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Two Adaptive Image Pre-processing Chains for Face Recognition Rate Enhancement

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Abstract

In this paper, two adaptive image enhancement and de-noising chains are produced. Our aim is to enhance the face image quality that stored in a large database for face recognition applications. Each processing chain consists of three steps, the first chain is proposed to enhance Principal Component Analysis (PCA) and Kernel Principal Component Analysis (KPCA) recognition rate, in the first step of this chain, the face images are de-noised with Haar wavelet de-noising filter at level ten of decomposition, in the second step, the de-noised image is adjusted to enhance the image contrast, and in the third step the high pass filter 'Laplacian of Gaussian filter' is used for detecting edges in face images. The second chain is proposed to enhance Linear Discriminat Analysis LDA and Kernel Fisher Analysis (KFA) recognition rate, in the first step of this chain the image contrast is adjusted and entered to histogram equalization as second step and in the third step the image is de-noised with Haar wavelet de-noising filter at level ten of decomposition. Our approaches produced good result and contributed in raising the recognition rate in PCA, KPCA, LDA and KFA up to 10%, 20%, 5% and 4% respectively when 400 face images are used.

Keywords: *Image enhancement, image de-noising, high pass filter, Feature extraction, Face recognition rate*

1. Introduction

Face recognition represents an important area in computer vision and image processing fields, and covers a wide range of applications, such as mug-shot database matching, credit card verification, security system, and object surveillance. Face recognition is a challenging research topic since, even for the same individual, faces seems differently due to lighting conditions, expression, pose, occlusion, and other staggering factors in real life [1]. The most common existing technologies include Principal Component Analysis (PCA) [2, 3], Linear Discriminant Analysis (LDA) [4], kernel methods [5], Eigenfaces [2], Fisherfaces [6], Laplacian faces [7], elastic bunch graph matching [8], neural networks [9] and support vector machine [10]. Due to the obstacles in controlling the lighting conditions in practical applications, different results in image illumination is one of the most challenging problems in face recognition. The performance of the aforesaid techniques is subject to the variations in the lighting conditions. Over the last decade, some approaches have appeared to attempt to overcome the problem of face recognition under varying illuminations [11-18].

An important aspect in improving the performance of face recognition system is the enhancing of face image. The intended aim of face image enhancement is that the resulted

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images will have better visual quality than the input one. Face image can be improved, by enhancing the brightness, contrast and resolution of image. This is a part of pre-processing stage that can affect the feature extraction and finally recognition performance.

In this paper, the effects of image enhancement and image denoising on the face recognition are considered. The aim is to take the benefit of some image enhancement methods combined with image de-noising and compression methods to enhance the feature extraction process for PCA, KPCA, LDA and KPCA and hence increasing the face recognition rate and achieving performance with high accuracy.

Section 2 describes a brief literature review to some related work, Section 3 describes the framework of the adaptive approaches, Experiments and results are shown in Section 4, and finally the conclusions are described in Section 5.

