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FACE RECOGNITION WITH ILLUMINATION VARYING CONDITIONS AND OCCLUSIONS

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Abstract

Face recognition with illumination varying conditions and occlusions is one of the most important challenges in the field of digital image processing. Despite of the fact that a number of studies (Patel & Yagni, 2013; Azeem, Sharif, Raza & Murtaza, 2014) have improved the accuracy of different techniques by normalizing and compensating the illumination variations using some pre-processing methods, a lot of these methods are still facing many serious challenges with illumination changes and occlusion. In this paper we suggest the use of tow pre-processing methods that will have a great impact on the performance and the robustness of the recognition procedures in case small sample size (SSS) as training set .

Keywords

Face recognition, Illumination normalization and occlusion, small sample size.

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1. Introduction

In the last decade, face recognition has obtained a significant consideration by the researchers in the field of biometrics and computer vision. In computer-based security systems, faces identification represents an important application where the main challenge is to match accurately the input image with another one already stored in the database of the system. Facial images can be visual, thermal, or fused images (visual and thermal).

According to some studies (Anila & Devarajan, 2012; Dharavath, Talukdar & Laskar, 2014), visual image based recognition systems may have a poor performance according to the lighting conditions (low or high). However, many methods were already introduced (Han, Shan, Chen & Gao, 2012) to handle difficult lighting conditions problems such as (HE, LT, GIC, DGD, LoG, SSR, GHP, SQI, LDCT, LTV, LN, and TT). These methods are not sufficiently effective enough to get a high recognition rate. Table 6 shows some results where a group of these methods was applied on the same database used in this paper.

Another approach (Forczmanski, Kukharev & Shchegoleva, 2012) uses 2DDCT (Two-Dimensional Discrete Cosine Transform) method together with the brightness correction in order to achieve fusion of features according to the current mean value of brightness as well as removing the low-frequency components of the spectrum. This system addresses the problem of face recognition for images with lighting problems (e.g. flashes, shadows, and very low brightness level). The presented experiments of this system were conducted on image database "Extended Yale B" and illustrated in Table 5. Much better results, which are also illustrated in the same table, either for recognition rate or the number of misclassified images may be determined using the proposed techniques in this paper. The detailed explanation about these techniques will be clarified in the following paragraph.

With partial face occlusion (e.g. hand on a face or sunglasses occlusion case); as very important features of a face are hidden the recognition rate will be severely decreased. Several studies have already treated this problem (Tan, Chen, Zhou & Zhang, 2005; Mokhtare & Faez, 2016; Wright, Yang, Ganesh, Sastry & Ma, 2009).Table 6 shows some results where a group of these methods was applied on the same database used here.

In this paper, we deal with the above-mentioned challenges by using some robust pre-processing methods in order to improve the quality of the originally given images. The

Difference of Gaussian (DoG) will be combined with two different techniques, fitting distribution (FIT) and rank normalization technique. Extracting discriminative features will be performed by using the Principal Component Analysis (PCA) together with the Linear Discriminate Analysis (LDA) which is already considered as a robust feature extractor. Then the extracted features will be classified using a correlation classifier. In order to prove the efficiency of our proposed methods, some experiments will be illustrated and compared with some previous studies that are using illumination normalization techniques. As the "Extended Yale-B" data base provides an excellent testing platform for some cases of extreme variation in illumination (Lee, Ho & Kriegman 2005), it will be utilized in our study.

2. Pre-processing methods:

In this section, we describe tow robust pre-processing methods. The first method combines DoG with the fitting distribution while the second one combines DoG with the Rank normalization method.

2.1 Difference of Gaussian (DoG) with FIT distribution method:

The Difference of Gaussians; is a grayscale image enhancement algorithm that involves the subtraction of one blurred version of an original gray scale image from another less blurred version of the original one. DoG filtering will be firstly applied to reduce the local variations in visible face imagery and to enhance the edges. The FIT distribution is a predefined histogram distribution of an image when it works with DoG they perform the best performance where the gradient information becomes more stable, Figure 1. In this case, the histogram looks like a distribution with some pre-selected parameters, it is a histogram remapping technique.

