# A Comparison of Face Recognition Algorithms for Varying Capturing Conditions

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***Abstract—*** In the recent years, great success has been achieved in the field of recognizing faces but when it comes to unconstrained environment, face recognition is still quite a demanding problem. This is due to some external factors that act as an obstruction in this process. These factors include variation in expression, pose and illumination, motion images, misalignment, etc. This research addresses different efficiently working algorithms in unconstrained scenarios. A comparison between Principal Component Analysis (PCA) and 2-Dimensional PCA (2DPCA) is performed in this paper in the end. The performance of these systems is also checked by modifying the lighting condition of the test images. The performance and robustness of these systems was evaluated and tested through experiments.

***Keywords—*** Face recognition, unconstrained environment, PCA, 2DPCA, pose variation, illumination variation, blur, facial expressions.

## INTRODUCTION

The process of distinguishing a previously identified face is called facial recognition. In other words, it is the process of correctly matching a face image of a person with another image of the same person. There are two types of environments i.e. constrained and unconstrained environment for face recognition. Constrained environment is an environment where the factors that can affect the recognition process are controlled. For example, in identity card photo the picture of the person is taken under controlled lightning with frontal pose and with an expression that does not create hindrance in the recognition process. For efficient recognition of faces in a constrained environment, many successful techniques have been presented in the past. But in an unconstrained environment, the subjects are non-cooperative which means that the factors affecting the face recognition process are not controlled. For example, face recognition in a video from CCTV becomes difficult because here the factors such as illumination, expressions, pose, etc. are not controlled. Changes in lighting can cause a shadow on person's face making it partially visible. Similarly, other factors such as motion images, people wearing accessories, blurry images can cause difficulty in accurate recognition of faces[1].

The two main tasks of face recognition are verification and identification. Through verification, the claimed identity of an unknown person is validated. It is also known as one-to-one matching. On the other hand, the identity of an unknown person is determined through identification. It is also known as one-to-many matching. To carry out this process, the image of the unknown person is compared with the images of known persons that are already present in a database.

For face recognition, a simple or surveillance camera or infrared imagery, etc. can be used to get the images. Face recognition is used in identity verification, security, surveillance, forensics, etc. [2].

Although research has already been done in this area and researchers have presented different algorithms, further advances can still be made in order to make the systems more efficient as no algorithm is without any limitations.

In this paper, comparison of two PCA based face recognition systems is done. After studying various algorithms, we selected two algorithms [3] and [4] based on availability of code, great performance and low error rate. Images are taken from ORL database to carry out the testing of these algorithms. MATLAB is used for simulation purpose and these algorithms are tested under different conditions such as changing expression, illumination, pose and facial details for comparison.

The rest of the paper is organized as follows: In section II, some of the methods and techniques used for face recognition are discussed. The steps generally used in face recognition process are briefly described in section III. Section IV describes the methodology of the selected algorithms. Experimental results and conclusions are mentioned in section V and VI respectively.

## LITERATURE REVIEW

The main obstacles in face recognition are pose, illumination and expression variation, blur, occluded faces, twin faces, aging and scaling. To help solve this issue, researchers have presented different algorithms based on appearance or model [5] as can be seen in figure 1. A few algorithms are briefly described in the following passages.