2. Literature Review

Many approaches used face image preprocessing techniques to normalize the images under different illumination conditions. For example, Gamma intensity correction and histogram equalization (HE) are widely used for illumination normalization [17]. However, uneven illumination variation is still difficult to overcome with the using of these global processing techniques. Recently, region-based histogram equalization (RHE) [17] and block-based histogram equalization [18] have been proposed to deal with uneven illumination variations. Although the recognition rates can be improved compared with HE, their performance is still not satisfying techniques. In [17], the authors proposed a normalization method called quotient illumination relighting. This method is based on the assumption that the lighting techniques of the images are recognized or can be estimated. In [19], by combining symmetric shape-from shading method and a generic 3-D model, the performance of face recognition under varying illuminations is improved. However, this method is only effective for frontal face images and it is supposed that all faces share an identical common appearance. These assumptions decrease their effectiveness in reality. In [20], a logarithmic total variation (LTV) model was advanced. This model can factorize a single face image and get the illumination invariant facial construction, which is used for face recognition. In [21], used (LOG-DCT) method based on LTV model and logarithm discrete cosine transform [22], a new illumination normalization method was lately produced. In face recognition literature, there are different face representation methods based on global features, including a big number of subspace-based methods and some spatial-frequency techniques [23]. In face recognition, individuals are identified by use of a large database of face images. In conventional appearance-based systems, the intensity of each pixel in a face image is entered as input feature. Because, there are more than many thousands of pixels in a face image [24], facial image data are always high-dimensional and significant computational time is required for the successful classification aim. Thus the subspace methods, by projecting objects to a lower dimensional space, are commonly used. In practical cases, when the image dimension is very large, one is often forced to use linear techniques. Two important linear techniques for extracting characteristic features and also dimension reduction are PCA and LDA. Many researches focused on projective transforms. The essential part of these methods is creating feature vector for each face image, then classify the input face image in large database. Creating feature vector also has the utility of minimizing dimension of the input images [25]. Principal component analysis method achieved the dimension reduction by projecting the original face image data onto lower dimensional subspace crossed by the best eigenvectors of the covariance matrix. Linear Discriminant Analysis method looks for the projective axes on which the data points of different classes are distant from each other , this mean searches for

the maximizing between class scatter, while constraining the data points of the same class to be as near to each other as possible , this mean searching for the minimizing within class scatter [4]. Kernel PCA and kernel fisher analysis are non linear form of PCA and LDA respectively. Several researchers proposed techniques based on spatial-frequency methods, such as Discrete Cosine Transform (DCT) and Fourier transform [24-27]. In these methods, face images are mapped to a lower frequency domain bands have most facial discriminating features and discarding high bands having noise [24].

Two adaptive chains of procedures will be shown in this paper, the first adaptive approach used de-noising and enhancement processes to enhance PCA and KPCA face recognition rate and the second adaptive approaches used enhancement and de-noising processes to enhance LDA and KFA face recognition rate.

3. The Adaptive Approaches

In our work, we applied the enhancement approaches on AT&T ORL database that consists of 40 directory, each directory has ten images belong to same individual with (92×112) image size, all images are in PGM file formats, this mean there is 400 face image in this database will be processed by our two approaches. Each approach has a chain with three steps, at the end of these processing steps, the result of each approach are queued to generate new enhanced database, and then, all face images are converted to jpg file format.

3.1 The First Pre-processing Chain Approach

This chain is (de-noised – enhanced) approach, since image denoising using Haar wavelet filter is applied first, then the image enhancement process is followed the de-noising process, the aim of this adaptive approach is to enhance the recognition rate of PCA and KPCA with three steps as shown in Figure 1:

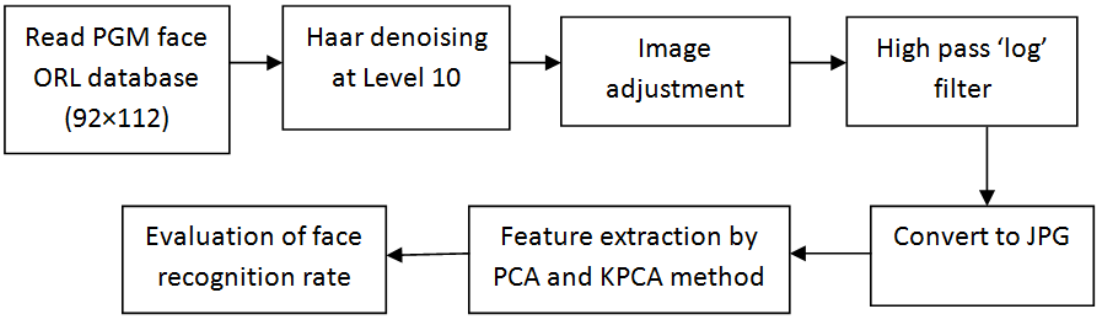


Figure 1. The first pre-processing chain Approach block diagram

3.1.1 Haar 10 Wavelet De-noising Filter

Wavelet de-noising is a wavelet transformation function, is well-suited for image compression. Most of the energy of the two-dimensional Haar Wavelet Transform (HWT) are concentrated in the upper left-hand corner of the transform and the remaining three parts (quarters) are conserved primarily of values that are zero or near zero. This transform is local, as well, it produces any element of the HWT is organized from only four elements of the original input image [27].