Figure 1: *Applying DoG with FIT distribution,*
Original images (upper row), processed images (lower row).

In other words, it is a substitute of histogram equalization which increases the noise in the background of an image because of its uniform density distribution. While, in the actual suggested technique has different options for the desired distribution are allowed, and the best-suited one for the actual face recognition task has to be tested and selected (Struc, Zibert & Pavesic, 2009). Therefore, this function is useful for image enhancement rather than histogram equalization. Currently, three different target distributions are supported, the normal, lognormal and exponential distribution.

2.2 Difference of Gaussian (DoG) with Rank normalization method:

The second method combines DoG with the rank normalization technique that arranges all the pixels in an incremental order from the smallest intensity to the biggest intensity. Then, the most negative pixel value is assigned to the rank one, while the most positive value is assigned to the rank N which is the total number of pixels in an image. This method performs also a good enhancement to the quality of the image. Unlike to the histogram equalization, this method works faster and provides more flexibility regarding the output range of the pixels intensities values .Figure 2 shows the effect of this technique, For the both preprocessing methods; the values of the used parameters are summarized in Table1.

Figure 2: *Applying DoG with Rank normalization method, Original images (upper row), processed images (lower row)*

Table1: *Default parameter values for each proposed method*

Methods	Procedures	Parameters	Values
DoG + FIT distribution	DoG Filtering	(s1, s2)	(1,2)
	FIT distribution	(d,p)	(3,0.005)
DoG + Rank normalization	DoG Filtering	(s1, s2)	(1,2)
	Rank normalization	(M,s)	('one', 'ascend')

Where:

- S1= [0, 1] pixels; low frequency filtering parameter, S2 >1 pixels; high frequency filtering parameter.
- (d) Determines the type of the target distribution; d = 1 normal distribution (default), d = 2 lognormal distribution, and d = 3 exponential distribution.
- (p) Determines some internal parameters for each type of target distribution, in our case with d =3, P = 0.005.
- (M) is a string parameter determining the range of the output intensity values, for M = 'one' convert output to [0 1] (default), M = 'tow' convert the output to [0 N],where N is the total number of pixels in an original image. Finally, M = 'three' convert output to [0 255].
- (s) is a string parameter defining the sort operation which ascends or descend sorting of pixels.

3. Features extraction and distance correlation classifier

Features extraction is a task of reducing the high dimensional training data to a set of features to investigate different properties of data (morphological, geometric etc.) (Wang

& Paliwal, 2003; Pratt, 2001). A good feature extraction technique should maintain and enhance those features of an input image to make the distinct pattern classes separated from each other.

In this paper, we have selected the approach called "LDA using PCA sub sampling or sub space" as a robust feature extractor. This is an effective technique to solve the problem of Small Sample Size (SSS) (Sahu, Singh & Kulshrestha, 2013) which may arise from the small number of available training samples comparing with the dimensionality of the sampling space. In this case, the PCA subspace is used to reduce the dimensions of an image to such an extent where a small sample size problem can be avoided.