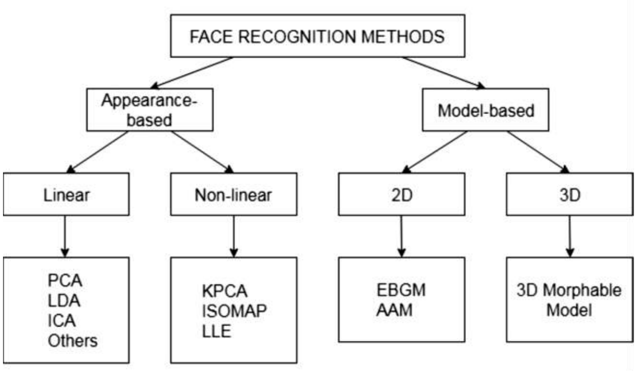



*Figure 1: Classification of face recognition methods*

Pose-Aware Models (PAMs) that were learned using the Convolutional Neural Networks (CNNs) were used to perform face recognition under varying pose [6]. Variations in pose include images having frontal, half or full profile. 2D in-plane alignment and 3D out-of-plane alignment were used to train five Pose-Aware CNN Models. For each type of alignment, a specific model was learned that was trained using the images from CASIA WebFace database. Two CNN models namely $PAM_{in\text{-}f}$ and $PAM_{in\text{-}p}$ were learned for in-plane alignment. In this approach, the images were divided into either profile or frontal, that caused a major drawback i.e. intra-pose variation that can affect the recognition process. Another problem with this approach was to find databases containing full profile images. For out-of-plane alignment, three CNN models were learned from the new target distributions for each mode. These target distributions were full and half profile and frontal. CNN models trained on ImageNet were fine tuned to train these CNNs. PAM was compared with and was found to be better than both the state-of-the-art and the single frontal model.

Another algorithm employing Deep Convolution Neural Network (DCNN) [7], was proposed to detect multi-view pose invariant faces. For the detection of faces and for recovering the images, a visual matching technology was used. Similarities between the images were calculated using the Bayesian analysis and the neural networks were trained to improve the results produced by the Bayesian analysis. This method achieved a high recognition rate when it was compared with other methods.

An unsupervised pose-robust method for unconstrained environments was proposed in [8], and it was based on filter transformation. In this method, feature extraction was done by using a filter called Gabor filter. The transformation of this filter was done according to shape and pose. After this, a deformed 3D model was created by using a model like 3D Morphable Model (3DMM). This method was also found to be faster and effective when compared with other methods.

The authors in [9] put forward two methods for solving blur, different lighting conditions and facial expressions. These methods were called Blur and Illumination-Robust Face Recognition (BIRFR) and Blur, Illumination and Expression-Robust Face Recognition (BIEFR). They provided solution for more than one affecting factor. In this method, facial expression removal (FER) was used to make the expressions of people in the images neutral. For classification, LBP features were used that were extracted from test and transformed images. Improved results were achieved with the removal of expressions. Both these methods achieved a high recognition rate when they were compared with other algorithms. Since these algorithms were proposed mainly for changes in illumination and facial expressions, and blur, their main drawback was that these methods were not able to solve problems caused by other factors such as occlusion, pose, and faces with makeup.

A technique was proposed by Srisawasd and Wongthanavasu in [10] to overcome the factors affecting face recognition. Their method helped in overcoming pose and illumination changes. In this method, illumination was adjusted in the images used for training. Then a dataset was created that contained the mirror images, in different poses, of the adjusted images. Images were frontalized using the Active Appearance Model (AAM) that used landmark localization and base mesh. This whole process was repeated for the test images also but here the mirror images were not created. Features were extracted using the frontalized images and Support Vector Machine (SVM) classifier was used for classifying the training and test images. This method achieved good results but in order to use this approach on large datasets, more work needs to be done.

A face frontalization approach based on a 3D Morphable Model (3DMM) was proposed in [11]. In this approach, the head pose was estimated by obtaining a 2D landmark and a 3D model. To fit the image of the face the 3D model was deformed and then the image was rendered. The front image of the face was rendered by interpolating the 3D position of the coordinates of the image. These coordinates were present inside the convex hull of the projected model. The 3D model was back-projected on the frontal image to obtain the descriptors. This method was evaluated on two datasets and was shown to be effective when compared with other face frontalization algorithms and state-of-the-art datasets but if the convex hull is estimated inaccurately then can give rise to problems and introduce artifacts into the resultant image. Similarly, the landmark detector should also be accurate otherwise more problems will be created.

Moeini [12] proposed a method that can deal with pose and expression. A 3D Probabilistic Facial Expression Recognition Generic Elastic Model (3D-PFER-GEM) was used to create 3D models in various poses. A Feature Library Matrix (FLM) was generated using the triplet angles. The probe images were used to extract features. These features were then compared with the generated array of FLM by using the Support Vector Machine (SVM). Here, the feature extraction is done through an offline process whereas the comparison of feature libraries and the probe features is done through an online process. This made this method very fast as compared to other methods that were also created for pose-invariant face recognition. This method achieved an accuracy of 93.16% when Labeled Faces in the Wild (LFW) dataset was used. A model for face frontalization was proposed by Deng et al. [13]. He presented two methods namely Lighting-Normalized Face Frontalization (LNFF) and Lighting-Recovered Face Frontalization (LRFF). In this method, a basic frontal image was created from an input image and a 3D model. Only five landmarks were used for this purpose. Facial quotient image and lighting coefficients were used to obtain the occluded part of the image. This image was called LRFF as it contained recovered lighting. On the other hand, canonical light was used to achieve LNFF. Through this process, pose and lighting variations were effectively reduced simultaneously. When compared with other methods, LRFF produced much better results. The authors also proposed a LRA-based classifier and it was combined with LNFF. The combined performance i.e. LNFF+LRA achieved 6% better results than other methods. This method also had drawbacks. One drawback is that a good amount of time is needed for rendering the background and the face. Secondly, during the face symmetry, artifacts were produced due to the cast shadows.

