128 possible values for the central pixel label. This process is repeated for the entire image producing a LBP labelling matrix, which has the same size as the input images, which is used to estimate the vector features for the face image.

To reduce the classifier complexity and avoid the over fitting problem, besides the reduction of the input image size, described above, this paper proposes a modification of the hLBP algorithm, called WBP method, which reduces the computational complexity of the original hLBP algorithm without degrading the recognition performance. The first step of this method consists on dividing the input image into $l\times m$ non-overlapping windows of 3×3 pixels such that the input size of the original image (M×N) could be represented as 3l×3m. Then, the WBP is defined as follows:

$$WBP(j,k)=\sum_{p=0}^{P-1} s\left(I_{j,k}(x,y)-g_c\right)2^p, \quad (2)$$

Where $x=3j+r$, $y=3k+q$; $r=0,\ 1,\ 2$; $q=0,\ 1,\ 2$; $j=0,1,..$(M/9-1); $k=0,\ 1,\ldots,$(N/9-1); $I_{j,k}(x,y)$ represents the (j,k)-th block of 3×3 pixels of the down sampled input image, gc is the central pixel of the same block and $s(I_{j,k}(x,y)-g_c)=0$ if $I_{j,k}(x,y)<g_c$ and 1 otherwise. Finally $0\leq p\leq 7$ is the position of each pixel in the neighbourhood around the central pixel, in a clockwise direction, starting in the upper-left corner of the 3×3(j,k)-*th* block. Next the feature matrix obtained from (2) is re-arranged in a vector of size MN/81 which is fed into the classification stage. The main concept behind this proposal is that the face texture can be considered uniform inside a small window; thus, the 3×3-pixel non-overlapping windows can be used to characterize the face image instead of the overlapped windows used by the original hLBPH.



a) Image segmentation in blocks of 3×3 pixels.

b) Comparison of the pixel with the remaing pixels.

c) Representation of each pixel in the neighborhood by 25^p.

d) Representation of the central pixel of each block using the WBP.

Figure 3. WBP representation of the image under analysis.

An example of WBP implementation is shown in Figures 3, where the original image is firstly divided into (MN/9) windows of 3×3 pixels (Figure 3-a). Additionally, the result of the comparison of neighbouring pixels with the central pixel is shown in Figure 3-b, the substitution of pixel values is shown in Figure 3-c, and the resulting WBP image is shown in Figure 3-d. The size of the resulting matrix is NM/81. For example, when input images size is 198×288 pixels, after the down sample and WBP processes are applied, the size of the resulting label matrix becomes 22×32 pixels. This matrix is then introduced in the classifier for training or recognition.

2.3. Classification Stage

After estimating the feature vectors, they are fed into a classification stage, which must perform the identification or verification task. In this paper, to keep the computational complexity as low as possible, the K-means algorithm is used in which, during the training period the template of the *k-th* class is given by the average of the training face images belonging such class. During the identification task, the classification stage estimates the distance between the centre of each cluster and the features vector image under analysis, classifying it as belonging to the class with the smaller distance; while during the verification task the system validates the identity of the person under analysis if the estimated distance is smaller than a given threshold. In this paper two different distance were evaluated, the Euclidean distance given by

$$d_{st} = \sqrt{(x_s - y_t)(x_s - y_t)^T}, \tag{3}$$

and the cosine distance is given by

$$d_{st} = 1 - \frac{x_s y_t^T}{\sqrt{(x_s x_s^T)(y_t y_t^T)}}, \tag{4}$$

Where x_t is the estimated feature vector of the image under analysis and y_t is the centre of the *t-th* class.

2.4. Computational Complexity

In addition to the performance comparison among the proposed and conventional methods, it is important to evaluate the number of operations required by each method to analyse whether the method is feasible for use in applications in which the computational power is limited, for example, in mobile devices such as smartphones and tablets.

When the proposed algorithm is used to estimate the feature vector of an N×M input image, the proposed algorithm requires 16NM/9 multiplications and 16NM/9 additions to reduce the image size by a factor of 9 using the bi-cubic interpolation. After the image size reduction, the LBP coefficients are estimated using non-overlapping blocks of 3×3 pixels, which require 8NM/81 additions and 8NM/81 comparisons. Thus assuming that the three operations have similar complexity, the proposed algorithm requires 304NM/81operations. On the other hand, the conventional hLBPI, for estimating an L-dimensional feature vector, where L is the total number of training images of N×M pixels, requires 8NM additions and 8NM comparisons for LBP estimation. The LBP matrix is then arranged in a column vector, X, of size NM which is multiplied by the matrix **Φ**, of size L×NM obtained from the PCA analysis. Thus the estimation of the feature vector, given by Y=ΦX, requires NML additions and NML multiplications. Then, the estimation of the feature vector of a given input image of size N×M requires (24+L)NM additions, (16+L)NM multiplications and 8NM comparisons. Thus assuming that the three operations represent the same computational cost, the hLBPI-based face recognition algorithm requires approximately (48+2L)NM operations to estimate the feature vectors of an input image of size N×M pixels. A comparison of the computational complexity of other recently proposed methods for features vector estimation during the testing operation [7, 8, 16, 32] is shown in Figure 4.