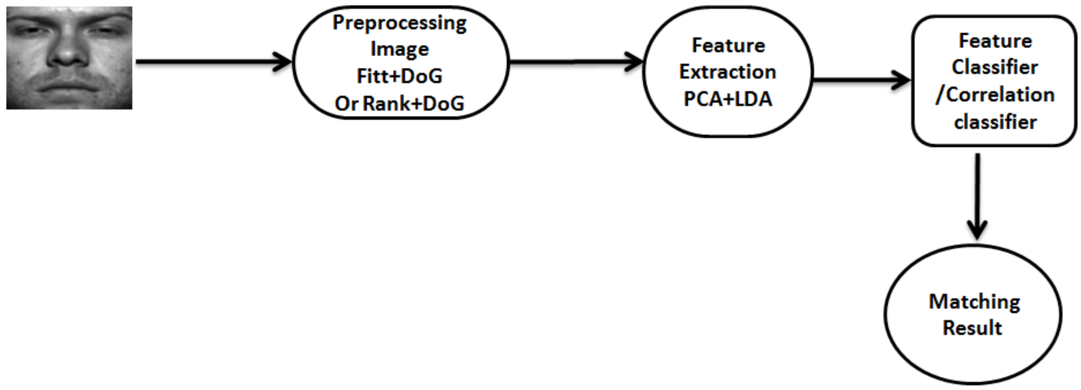


Figure 3: *Overview of the proposed system*

The last discussed robust technique has to be also effective in non-ideal conditions, as an example with occluded images, in such cases the occluded pixels have to be avoided while only the true pixels have to be sampled. Something also has to be noted, that the complexity of face recognition under non-ideal conditions depends on the number of the used classes and the percentage of the occluded pixels implied within the test image (Fidler & Leonardis, 2003). Thus, facial image of size [n×m], has to be converted into a features vector [n×1] then the similarity between vectors has to be calculated using the distance correlation classifier. Figure 3 describes briefly our proposed system.

4. Experimental Results

As our proposed face recognition system mainly deals with illumination and occlusion problems, we use the "Extended Yale-B face database" that provides an excellent testing platform for those cases of extreme variation in illumination (Lee, Ho & Kriegman, 2005). It consists of still images in a frontal pose for 38 subjects; each one has 64 images captured with different illumination conditions.

Experiment 1: Testing all database with and without occlusion in case (SSS) as a training set.

We have tested our system with only 1 or 2 training images from the first subset; the database (Lee, Ho & Kriegman, 2005) consists of 5 subsets containing 2166 testing images. Table 2 shows the results for each proposed methods.

Table 2: *Experimental results on "extended Yale-B" database with the both proposed techniques in case (SSS)*

No of training images	Method	RR without occlusion	RR with 40% occlusion
1	DoG with Rank normalization/PCA-LDA	93.16%	86.14%
	DoG with FIT Distribution/PCA-LDA	93.35%	85.92%
2	DoG with Rank normalization/PCA-LDA	99.35%	94.64%
	DoG with FIT Distribution/PCA-LDA	99.54%	95.15%

From table 2, we can note the high recognition rate (RR) without occlusion by using one or two images for each selected person as a training set. Also with a partial face occlusion of 40% where some basic facial features are covered, the recognition rate doesn't descend than 85.78% for only one training image, while it is more than 95.20% for two training images. The high recognition rates obtained here, especially in the case of partial occlusion, prove the efficiency of the preprocessing methods working here perfectly with PCA and LDA. Figure 4 shows a testing sample with a partial face occlusion of 40%.

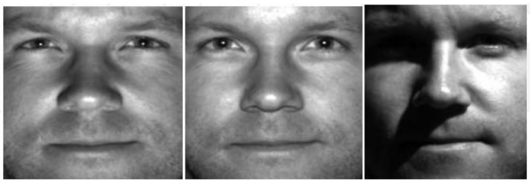
Figure 3: *Samples of testing images with a partial face occlusion of 40%*

Experiment 2: Recognition without occlusion using more than 2 training images.

In this experiment, the subset 1 is considered to be our training set while the remaining subsets are the testing sets. The images in the database (Lee, Ho & Kriegman, 2005) are divided into five subsets according to the direction of the light source from the camera axis as shown in Table 3.Five samples (images)for the same subject taken from the 5 allowed directions are shown in Figure 5.

Table 3: *Five allowed directions in the "extended Yale-B" database*

Subset	Angels	Image numbers
1	Θ < 12	263
2	20 < Θ < 25	456
3	35 < Θ < 50	455
4	60 < Θ < 77	526
5	85 < Θ < 130	714



subset (1) subset (2) subset (3)

subset (4) subset (5)

Figure 5: *Selected samples from all the allowed subsets*

In Table 5, we compare our proposed pre-processing techniques with another existing method that handle the illumination variation problem (Forczmanski, Kukharev & Shchegoleva, 2012), by applying the gamma correction, intensity logarithm and 2-D discrete cosine transform (2DDCT) in order to reduce the intensity gradient and to transform the original data into the space of spectral features. To achieve this comparison, 2151 images were tested with 6 training images. From Table 5 we can conclude that the error rates of our proposed methods are smaller than that of the existing method. In face recognition works the computation time is a critical factor; our proposed methods utilize simple image processing techniques. Therefore, they require a very short execution time as it is shown in Table 4. Other techniques like MSR, LTV and GB (ZHAO, LIN, OU & YANG, 2015) that use some iterative optimization treatment are considered as time-consuming methods .