Another face recognition method that employed Principal Component Analysis (PCA) and Genetic Algorithm (GA) was presented by Zhi and Liu [14]. In this method, features were extracted using PCA whereas the search process was optimized through the use of GA. The authors tested this method on CAS-PEAL Face Database. They showed that the recognition rate and the accuracy are in direct proportion to the number of features and to the number of variations respectively. One drawback of this method is that when the number of iterations is increased, more computational time is needed which is not a good thing. So, in order to achieve high performance in less time, it was needed to balance the iterations. On the other hand, this method performed segmentation quite well.

Another method for face recognition involved the use of Radial Basis Function (RBF) network [15]. Low resolution video image sequences were used in this method. A controlled set containing images of persons in different poses was used to train this network. Preprocessed images were created by using DoG filtering and Gabor wavelet analysis. Here DoG stands for Difference of Gaussian. The accuracy of the RBF network was found to be 94% when images from the same set were used for training and testing of this network. This network achieved very good results with large databases as well. Apart from the aforementioned factors, the researchers mentioned some new factors such as focus blur, motion blur, distractor images, weather conditions, etc. that can degrade an image [16]. They used Unconstrained Face Detection Dataset (UFFD) that was created by themselves and it contained images that were degraded by the factors that they had mentioned. They tested four face detection methods on this dataset. They also combined the effects of illumination, blur, snow, rain, etc. on the images in the UFFD and then tested these methods on that dataset. The performance of these methods was reduced when these factors were added to the dataset.

## STEPS IN A FACE RECOGNITION SYSTEM

The face of a person is recognized by matching his face image with the images that are present in the system's database. The first step to carry out this process is to acquire the image of that person from a source such as a camera, a CCTV footage, etc. The acquired image is then inputted into the system which first detects the location of the person's face in that image. Then the features of the person are extracted so that they can be compared with the features of persons in present in the database. The matching scores are calculated next and then the best matching score is selected resulting in the image being recognized [17].

## METHODOLOGY

Principal Component Analysis (PCA), as shown in figure 2, is a method that is used to reduce the dimensionality of larger datasets. To achieve this, the large set of variables is transformed into a small set in such a way that it still contains most of the information that was present in the large set [18]. It also converts a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables known as principal components [19]. 2D samples of face images are transformed into 1D image vectors in face recognition methods that use PCA. One way to do this is through concatenation [17].

On the other hand, 2DPCA is based on 2D matrices which mean that the original image matrices can be used directly to create an image covariance matrix. The calculation of eigenvectors is done by using training images which consists of all the poses or classes. Facial recognition and image compression can be successfully achieved through PCA. Patterns in data of high dimension can also be found by using PCA [20]. The first algorithm employs PCA for face recognition. Feature vectors are generated for training and testing images. After this, the PCA transform was applied and the Manhattan distance is calculated. The second algorithm is based on 2DPCA in order to perform face recognition. First we specify the number of training and testing samples and the eigenvectors. Image covariance matrix is computed next and a transformation matrix is created using eigen-decomposition. After this, the training feature matrices are derived and then testing and classification is done.