HWT can be defined as the orthogonal matrix, to apply the HWT to a digital grayscale image, the image is stored in matrix A with even dimensions M x N, then the normal thing is trying to compute WM A. this matrix multiplication can be viewed as WM applied to each

column of A so the result should be an M x N matrix where each column is M/2 weighted averages followed by M/2 weighted differences. We have used the Haar matrix to treat the columns of image matrix A. It is eligible to treat the rows of the image as well. We proceed by multiplying WMA on the right by WNT. Transposing the wavelet matrix set the filter coefficients in the columns and the multiplication on the right by W_N^T means that the rows of WMA will be dotted with the columns of WNT (columns of WN). So the two dimensional HWT is defined as [28]:

$$B = W_M A W_N^T$$

Figure 2 shown the result of applied transform to one level of decomposition and the representation of the image transformation for further decomposition levels is shown in the right part of the figure. The de-noising process can be summarized by the following steps:

Step1: use a wavelet filter (Haar filter) with level 10 of decomposition. Then compute the 2D-DWT of the noisy image.

Step2: Threshold the non-LL subbands.

Step3: Perform the inverse wavelet transform on the original approximation of LL-subband and the modified non-LL subbands.

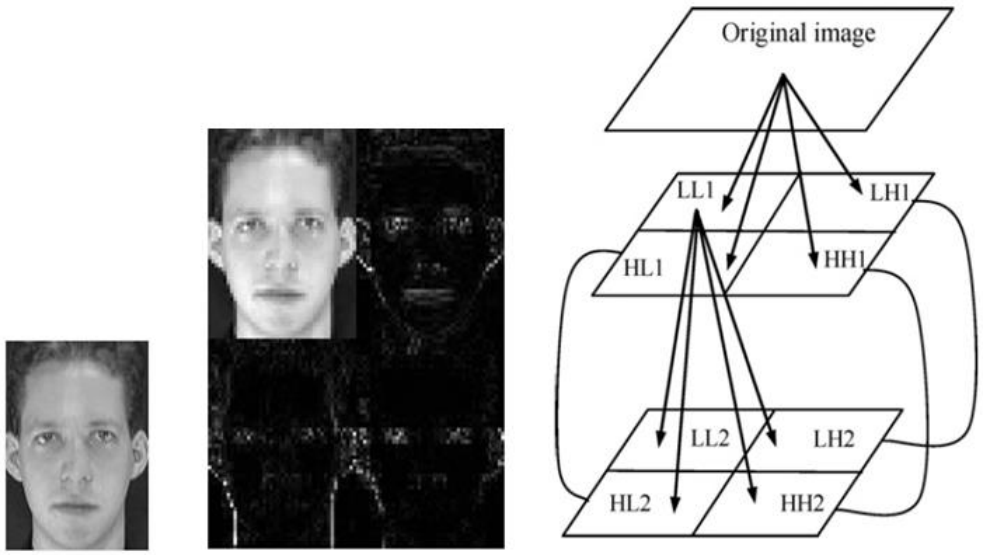


Figure 2. LL, HL, LH and HH wavelet decomposition

We used de-noising by Haar wavelet filter at level 10 of decomposition, this filter is used in [29] and contributed in raising the recognition rate from (0.5%-3%) when used with many feature extraction methods. Figure 8 shows sample of image de-noised by Haar 10 filter.

3.1.2 Adjust Image

Image adjustment maps the intensity values in grayscale image I to new values in J such that 1% of data is saturated at low and high intensities of I. This increases the contrast of the output image J, Figure 2 shows the result of applying image adjust on the face image [24].