Table 4: *Computation time for the both proposed methods*

We applied our experiment using laptop core 7 by MATLAB 2015 on 38 persons, for each one 64 images have been already saved. Thus, we have a total of 2432 images. The size of each image is 128×128.

Time	*DoG with Fit distribution method*	*DoG with rank normalization method*
Training time(6 training images)	*3.5sec*	*3sec*
Testing time(all database)	*28 sec*	*24 sec*

Table 5: *Recognition rates for our proposed techniques comparing with an existing methods.*

Pre-process. /Features Extract.	**Subset No.2**	**Subset No.3**	**Subset No.4**	**Subset No.5**	**All data set**	**Error rate**
Recognition rate-gamma correction. (G) and brightness logarithm(Log)+2DDCT6 training images for each person (subset1)	100	100	100	96.0	98.7	1.3
Misclassified images	0	0	0	29	29	
Recognition rate-DoG with FIT Distribution /PCA-LDA 6 training images for each person(subset1)	100	100	99.62	99.72	99.81	0.19

Misclassified images	0	0	2	2	4	
Recognition rate-DoG with Rank normalization/PCA-LDA6 training images for each person(subset1)	100	99.34	99.81	99.72	99.72	0.27
Misclassified images	0	3	1	2	6	
No. of test images	456	455	526	714	2151	

In order to prove the efficiency of our proposed techniques, we have performed some experiments to show that the recognition rates achieved by PCA and LDA with our proposed pre-processing methods are higher than those methods listed in Table6. All these methods were applied on the same database "Extended Yale B database". In this case, 2166 image was tested with 7 training images. We choose the high recognition rate for each method and give these rates in Table 6; at any case our recognition rate still higher than the others. Figure 6 shows a visual comparison of a facial image normalized with different illumination pre-processing methods under difficult lighting conditions (Han, Shan, Chen & Gao, 2012), In figure 7, the treatment of samples of testing images using our proposed techniques is illustrated.

Table 6: *Recognition rates with different methods applied on the same database.*

Illumination Preprocessing Methods																
Feature Extraction	***ORI***	***HE***	***LT***	***GIC***	***DGDx***	***DGDy***	***LoG***	***SSR***	***GHP***	***SQL***	***LDCT***	***LTV***	***LN***	***TT***	***DoG+ FIT.***	***DoG+ Rank.***
Correlation	**43.2**	**45.2**	**50.0**	**44.4**	**37.4**	**42.0**	**44.1**	**52.8**	**53.4**	**86.5**	**73.7**	**48.8**	**50.1**	**87.4**	**-**	**-**
Eigen face	**47.6**	**31.4**	**58.3**	**59.3**	**38.6**	**39.8**	**50.1**	**51.6**	**49.5**	**58.2**	**50.4**	**20.3**	**42.9**	**50.2**	**-**	**-**
LBP	**60.7**	**62.2**	**62.0**	**61.0**	**62.0**	**70.3**	**72.8**	**58.7**	**69.5**	**57.9**	**62.7**	**52.8**	**55.8**	**90.3**	**-**	**-**
LGBP	**95.4**	**95.9**	**98.9**	**96.1**	**85.5**	**83.1**	**74.8**	**98.4**	**91.0**	**99.1**	**98.3**	**92.1**	**98.2**	**98.9**	**-**	**-**
Fisherfaces	**54.2**	**54.8**	**62.8**	**67.7**	**53.1**	**59.2**	**54.6**	**55.5**	**55.4**	**72.6**	**74.1**	**78.0**	**67.4**	**71.6**	**-**	**-**