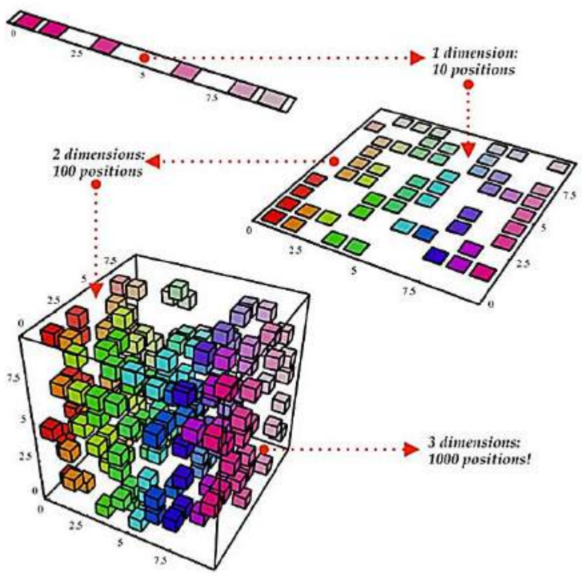



*Figure 2: Principal Component Analysis*

## EXPERIMENT AND RESULT ANALYSIS

### *A. Experimental Setup*

For evaluating the algorithms, we used the ORL Database of Faces [21]. It contains face images, of persons, that are of size 92x112 pixels and each pixel have 256 grey levels. We converted the files in this database in BMP format but they are originally present in PGM format. This database contains images of forty different persons and each person has ten images of himself taken at different times by changing the lighting, facial expressions and facial details as shown in figure 3. Dark background is used for all the images. The subjects are facing the camera i.e. they are in frontal position but some may show some side movement. Separate directories are created for each person where only that person's images are stored. So, here, forty directories were created.

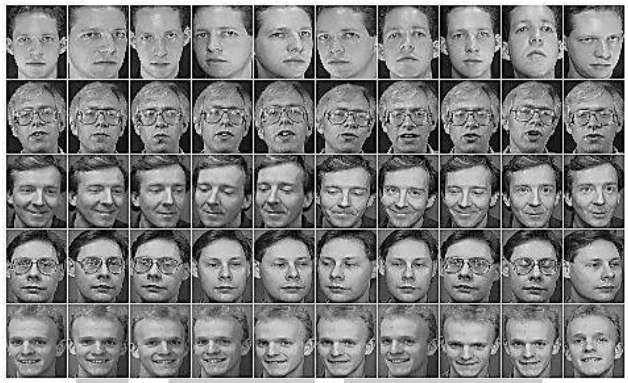


*Figure 3: ORL database of faces*

### *B. Results and Discussion*

For PCA, five images of a person were selected randomly and were put into the training set whereas the remaining images were placed into the test set. Similar process was done for each person in the dataset. The correctly identified test images are shown in figure 4 but some images were mismatched as shown in figure 5.

From figure 5(a), it can be seen that due to almost similar looking images of the women, the system recognized them as the image of same person. But same cannot be said for (b) as both the images have different facial expressions and also different facial features.

However, this system obtained a precision rate of 92.85%.


(a) (b)

*Figure 4: Test images matched correctly w.r.t.: (a) pose and (b) expression*


(a) (b)

*Figure 5: Incorrectly matched test images*

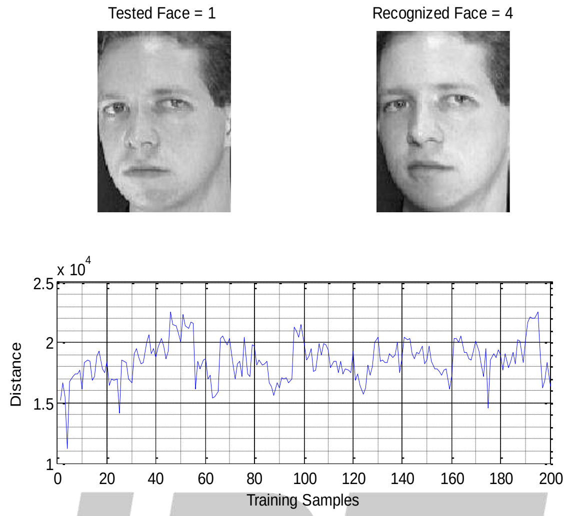
*Table 1: Original and modified algorithm of PCA*