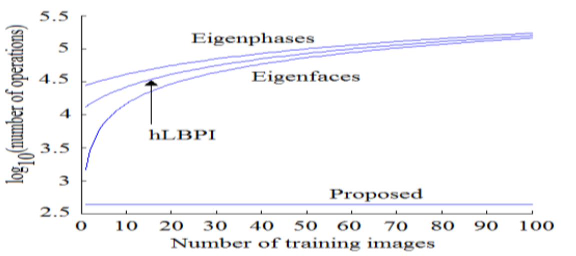


Figure 4. Computational complexity of proposed scheme compared with other previously proposed algorithms.

3. Evaluation Results

The proposed face recognition system was evaluated using identity verification as well as person identification task, where in the first task the system must to verify the identity of the person under analysis, whereas in the second task, the system must determine the identity of the person by finding in the database those characteristics that more closely resemble the ones of the person under analysis [8]. In both cases the performance of proposed algorithm is evaluated and compared with the results obtained using other high performance schemes such as hLBPI [32] the eigenphase [8], Laplacianfaces [16], Fisherfaces and eigenfaces [7] when the SVM and k-means with Euclidean and cosine distance are used in the classification stage. In all cases, the AR [25] and Yale [36] databases were used, which contain face images with different ethnic characteristics, illumination conditions, eyeglasses, and certain other occlusions.

For increasing the number of illumination conditions, the AR database [25] was expanded only for testing, including 4 additional images per each one contained in the original AR database. This allows us to increase five times the number of face images in the AR database, obtaining a larger number of face images with different illumination conditions. To this end, the 20 face images, $I_o(x, y)$, of each person belonging to the sets AR(A) and AR(B) were used to generate 80 additional images of each person with different illumination conditions by means of the intensity transformation given by

$$I(x,y) = \left\lfloor 255\left(I_o(x,y)/255\right)^{\gamma(x)} \right\rfloor \tag{5}$$

Where $\gamma(x)$ is defined according to the desired effect on the resulting image, i.e., if it is desired that the whole image becomes darker, then $\gamma(x) = C, C > 1$ is used, while to obtain a brighter image $\gamma(x) = C, C \le 1$ is used, where $\lfloor q \rfloor$ denotes the integer part of q. However, to generate face images with spatially varying illumination $\gamma(x)$ was selected as follows

$$\gamma(x) = -\frac{2(C-1)x}{M} + C, \qquad 0 \le x \le M/2, \tag{6}$$

to produce face images where the illumination increases form left to right, and

$$\gamma(x) = \frac{2(C-1)x}{M} - (C-2), \qquad M/2 \le x \le M \tag{7}$$

To produce images where the illumination decreases from left to right. These effects are illustrated in Figure 5, where Figure 5-a is the original image, 5-b and 5-c show the resulting images obtained with $\gamma(x)$=2.1 and $\gamma(x)$=0.5, respectively, and 5-d and 5e show the modified images obtained using Equations (6) and (17) with C=2.1, respectively.

The expanded version of the AR database includes a total of 12,000 face images that is, 100 images of 120 different persons where 65 are males and 55 females. The expanded AR database was divided into set AR(A) which consists of 70 face images per person with several illumination conditions and facial expressions; and the set AR(B) with 30 face images per person with partial and several illumination changes. Figure 6 shows some examples of the face images included in both AR(A) and AR(B). For system training 7 randomly selected images of each person belonging to the original set AR(A) were used. Figure 7 provides an example of training images of one the persons included in the set AR(A) database.

The proposed schemes were also evaluated using 1,395 images belonging to the Yale database, which includes 45 images of 31 different persons. Figure 8 shows some examples of such images. As above, seven images of each person were used for training. In all cases, the images of each person included in the database used for training were randomly selected.

a) Original image. b) Dark image. c) Clear image. d) Left side darker. e) Right side darker.

Figure 5. Image examples from the extended AR Database.

a) Images from the AR. b) Images from the AR.