Figure 3. De-noised face image by Haar at level 10 of decomposition is on the left, and the adjusted face image is on the right

3.1.3 Laplacian of Gaussian

Laplacian of Gaussian (LOG) is high pass filter and useful for finding edge, also useful for finding blobs, First the image is smoothed by Gaussian filter in order to reduce its sensitivity to noise, Then, find zero-crossings by Laplacian filter [30]:

$$LoG = \Delta G_\sigma(x,y) = \frac{\partial^2}{\partial x^2} G_\sigma(x,y) + \frac{\partial^2}{\partial y^2} G_\sigma(x,y) = \frac{x^2+y^2-2\sigma^2}{\sigma^4} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

$$\nabla^2 G_\sigma(x,y) = \left(\frac{x^2+y^2}{\sigma^4} - \frac{2}{\sigma^2} \right) G_\sigma(x,y)$$

The LoG factor computes the second spatial derivative of an image. This means that in regions where the image has a regular intensity (for example, where the intensity gradient is zero), the LoG response will be zero. In the proximity of a change in intensity, however, the LoG response will be negative on the lighter side and positive on the darker side. This means that at a rationally sharp edge between two areas of regular but different intensities, the LoG response will be zero at a long distance from the edge, positive only to one part of the edge, negative to the other part of the edge, and zero at points in between, on the edge itself [30-33].

Figure 4. Applying of high pass filter on the original face image is on the left and the applying of log filter on the de-noised – adjusted face image is on the right

We used 'LoG filter to detect the edges in face image, as a contribution to enhance edge detection that specify the main face metrics, and hence enhanced the face recognition rate. Figure 4 shows the result of applied 'LoG' filter on the original face image and on the right part is the result of applying 'LoG' filter on the de-noised- adjusted face image of our approach.

3.1.4 The Adaptive Approach Procedure

Input: PGM ORL database

Output: JPG de-noised-enhanced database

Processing:

Step1: Load face images database (suppose all face images are noisy images by default).

Step2: Perform multiscale decomposition of the noisy image with the help of Haar wavelet filter.

Step3: Calculate the wavelet coefficients of noisy image at level 10 of decomposition.

Step4: Select only coefficients more than the threshold and shrink less than the threshold to 0.

Step5: Combined the wavelet coefficients with the same spatial location across adjacent scales as a vector; this means the row vector formed by concatenating the transposed column matrix of wavelet coefficients.

Step6: Invert the multiscale decomposition to reconstruct the de-noised image.

Step7: Adjusted the contrast with image adjustment

Step8: Entered the image to high pass filter using 'LoG filter'

Step 9: Convert the de-noised-filtered face images database from PGM to JPG format.

3.2 The Second Pre-processing Chain Approach

This chain is proposed to enhance the recognition rate of LDA and KFA with three steps as shown in Figure 5:

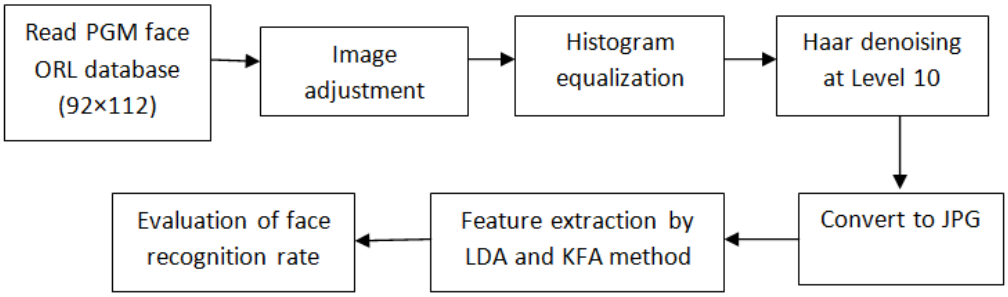


Figure 5. The second pre-processing chain Approach block diagram

3.2.1 Image Adjust and Histogram Equalization

In the first step of the second approach is the image adjustment to increase the contrast as shown in Figure 6:

Figure 6. Original face image is on the left, and the adjusted face image is on the right

The performance of face recognition techniques is also affected by illumination [34]. Histogram equalizations is an effective method to deal with varying light conditions in large dataset of images. The problem is that the variation in illumination between images of distinct faces can be fewer than the variations between images of the same face under diverse illuminations conditions. It can even be displayed that illumination causes huge variation in face images than pose. At the very beginning of modern machine face recognition, it became very clear that different illumination in different images will be a problem [18]. Image pre-processing and normalization is played an important role in face recognition systems. Changes in lighting conditions will cause dramatic decreasing in the recognition performance [16].

