# Comparing Robustness of Two-Dimensional PCA and Eigenfaces for Face Recognition

Muriel Visani, Christophe Garcia, and Christophe Laurent

France Telecom R&D - DIH/HDM
4, rue du Clos Courtel
35512 Cesson-Sévigné Cedex - France
muriel.visani@rd.francetelecom.com

**Abstract.** In this paper, we aim at evaluating the robustness of 2D-PCA for face recognition, and comparing it with the classical eigenfaces method. For most applications, a sensory gap exists between the images collected and those used for training. Consequently, methods based upon statistical projection need several preprocessing steps: face detection and segmentation, rotation, rescaling, noise removal, illumination correction, etc... This paper determines, for each preprocessing step, the minimum accuracy required in order to allow successful face recognition with 2D-PCA and compares it with the eigenfaces method. A series of experiments was conducted on a subset of the FERET database and digitally-altered versions of this subset. The tolerances of both methods to eight different artifacts were evaluated and compared. The experimental results show that 2D-PCA is significantly more robust to a wide range of preprocessing artifacts than the eigenfaces method.

## 1 Introduction

During the last decade, automatic recognition of human faces has grown into a key technology, especially in the field of multimedia indexing and video surveillance. In this context, the views of the face to recognize can differ from the training set in the exact location of the face, the head pose, the distance to the camera, the quality of the images, the lighting conditions and partial face occlusions due to the presence of accessories such as eyeglasses or scarf. These different factors can affect the matching process.

Many face recognition algorithms [1,2,3] have been developed. Most of these techniques need accurate face detection / localization [4,5] and normalization [6]. This last step ensures that the face to recognize is aligned with those used for training. Normalization is a critical step that can generate many artifacts.

Statistical projection methods, such as the *eigenfaces* method [1] are among the most widely used for face recognition. The eigenfaces method is based on Principal Component Analysis (PCA), and have shown good performance on various databases. Very recently, Yang *et al.* [3] have introduced the concept of Two-Dimensional PCA (2D-PCA), and have shown that it provides better results than the eigenfaces method on three well-known databases. Lemieux *et al.* [7]

A. Campilho, M. Kamel (Eds.): ICIAR 2004, LNCS 3212, pp. 717–724, 2004.

have evaluated the robustness of the eigenfaces method to normalization artifacts on the AR Face Database [8]. They have shown that the eigenfaces method is robust up to a certain point over a representative range of errors. Passed this point, the performances can decrease dramatically. They have also shown that the eigenfaces method hardly deals with usual artifacts such as translation errors. Indeed, a misalignment of 5% can reduce the recognition rates by 40%.

The aim of this paper is to evaluate the robustness of 2D-PCA and compare it to the robustness of the eigenfaces method on a subset of the FERET[1] [9] face database. The following parameters are tested: image rotation, scaling, vertical and horizontal translations, gaussian blurring, addition of white noise and partial occlusions of the face. The first four parameters model the effects of an inaccurate localization of the facial features, while gaussian blurring and addition of white noise simulate respectively poor resolution and low quality images.

The paper is organized as follows. Section 2 details the 2D-PCA method. Section 3 describes our experimental protocol. Experimental results and in-depth analysis are given in Section 4. Section 5 concludes this paper.

## 2 Brief Description of Two-Dimensional PCA

While the eigenfaces method [1] is a baseline technique, Two-Dimensional PCA [3] is a very recent approach that we propose to describe in this section. The model is constructed from a training set containing $n$ images. While the eigenfaces approach considers an image with $h$ rows and $w$ columns as a vector of size $h \cdot w$ (by concatenating its rows of pixels), 2D-PCA keeps the 2D structure of an image by considering it as a matrix of pixels, with $h$ rows and $w$ columns. The goal is to obtain a set of $k$ vectors $P = [P_1, \ldots, P_k]$, of size $w$, so that the *projection* of the training set on $P$ explains the best the scatter of the training set. These vectors $P_i$ will be referred to as *2D-components* in the following. The $h \times k$ projected matrix $\hat{X}_i$ of $X_i$ on $P$ is $\hat{X}_i = X_i \cdot P$, where $X_i$ is the $h \times w$ matrix of the i$^{\text{th}}$ image of the training set and $P$ is the $w \times k$ matrix whose columns are the $k$ 2D-components.