Figure 6. Image examples from the AR database.

Figure 7. Example training images of a person from AR(A) set of AR Database.

Figure 8. Images of different persons included in the yale database.

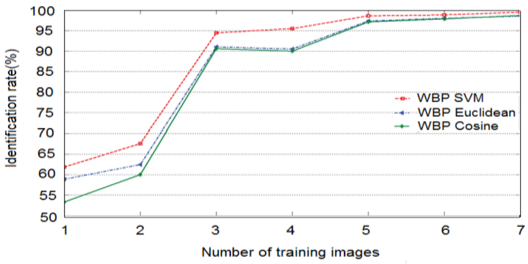


Figure 9. Identification rate obtained using different numbers of training images using with the k-means with the Euclidean distance, and k-means with the cosine distance.

In practical applications, the relationship between the number of training images and recognition performance is a critical issue. In most systems the recognition performance improves when the number of training images is sufficiently large. However, the number of training images may be reduced in practical applications; thus, it is important to evaluate performance degradation when the number of images is limited. To this end, the recognition performance of the proposed scheme was evaluated using different number of training images. The results of this experiment, obtained by averaging several experiments with different training sets, are shown in Figure 9. This figure shows that, when 3 or more images are used for training, the proposed scheme provides a recognition rate higher than 90%; achieving a recognition performance of 98% when 7 training images are used. The evaluation results shown in Figure 9 were obtained using the expanded AR database, the WBP proposed method, and 3 different classifiers, including the SVM, k-means with the Euclidean distance and k-means with the cosine distance.

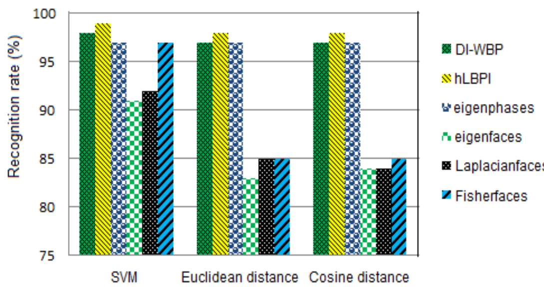


Figure 10. Recognition performance of proposed approach using: SVM, Euclidean distance and cosine distance in the classification stage. The performance of hLBPI, eigenphases, eigenfaces, Laplacianfaces and Fisherfaces are also shown for comparison.

3.1. Identification

Figure 10 shows the recognition performance of proposed scheme when it is asked to perform an identification task, using the set (A) of the AR database. The recognition performance of other efficient face recognition methods [7, 8, 16, 32] is also shown for comparison. All face recognition systems were trained using 7 images of each person. Figure 10 shows that the proposed scheme provides a recognition performance quite similar to those provided by other recently feature extraction methods, such as hLBPI [32] and eigenphases [8]; and better performance than other commonly used schemes [7, 16]. In all cases the proposed approach requires much less operations number as shown in Figure 4.

Figure 11 shows the face recognition performance of proposed scheme when it is required to identify persons included in the sets AR(A) and AR(B). Here the proposed system was trained using the set AR(A), while the testing was carried out using the set AR(A) and AR(B). The Yale database was also used for both, training and testing. Figure 11 shows that proposed scheme provides quite similar recognition performance that the hLBPI when the image under analysis presents several illumination conditions and even ethnic characteristics included in the AR database set (A) and Yale database, although the performance degrades when the face presents some kind of occlusions (set (B) AR database).

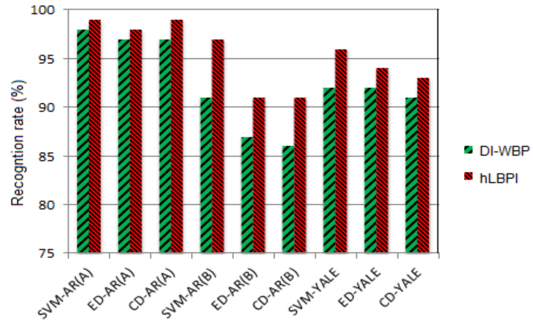


Figure 11. Recognition performance of proposed algorithm when it is evaluated using the AR(A), AR(B) and Yale databases, where the SVM, the Euclidean distance (ED) and the cosine distance (CD) are used in the classification stage. The performance of hLBPI is also shown for comparison.