Histogram equalization is a functional method in stretching the range of gray levels and expands the contrast of image. It also makes the variation of the order of gray levels of the original image perfectly controllable. Therefore, it can improve images effectively [24, 34].

Figure 7 is the result of applying histogram equalization, it can be seen that the contrast of face image and the background become more, and the looking over of the face image is more evident.

Figure 7. Original face image on the left, the histogram equalization face image in the center, and the result of (adjusted-histogram) image is on the right

3.2.2 Haar 10 Wavelet De-noising Filter

We applied the same wavelet filter that used in the first approach but after the contrast of face image is adjusted and enhanced by using HE, Figure 8 shows the result of applying Haar

wavelet filter at level 10 of decomposition on the face images of PGM ORL database, Figure 9 shows the result of entering the image enhancement (adjust –histeq) to process with Haar filter for de-noising to get the enhanced- de-noised face image.

Figure 8. Faces de-noised by Hear filter at level 10 of decomposition

Figure 9. Sample of enhanced and de-noised database by our second approach

3.2.3 The Adaptive Approach Procedure

Input: PGM ORL database

Output: JPG enhanced- de-noised database

Processing:

Step1: Load face images database (suppose all face images are noisy images by default).

Step2: Adjusted the contrast of image with image adjustment.

Step3: Equalized image with Histogram Equalization.

Step4: Perform multiscale decomposition of the noisy image with the help of Haar wavelet filter.

Step5: Calculate the wavelet coefficients of noisy image at level 10 of decomposition.

Step6: Select only coefficients more than the threshold and shrink less than the threshold to 0.

Step7: Combined the wavelet coefficients with the same spatial location across adjacent scales as a vector; this means the row vector formed by concatenating the transposed column matrix of wavelet coefficients.

Step8: Invert the multiscale decomposition to reconstruct the de-noised image.

Step 9: Convert the de-noised-filtered face images database from PGM to JPG format.

4. Experiments and Results

In our work, we compared the proposed enhancement approaches with the ORL database, the result of first approach after entering the de-noised-enhanced face images database to PCA and KPCA feature extraction methods is illustrated in Table 1 and the result of the second approach after entering the enhanced-de-noised face images database to LDA and KFA feature extraction methods is illustrated in Table 2.

Table 1. Comparison between original PGM database with the de-noised- enhanced approach using PCA and KPCA

Database used	PCA	KPCA
ORL PGM database[35,36]	66.07%	49.29%
Haar 10 – enhanced database	76.56%	70.70%

Table 2. Comparison between original PGM database with the de-noised-enhanced approach using LDA and KFA

Database used	LDA	KFA
ORL PGM database[35,36]	86.07%	85.07%
Haar 10 – enhanced database	91.94%	89.74%

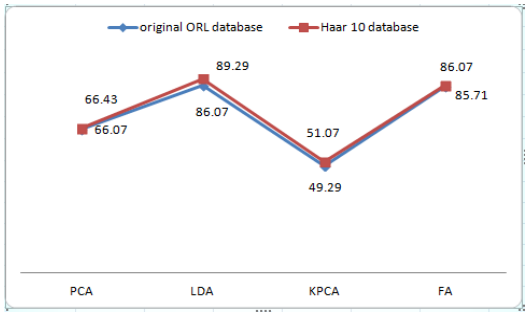
Table 3 illustrated the performance of different feature extraction when original AT&T ORL database is used, when image adjustment and histogram equalization (HE) are applied separately to create (Adjust DB) and (HE DB) respectively, and when the two procedures applied successively to create (Adjust + HE DB), all these database are compared with our first approach (de-noised- enhanced database) and second approach (enhanced-de-noised database). From the result that illustrated in the table, it is clearly to display that the first approach achieved the highest rate for PCA and KPCA and the second approach gave the highest recognition rate for LDA and KFA when compared with all other databases.