| ORIGINAL | | | | MODIFIED | | | |
|---|---|---|---|---|---|---|---|
| Ts. Im | Class of Ts. Im | DC | E | Ts. Im | Class of Ts. Im | DC | E |
| 241 | 25 | 25 | 0 | 241 | 25 | 39 | 1 |
| 242 | 25 | 25 | 0 | 242 | 25 | 39 | 1 |
| 245 | 25 | 25 | 0 | 245 | 25 | 39 | 1 |
| 247 | 25 | 25 | 0 | 247 | 25 | 39 | 1 |
| 250 | 25 | 25 | 0 | 250 | 25 | 39 | 1 |
| 251 | 26 | 26 | 0 | 251 | 26 | 26 | 0 |
| 252 | 26 | 26 | 0 | 252 | 26 | 26 | 0 |
| 255 | 26 | 26 | 0 | 255 | 26 | 26 | 0 |
| 257 | 26 | 26 | 0 | 257 | 26 | 26 | 0 |
| 260 | 26 | 26 | 0 | 260 | 26 | 26 | 0 |
| 261 | 27 | 27 | 0 | 261 | 27 | 27 | 0 |
| 262 | 27 | 27 | 0 | 262 | 27 | 27 | 0 |
| 265 | 27 | 27 | 0 | 265 | 27 | 27 | 0 |
| 267 | 27 | 27 | 0 | 267 | 27 | 27 | 0 |
| 270 | 27 | 27 | 0 | 270 | 27 | 27 | 0 |
| 271 | 28 | 28 | 0 | 271 | 28 | 39 | 1 |
| 272 | 28 | 28 | 0 | 272 | 28 | 39 | 1 |
| 275 | 28 | 19 | 1 | 275 | 28 | 39 | 1 |
| 277 | 28 | 37 | 1 | 277 | 28 | 39 | 1 |
| 280 | 28 | 28 | 0 | 280 | 28 | 39 | 1 |

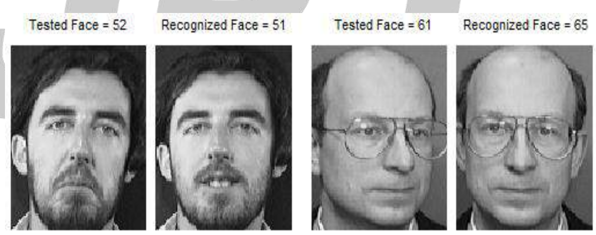
For testing PCA for non uniform illumination, we randomly changed the lighting of images in the test set through the use of a filter called Gaussian filter. Not a single image on which the filter was applied was matched correctly as seen from figure 6. On the other hand, table 1 compares the performance of the original and the modified PCA algorithm where Ts. Im, DC and E stand for tested image, detected image and error respectively. The 0s in E represent the correct matches. The recognition rate of this modified algorithm was calculated as 62.9%.


*Figure 6: Results for non uniform illumination*

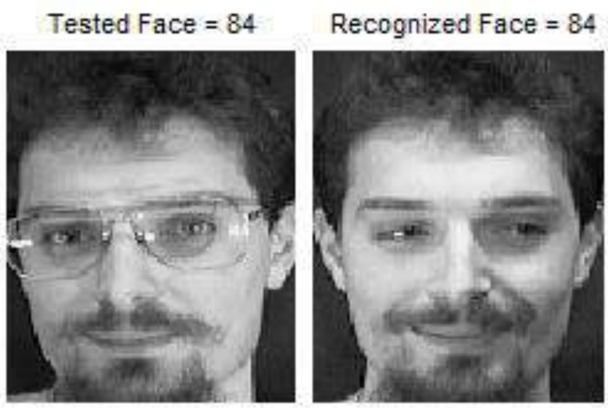
In 2DPCA, the process similar to PCA is applied for separating the images but here instead of random selection, first five images of a person were placed in the training set and the other five in the test set. This system identified most of the images as shown in figure 7 except a few images as shown in figure 8. It is clear from (b), (c), and (d) in figure 7, that this system tackles the problem of facial expression, pose and appearance quite well.