LEC	57.5	76.0	97.3	91.3	62.9	61.6	55.2	97.1	65.0	97.6	97.3	93.5	96.5	98.4	-	-
LDA+PCA	56.3	-	-	-	-	-	-	-	-	-	-	-	-	-	99.5	99.4

Also we note from table 6 where the original image without preprocessing (ORI), the low rate of recognition when used feature extraction without proposed preprocessing methods

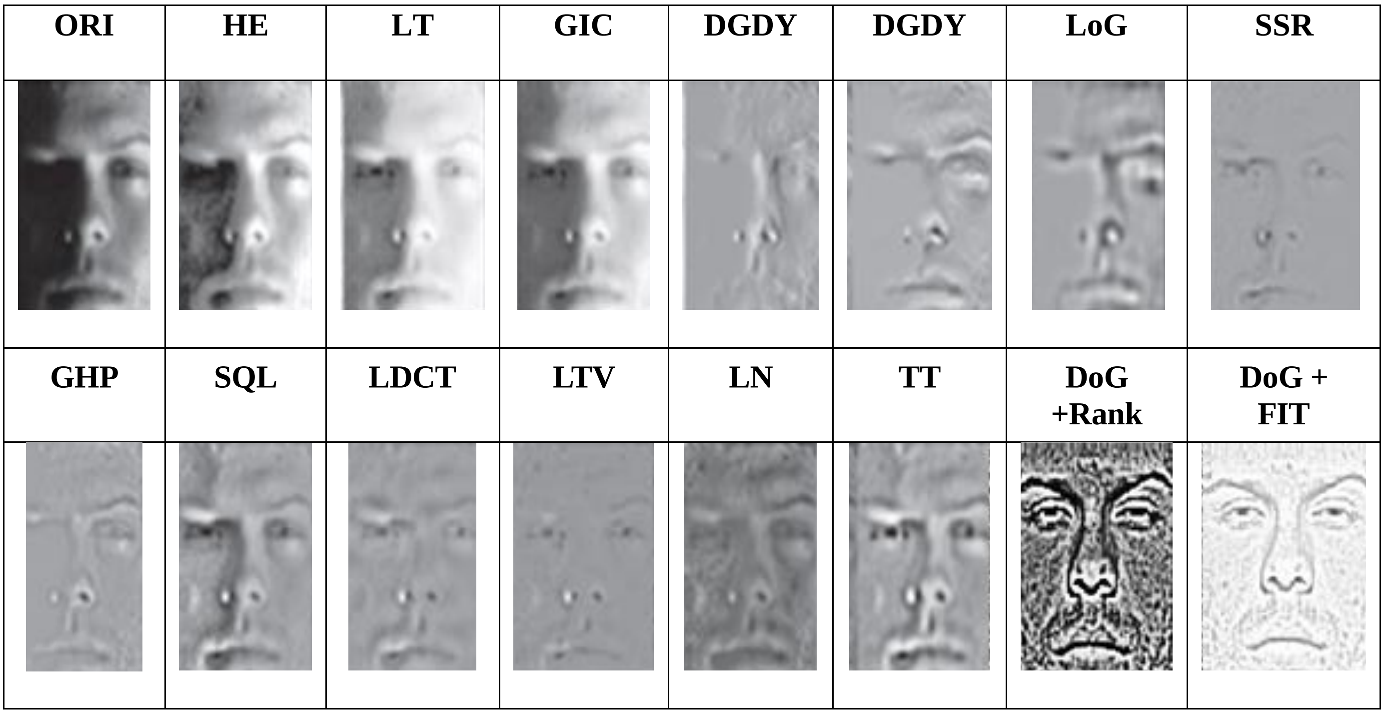
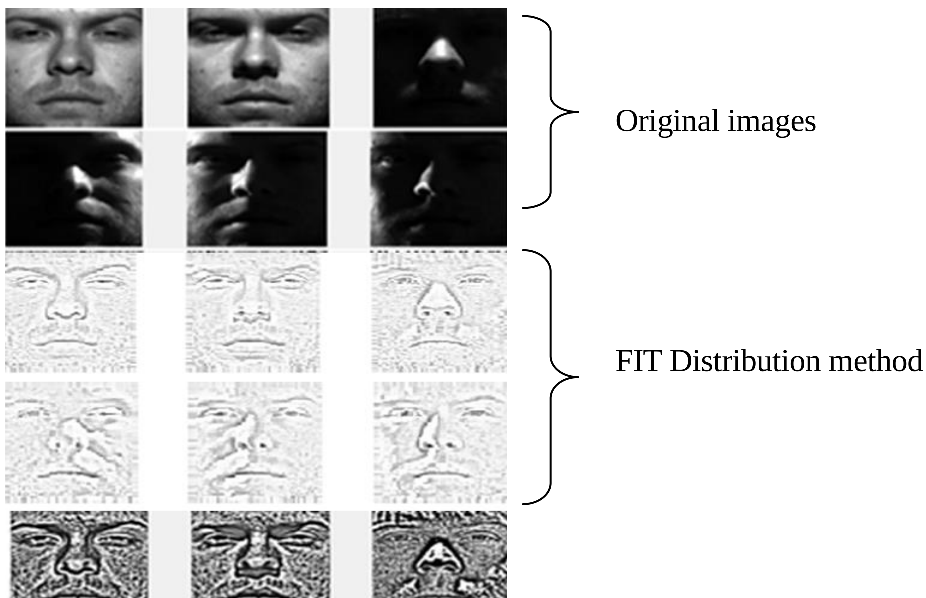