Yang *et al.* [3] introduced the maximization criterion $J(P) = trace(\hat{S})$, where $\hat{S}$ is a generalized covariance matrix of the $n$ projected image matrices $\hat{X}_i$:

$$\hat{S} = \frac{1}{n} \sum_{i=1}^{n} (\hat{X}_i - \bar{\hat{X}})(\hat{X}_i - \bar{\hat{X}})^T \tag{1}$$

with $\bar{\hat{X}} = \frac{1}{n} \sum_{i=1}^{n} \hat{X}_i$. Yang shows that the criterion $J(P)$ equals $P^T S P$, where $S$ is a generalized covariance matrix of the $n$ image matrices $X_i$:

$$S = \frac{1}{n} \sum_{i=1}^{n} (X_i - \bar{X})^T (X_i - \bar{X}). \tag{2}$$

where $\bar{X}$ is the mean matrix of all the $n$ images of the training set.

It can be shown [3] that the vectors $(P_i)_{i=1\ldots k}$ maximizing the criterion $J(P)$ are the $k$ eigenvectors of $S$ with largest eigenvalues.

[1] Portions of the research in this paper use the FERET database of facial images collected under the FERET program.

Face images are compared after projection on $P$. Yang *et al.* proposed the following distance between projected face images $\hat{X}_a$ and $\hat{X}_b$:

$$d(\hat{X}_a, \hat{X}_b) = \sum_{j=1}^{k} \|\hat{X}_a^{\,j} - \hat{X}_b^{\,j}\|_2 \tag{3}$$

where $\|\cdot\|_2$ denotes the Euclidian norm and $\hat{X}_i^{\,j} = X_i P_j$ is the projected vector of image matrix $X_i$ on the j$^{\text{th}}$ projection vector $P_j$.

## 3 Description of the Experiments

In this section, we propose to compare the robustness of 2D-PCA using distance (3), with the robustness of the classical eigenfaces approach using $L_2$ distance.

Yang *et al.* [3] have proven that image feature extraction is computationally more efficient using 2D-PCA than using the eigenfaces method. They have also shown that 2D-PCA gives better recognition rates than the eigenfaces method in the presence of variations over time, variations in the sample size, facial expressions, lighting conditions and pose. They experimented on three correctly normalized face databases excluding FERET. In order to study independently the effects of inaccuracies in the normalization steps, we performed our experiments on a subset of the FERET database, and digitally-modified versions of this subset.

The subset used for training contains 200 pictures of 200 persons (one view per person). Most of the subjects have a neutral facial expression. None of them wear eyeglasses. An example is given in Fig.1(a). For each image, the positions of the eyes are known; they are used to perform face normalization, in five steps:

1. detecting and localizing the eyes in the image;
2. rotating the image so that the eyes are horizontally aligned;
3. scaling the image so that the distance between the eyes is set to 70 pixels;
4. cropping the image to a size of 130 pixels wide by 150 pixels high;
5. equalizing the histogram of the face image.

A successful normalization is illustrated in Fig.1(b). To simulate the effects of disturbing events, we have defined 8 parameters illustrated in Fig.1(c-j). The first four parameters simulate the effects of imprecise eye localization.

- **Vertical and horizontal translations:** when cropping the images, an inaccurate feature detection can lead to translations of the face in the image. Horizontal translation varies from -30 to 30 pixels (23% of the total width), positive values corresponding to translations to the right. Vertical translation varies from -19 to 19 pixels (12.7% of the total height), positive values corresponding to translations to the top.
- **Rotation:** a central rotation whose center is located exactly at the middle of the eyes is applied after face normalization. The rotation angle varies from 1 to 19 degrees, clockwise;
- **Scaling:** the difference between the observed inter-eye distance and the target distance (i.e. 70 pixels) is varied from -20% to 20%; positive values correspond to zooming in and negative values to zooming out.