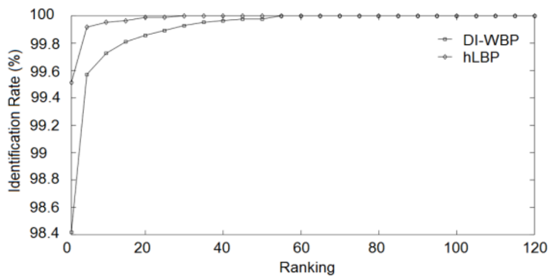


Figure 12. Ranking evaluation of image set AR(A).

Another important evaluation of any identification algorithm is the ranking. In this test, the ranking *(n)* denotes the probability that the image under analysis belongs to one of the *n* classes with highest probability. That is, a ranking of 10 is the probability that the image under analysis belongs to one of the 10 most likely persons. Figures 12, 13, and 14 present the ranking evaluation of the proposed algorithms using the different databases. The proposed algorithm achieves an identification rate of 100% (99.90) using the set AR(A) when the ranking is equal to 10. Thus, the probability that the person under analysis belongs to one of the ten persons with highest probability is equal to one. The ranking value increases when the AR(B) and Yale databases are used, as shown in Figures 12, 13, and 14.

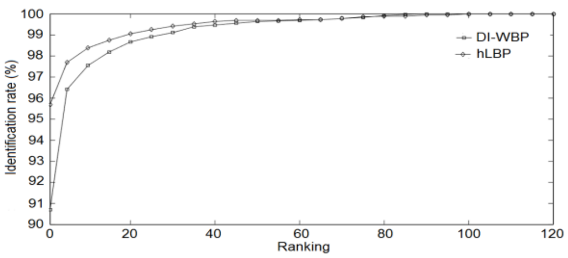


Figure 13. Ranking evaluation of image set AR(B).

In all cases, the system was trained with 7 images of each person belonging to either the AR(A) or Yale database sets, while the recognition system was tested with images that were not used for training from the AR(A), AR(B), and Yale database sets respectively. In the case of AR(A), the system provided a very good performance, as the recognition rates obtained were greater than 98% with DI-WBP. Although the recognition performance decreases when the images contained partial occlusion, as in the set of AR(B), in which the persons are wearing sunglasses, the proposed scheme still provides recognition rates higher than 90%. In all cases, the system was trained using images belonging to the set AR(A). The above results demonstrate that the proposed system recognized 7,441 of the 7,560 images in all situations. Similar results were obtained using the Yale database, where the proposed system achieved a recognition rate of approximately 92%.

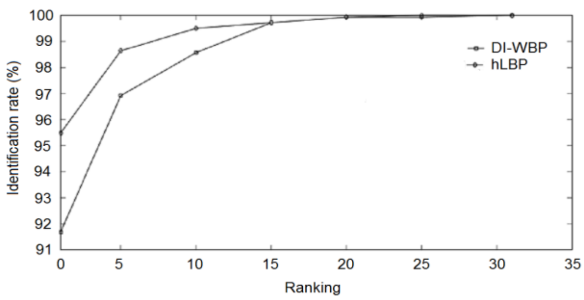


Figure 14. Ranking evaluation of the Yale database.

3.2. Verification

Figure 15 shows the Receiver Operating Characteristics (ROC) of proposed and hLBPI algorithms, when both are required to verify the identity of the person under analysis, using the set (A) of the AR face database. Figure 15 shows that proposed scheme provides an identity verification performance quite similar to that provided by the hLBPI algorithm with much less computational complexity. This figure also shows that both algorithms simultaneously provide small false acceptance and false rejections error rates. Figure 16 shows the ROC of proposed algorithm when it is required to perform the identity verification task using the AR(A), AR(B) and Yale databases. Evaluation results show that the proposed scheme again achieves simultaneously los false acceptance and false rejection rates when it is required to operate with face images with different characteristics as those shown in the above mentioned databases.

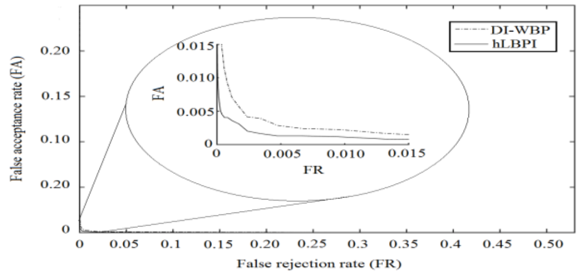


Figure 15. Receiver operating characteristics of proposed and conventional hlbpi algorithms.