Figure 6: *Visual comparison of a facial image normalized with different illumination pre-processing methods*



Rank normalization method

Figure 7: *Our proposed pre-processing techniques applied on samples of testing images*

Experiment 3: Face recognition with random block occlusion:

The face recognition technique with random facial occluded features is experimented here. In this case, we used the subsets 1 and the subset 2 of the database (Lee, Ho & Kriegman 2005) as our training sets while the subset 3 was selected as our testing set. The-subset3,is already divided into a number of subsets with different random occlusions ratios(10%, 20%, 30%, 40% and 50%) as illustrated in Figure8,after processing the illumination varying using the proposed preprocessing methods, we dealing with occlusion in the image Where LDA by sub-sampling is a development and modification of LDA using PCA subspace and designed to work in non-perfect conditions, especially in the case of occlusions, in this methods consider K Principal Eigen vectors, the eigen vectors with the highest eigen values have been taken. In our Experiment the value of k=37, LDA using PCA sub-sampling are avoid occluded pixels and use only true image pixels of the occluded image (Fidler & Leonardis, 2003).

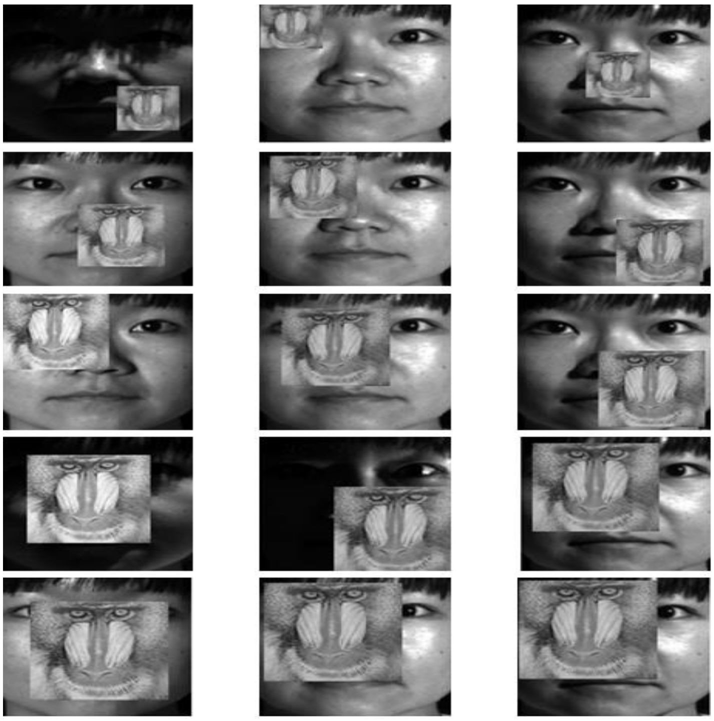
In Table7, we compare our proposed techniques with another existing method that handle the occlusion problem (Yang, Feng & Shiu, 2014).