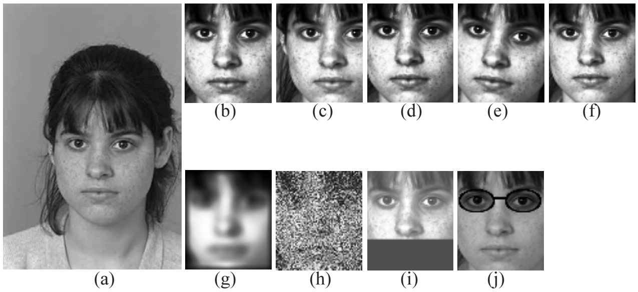



**Fig. 1.** (a) Original image (FERET database). (b) Correctly normalized image (size $150 \times 130$). (c) Horizontal translation (22 pixels). (d) Vertical translation (4 pixels). (e) Rotation (8 degrees clockwise). (f) Scaling (-7%). (g) Blurring ($\sigma = 5.5$). (h) Additive Gaussian white noise ($\sigma = 90$). (i) Scarf (47 pixels). (j) Glasses ($\beta = 0.2$)

In an uncontrolled environment, depending on the distance between the camera and the subject, the resolution of the face image to recognize can be much lower than the resolution of the training images. One solution is to digitally zoom on the corresponding face. Zoom results in an interpolation of the missing pixels leading to blur the image; this phenomenon is simulated by the following parameter.

– **Blurring:** the image is convolved with a gaussian filter, whose standard deviation $\sigma$ is varied from 0.5 to 9.5.

Images acquired through real cameras are always contaminated by various noise sources, but if the systematic parts of the measurement error are compensated for, the error can be assumed to be additive Gaussian white noise, simulated by the following parameter.

– **White noise:** Gaussian White noise is added to the whole face image; its standard deviation $\sigma$ is varied from 1 to 90.

Let us finally consider the effects of occlusions. Some of the most usual occlusions are due to the presence of eyeglasses or of a scarf hiding the inferior part of the face. The glasses can be more or less dark, and the scarf can be more or less raised on the face. The following two parameters simulate these occlusions.

– **Scarf:** a black strip is added to the face image. It covers all the surface of the image from the bottom to a given height, varied from 1 to 80 pixels (more than 53% of the total height).
– **Glasses:** two black ellipses of width 3 pixels, whose centers are the centers of eye pupils and whose axial lengths are 28 and 18 pixels, are added to the face image. They are connected by a black strip of size $3 \times 17$ pixels. Each pixel $I(x, y)$ inside one of these ellipses is replaced by $I'(x, y) = (1 - \beta) \cdot I(x, y) - \beta I_m$, where $I_m$ is the mean of all the pixels of the original image. $\beta$ is varied from 0 to 1; its increase results in darkening the interior of the ellipses. Near $\beta = 1$, the glasses are completely black.

Our aim is to study the effects of each of these parameters separately. Therefore, for a given experiment, only one parameter is tuned. The training set is the subset of the FERET database previously described, correctly normalized thanks to precise eye positions. Each test set corresponds to a fixed value of a given parameter applied to the training set, and therefore contains 200 digitally modified images of the training set, of the same size $150 \times 130$ pixels.