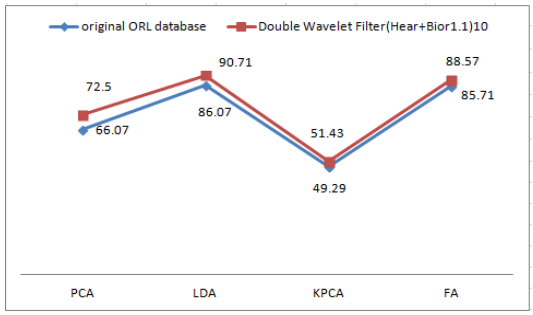
Table 3. Comparisons in the performance PCA, LDA, KPCA and KFA face recognition methods when different image processing procedures applied on ORL database of 400 face image

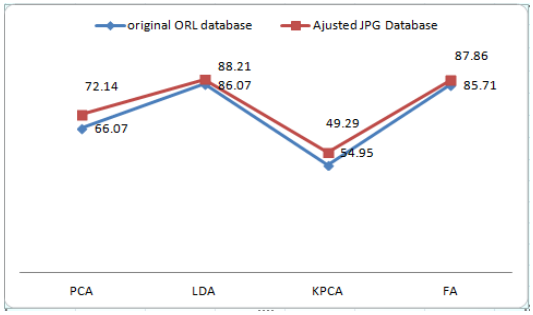
Database used	PCA	LDA	KPCA	KFA
Original PGM ORL db[35] [36]	66.07%	86.07%	49.29%	85.07%
Haar 10 de-noised DB	66.43	89.29%	51.07%	86.07%
de-noised DB by (Haar+Bior1.1)10	72.50%	90.71%	51.43%	88.57%
HE DB	66.43%	85.36%	50.36%	81.43%
Adjust DB	72.14%	88.21%	54.95%	87.86%
Adjust +hist DB	75.00%	91.43%	3.21%	86.43%
Our first approach	**76.56%**	86.81%	**70.70%**	79.12%
Our second approach	70.70%	**91.94%**	54.21%	**89.74%**

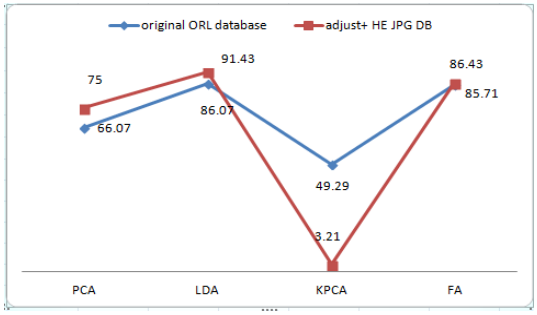
Our charts showed some results of our training enhancement methods on ORL database with the using of four feature extraction methods including PCA, LDA, KPCA, and KFA. Figure 10 and Figure 11 shows the comparison between ORL PGM database with the de-noising one by Haar at level 10 of decomposition and with denoising one by double wavelet filter (Haar and Bior 1.1) both at level 10 of decomposition. Figure 12 and Figure 13 shows the comparison between the original database with database after contrast adjusted by only

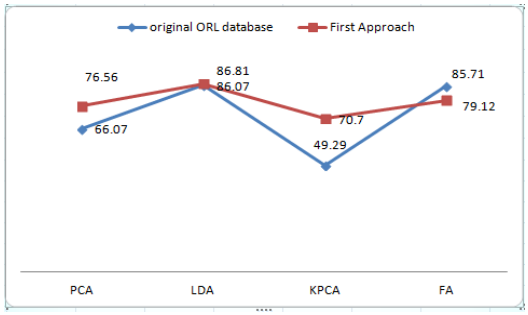
image adjust, and when applied image adjust with histogram equalization on the database respectively. Figure 14 shows the comparison of our first proposed chain processing approach with the ORL database and finally, Figure 15 shows the comparison of our second proposed chain processing approach with ORL database.