(a)

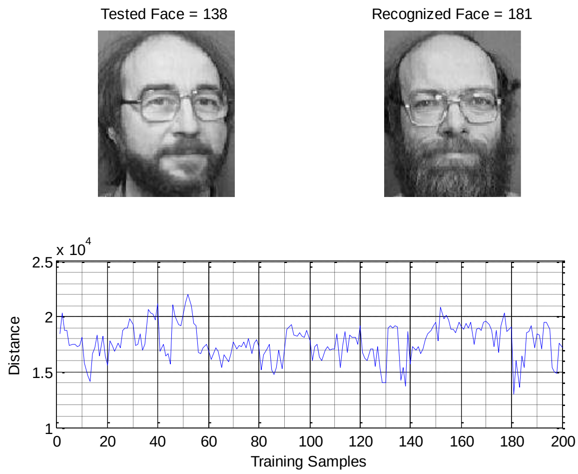



(b) (c)

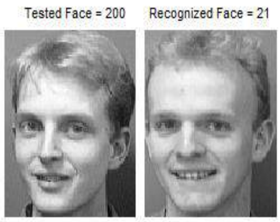



(d)

*Figure 7: Test images matched correctly w.r.t.: (a) illumination along with graph (b) expression (c) pose (d) facial appearance*




(a)





(b) (c)



(d) (e)

*Figure 8: Mismatched faces.*

From (a), in figure 8, it can be seen that both the images have almost similar facial appearance and expressions.

Therefore, the system identified these two images to be the images of same person. Similarly, in (b) and (c), where similar pose and almost similar expression made the system do incorrect matching.

From (d) and (e) of figure 8, it can be seen that the tested images are nowhere matching with the recognized image neither in facial expressions nor in facial appearance.

However, this system achieved a recognition rate of 90%.

*Table 2: Original and modified algorithm of 2DPCA*

| ORIGINAL | | | MODIFIED | | |
|---|---|---|---|---|---|
| DC | OC | E | DC | OC | E |
| 24 | 17 | 7 | 24 | 17 | 7 |
| 24 | 17 | 7 | 39 | 17 | 22 |
| 17 | 17 | 0 | 17 | 17 | 0 |
| 17 | 17 | 0 | 17 | 17 | 0 |
| 24 | 17 | 7 | 39 | 17 | 22 |
| 18 | 18 | 0 | 18 | 18 | 0 |
| 18 | 18 | 0 | 18 | 18 | 0 |
| 18 | 18 | 0 | 39 | 18 | 21 |
| 18 | 18 | 0 | 18 | 18 | 0 |
| 18 | 18 | 0 | 18 | 18 | 0 |
| 19 | 19 | 0 | 39 | 19 | 20 |
| 19 | 19 | 0 | 19 | 19 | 0 |
| 19 | 19 | 0 | 19 | 19 | 0 |
| 15 | 19 | -4 | 39 | 19 | 20 |
| 19 | 19 | 0 | 19 | 19 | 0 |
| 20 | 20 | 0 | 20 | 20 | 0 |
| 20 | 20 | 0 | 39 | 20 | 19 |
| 20 | 20 | 0 | 20 | 20 | 0 |
| 20 | 20 | 0 | 20 | 20 | 0 |
| 20 | 20 | 0 | 39 | 20 | 19 |

Gaussian filter was applied to the images to test 2DPCA for non uniform illumination and this resulted in the system not performing well as can be seen in table 2. It also shows the original class (OC), the detected class (DC) and error (E) in both the 2DPCA algorithms i.e. the original and the modified. The 0s in table 2 show correct matches while the incorrect matches are shown by numbers other than zero.

From table 2, it can be seen that the images that were matched incorrectly when we used the original algorithm, were also matched incorrectly when the modified algorithm was used. In the modified algorithm, all those images on which the lighting was applied were mismatched as seen in figure 6.

This system matched one hundred and twenty-three images and mismatched seventy-seven images out of two hundred images. The achieved recognition rate was 61.5%.

The first algorithm performed better, as compared to the 2DPCA algorithm, and achieved a recognition rate of 92.85%. Modifying the illumination of images in both the algorithms, a recognition rate of 62.9% was obtained in PCA whereas 61.5% recognition rate was achieved by 2DPCA.

## CONCLUSION

In this paper, we discussed different algorithms that are used for recognizing faces in unconstrained environments as this was the main purpose of our investigation. We discussed various methods for overcoming the problems caused by different lighting conditions, different postures, changes in appearances, images of low resolution, etc. After this we selected two algorithms that used PCA and 2DPCA and evaluated them using the ORL database. We also changed the illumination of images in both the algorithms and again tested them on the ORL database. Both techniques performed quite well with PCA achieving a recognition rate of 92.85% and 62.9% when changes were made in the illumination of the images. We used only one database but these systems can be evaluated on other databases as well and also different methods other than PCA can be compared in order to achieve more good results.

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