Table7: *Face recognition rates determined by different methods applied (on the same database for different occlusion ratios.)*

Occlusion ratio	**10%**	**20%**	**30%**	**40%**	**50%**
Method	***Recognition rates***				
NN	90.1%	85.2%	74.2%	63.8%	48.1%
SRC	100%	99.8%	98.5%	90.3%	65.3%
CRC_RLS	99.8%	93.6%	82.6%	70.0%	52.3%
CRC_RLS_GT	100%	99.8%	96.9%	88.1%	70.9%
RSC	100%	100%	99.8%	96.9%	83.9%

Coding Residual Map Learning based Adaptive Masking	100%	99.8%	98.5%	93.6%	77.9%
DoG+Rank normalization+ (PCA+LDA)	100%	100%	99.1%	98.9%	96.3%
DoG +Fit distribution +(PCA+LDA)	100%	100%	99.6%	98.0%	95.8%

As it is illustrated in Table 7, when the occlusion ratio reaches 50%, the accuracy of our proposed methods still bigger than 95%while the ratio for the other methods has dropped down.



Sample of subset3 occlusion ratio: 10%

Sample of subset3 occlusion ratio: 20%

Sample of subset3 occlusion ratio: 30%

Sample of subset3occlusion ratio: 40%

Sample of subset3 occlusion ratio: 50%

Figure 8: *Samples of the subset3 with different random occlusion ratios*

Experiment 4: Face recognition with random subset as training set:

The purpose of this experiment is to prove the efficiency, accuracy and stability of our proposed methods, where a random subset with 3 images per person is chosen as the training set, and the rest of the images for testing. In order to obtain stable results, we took average the results for 10 random tests ,And the final result by used fit distribution method is equal 97.96 and by rank normalization method is equal 97.59 , that prove the stability and efficiency of our proposed methods. Also We would like to point out that the use of our proposed methods with correlation classifier gave the highest recognition rate comparing with the Euclidean, Sub Euclidean, mahal, city block, and minkowski classifiers , and

The recognition rate are very close with cosine classifiers, When Hamming, Jaccard classifiers given the very low results.

We used the images of 38 people, for each one64 images have been already saved. Thus, we have a total of 2432 images. The size of each image is 128×128. To facilitate the use of our proposed techniques, we have provided the user by an interface illustrated in Figure 9, it contains many options such as testing all database with or without occlusion. Using this interface, we can calculate and display the training and testing time with some curves to show the recognition rates.