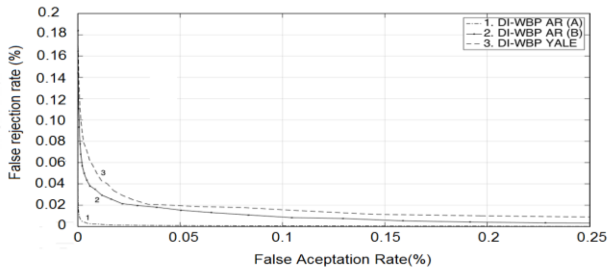


Figure 16. Receiver operating characteristics of proposed algorithm using three databases with different characteristics.

The performance of most face recognition systems depends on a suitable selection of the threshold value to accurately verify the identity of the person under analysis. To find a suitable mechanism for determining an appropriate threshold value several experimental evaluations were carried out. From them we obtained two important results:

a) The false acceptance probability, as a function of the threshold values, follows an exponential distribution as shown in Figure 17.
b) The relation between false acceptance rate Pfa and false rejection rate Pfr closely resembles an exponential function as shown in Figure 18.

Thus we can assume that the false acceptance probability is given by

$$P_{fa}(Th) = e^{-\alpha Th}, \tag{8}$$

$$P_{fr} = e^{-\beta P_{fa}}. \tag{9}$$

Then from Equations (8) and (9) it follows that $a=-Ln(P_{fa}(Th))/Th$ where $P_{fa}(Th)$) is the false acceptance rate obtained for a given threshold Th. Hence, for a desired false acceptance probability Po the suitable value of Th is given

$$Th = -Ln(Po)/\alpha \tag{10}$$

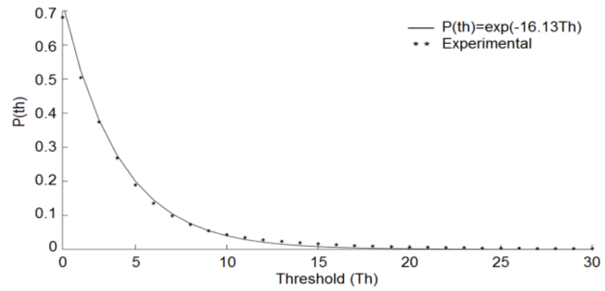


Figure 17. Relationship between the false acceptance rate and the threshold value.

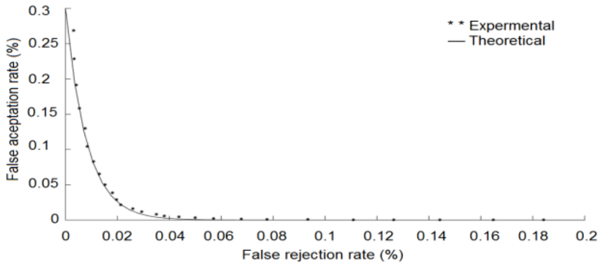


Figure 18. Relationship between the false acceptance rate and false rejection rate.

4. Conclusions

This paper proposed a feature extraction method suitable face recognition task, which is based on the LBP algorithm and specified as DI-WBP. The evaluation results demonstrate that the proposed DI-WBP approaches provide fairly good recognition rates, similar to the rate provided by the hLBPI under the same conditions. In most situations, the recognition rate of the DI-WBP is slightly lower than the recognition rates of the hLBPI because the feature vector estimation of the DI-WBP does not require PCA. This fact results in an important computational complexity reduction of approximately 2NML/9 relative to hLBPI, where L is the feature vector size. This value denotes the number of eigenvectors related to the most significant eigenvalues of the covariance matrix, as obtained in the PCA analysis, which is used for feature vector estimation. A larger value of L produces a more accurate feature vector, although the computational complexity increases. In most cases, the evaluation results also indicate that the proposed schemes provide better recognition rates than other high-performance methods, such as the Eigen faces, Laplacian faces, and Fisher faces, which possess significantly lower degrees of computational complexity. As expected, the recognition performance of the proposed methods, similar to the performance of several other methods, degrades when the number of training images is minimal (i.e., less than five images). However, the number of training images can be artificially increased easily using simple image processing operations such that the recognition performance of the proposed scheme would improve, at least with respect to changing illumination environments.

The evaluation results using the AR and Yale databases demonstrate that the proposed system also provides fairly good results when it performs identity verification tasks, because in this situation, the proposed schemes achieve false acceptance rate closed to zero when the threshold value is equal or larger than 0.7. Although in most practical situations the false acceptance rate must be kept as small as possible, depending on the application, either the false acceptance or false rejection rate may be reduced by changing the threshold value, although reducing one rate will increase the other. Finally a theoretical criterion is provided which allows selecting the threshold such that the system be able to provide a previously specified false acceptance or false rejection rate.

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