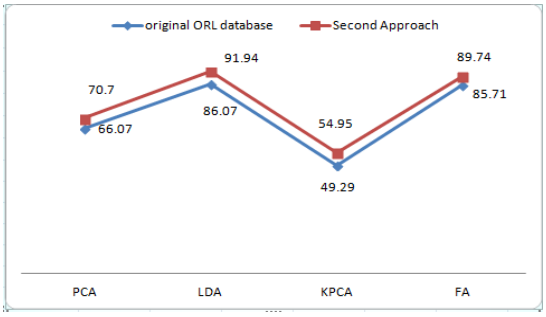


Figure10. the original ORL database and Haar 10 DB (1st row- left).

Figure 11. The original ORL database and de-noised DB by Double filter (1st row- right).

Figure 12. The original ORL database and Adjusted JPG database (2nd row- left).

Figure 13. The original ORL database and Adjusted + HE JPG database (2nd row- right).

Figure 14. The original ORL database and the First approach (3rd row-left).

Figure15. The original ORL database and the second approach (3rd row-right).

From the result of Figure 14 and Figure 15, our first approach contributed not only in raising the recognition rate of PCA and KPCA but also slightly raised LDA recognition rate up to (0.75%), and the second approach also raised the recognition rate of PCA up to (4%) and slightly raised KPCA up to (5%) than the original ORL database recognition rate, in addition to its aim in raising the recognition rate of LDA and KFA.

Table 4 illustrates comparison among the performance of PCA and LDA with two metrics (Euclidean distance and Machos distance), also, including the performance of PCA using neural network and LDA using neural network by Euclidean distance measure, all these methods are compared with the performance of our adaptive (first and second) approaches when applied on PCA and LDA using Machos distance.

Table 4. Comparison among different metrics of PCA and LDA and our two adaptive approaches on 400 images in ORL database (when 3 training image and 7 tests image are used)

Using Euclidean distance [37]				Mahcos [35,36]		1st approach	2nd approach
PCA	PCA+NN	LDA	LDA+NN	PCA	LDA	PCA	LDA
73%	76%	82%	84%	66.07%	86.07%	76.56%	91.94%

It is clear from the above table that our face image enhancement approaches produced the highest rate and exceeded the performance of neural network face recognition techniques.

5. Conclusions

The main purpose of any face recognition system is to retrieve face images which are very similar to a specific class of face images in a large database. The retrieved face images can be used for many applications, such as monitoring system in airport, visual surveillance, criminal face verification in police office, extracting specific faces from the web, and photo management.

The novelty of this paper focused on raising the face recognition rate by using image enhancement, image de-noising, and image compression using JPG file format, with the combine of PCA, LDA, KPCA and KFA feature extraction and dimension reduction. This paper produced two approaches for face image enhancement to improve the face recognition rate. In the first approach we used denoising at level ten of decomposition, adjust image contrast and high pass filter, then the resulted images are converted to JPG , this approach contributed in raising the recognition rate to 10% and 20% in PCA and KPCA respectively. The results obtained using this method indicate sharper edges gives more details by detecting the boundaries of eyes, noise, mouth , glasses , hair and so on. In the second approach we applied the enhancement process prior to image denoising by Haar 10 wavelet de-noising process, adjust image contrast and histogram equalization are used successively for image enhancement then the de-noising are applied to get enhanced-de-noised database, then the resulted database are converted to JPG, this approach contributed in raising the recognition rate to 5% and 4% in LDA and KFA respectively. The result that obtained from this method retrieved features for each class which are more related to the entire class, since this enhancement approach contributed to increase the similarity characteristic within class scatter (minimizing the distance within class scatter) and minimized the similarity between class scatter (maximizing the distance between class scatter).

Our approaches are implemented easily by using Matlab 7.0, this work proved that not only the enhancement or the modification in the mathematical representation of face recognition techniques will lead to superior result, but also the enhancement of face image has big contribution in raising the recognition rate and can achieve promising performance in some face recognition techniques.

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