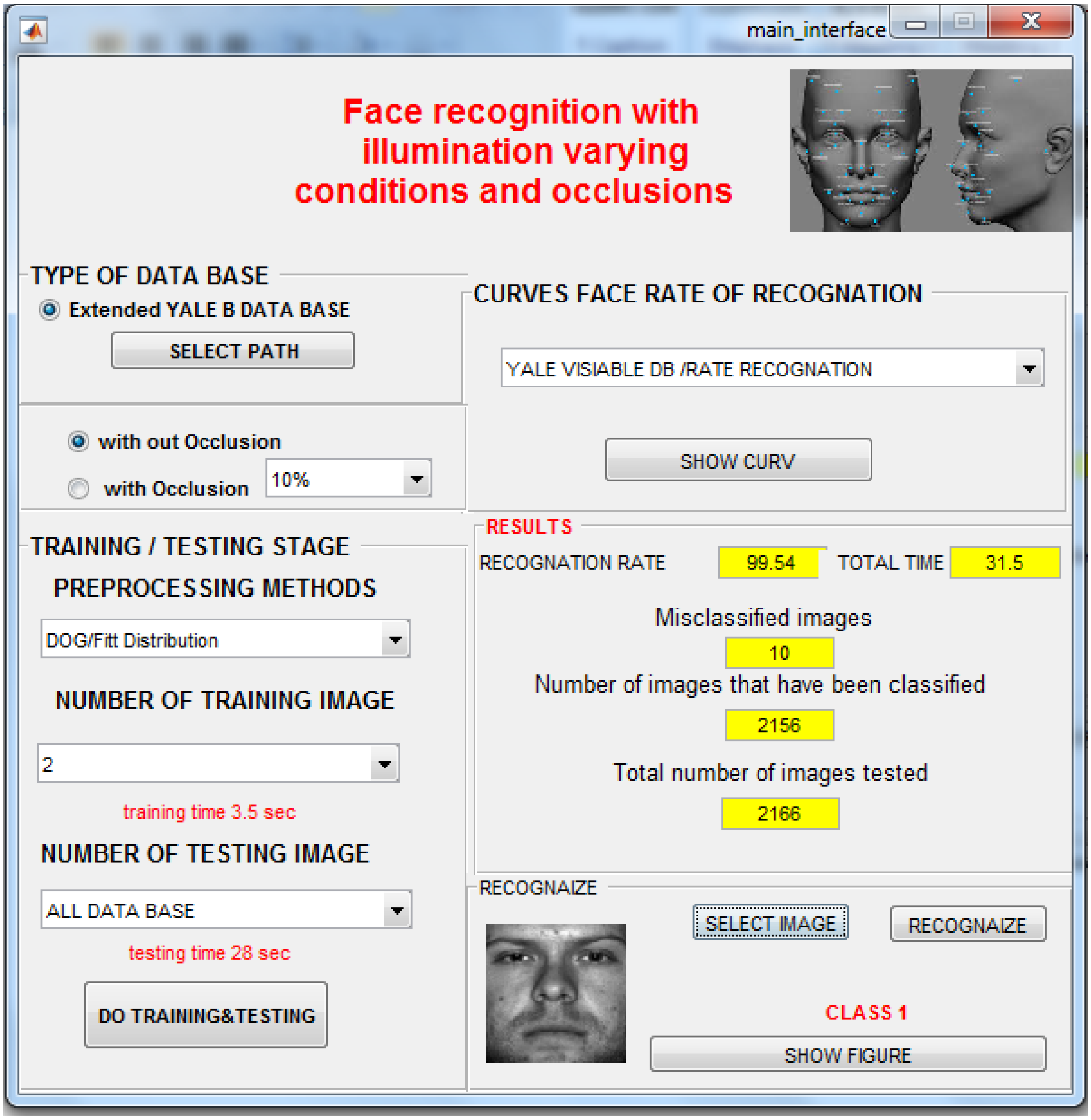


Figure 9: *The main interface for our proposed system*

5. Conclusion and future work:

Many existing methods in the field of face recognition perform well under certain conditions, but they still facing some challenges with illumination changes and partial face occlusions. In this paper, we have presented two new methods for face recognition under uncontrolled lighting conditions and random partial occlusion depending on some robust preprocessing techniques; PCA as a technique to reduce the dimensions of an image, LDA as a features extractor, and finally the correlation classifier. All of them were used together. The Combination of PCA and LDA was used to improve the capability of features extraction when a small number of training samples is available and in the case of having some occluded features. Correlation classifier was used to reduce the number of misclassification states.

Our proposed methods addressed three important problems in face recognition solutions at the same time, a small training sample size, and various changes in lighting and finally occlusion The results mentioned above showed efficiency and effectiveness of this methods, which provides a strong base based upon researchers and developers and those interested in the development of their research in this area. In addition to this proposed method has a high performance in terms of accuracy of the results, ease of use and low processing time, which saves time and effort.

Our experiments were performed using the "Extended Yale B database". The results show that the very high recognition rates were achieved when our proposed preprocessing methods were used comparing with a lot of other existing methods. Other recognition challenges such as facial expressions and poses will be affronted in our future works.

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