## 4 Experimental Results

In order to obtain the best performances, for both techniques and for each parameter, we first studied the number $k$ of projection vectors providing the best recognition rates. The projection vectors are sorted by their associated eigenvalue in descending order, and the first $k$ are selected. In Fig.2-3, the number of selected projection vectors is systematically given after the name of the algorithm used (eg. 2D-PCA(6) means that 6 2D-components have been selected to implement the 2D-LDA algorithm). Even though most of our experiments highlighted an optimal number of projection vectors, it can be noticed that, for some parameters, recognition rates grow with $k$. This phenomenon, often observed with eigenfaces, is illustrated in Fig.2(a). Concerning horizontal translations, the best results were obtained with only one 2D-component and decreased dramatically when using more 2D-components. This phenomenon, illustrated in Fig.2(b), is very interesting and opens the way to a normalization process using 2D-PCA.

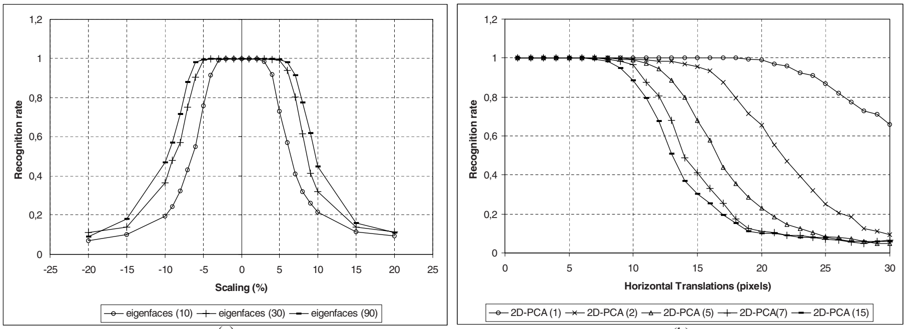
To evaluate the robustness of both methods, we studied the variations of the recognition rates when each parameter is tuned independently. From Fig.3, we can extract the *tolerance ranges* to each parameter, given in Table 1. The tolerance range to a parameter is the variation range of this parameter within which the recognition rates are greater than 95%.

Concerning horizontal translations (see Fig.3(a)), 2D-PCA is much more robust to horizontal translations than the eigenfaces method. The tolerance range for 2D-PCA with only the first 2D-component is $[-20, 22]$ (about 17% of the total width) and only $[-6, 6]$ (4,6%) for 70 eigenfaces. When adding more 2D-components (see Fig.2(b)), the recognition rates decrease but are still better than the recognition rates provided by the eigenfaces method.

Fig.3(b) shows that, for vertical translations, the optimal number of projection vectors is 90 eigenfaces against only 13 2D-components; however 2D-PCA achieves much greater recognition rates. 2D-PCA's tolerance range is $[-4, 4]$ (2.7% of the total height) against $[-3, 3]$ (2%) for the eigenfaces method.

Tolerance range to rotation (see Fig.3(c)) for 2D-PCA is $[0, 8]$ with only 4 2D-components and $[0, 6]$ with 90 eigenfaces. The recognition rates of 2D-PCA are significantly greater than those of the eigenfaces method with the rotation angle varying from 1 to 19 degrees.

When studying the robustness to scaling (see Fig.3(d)), we can notice that both methods appear to be as robust to zooming in as to zooming out. 2D-PCA is more robust to scaling than the eigenfaces method. Using only 13 2D-components provides better results than using 90 eigenfaces: 2D-PCA has a tolerance of $\pm 7\%$ to scaling, while the eigenfaces method's tolerance is $\pm 6\%$.



(a) (b)

**Fig. 2.** (a) Effects of scaling on PCA. Recognition rates grow with the number $k$ of selected eigenfaces, until $k$ reaches 90. (b) Effects of horizontal translation on 2D-PCA. The best recognition rates are obtained with the first 2D-component only. The recognition rates decrease when more 2D-components are added.

**Table 1.** Tolerance ranges to the eight parameters tuned independently.

| | **2D-PCA** | **Eigenfaces** |
|---|---|---|
| Horizontal Translations (% of total width) | ± 17 % | ± 4,6 % |
| Vertical Translations (% of total height) | ± 2,7 % | ± 2 % |
| Rotation (degrees) | [0 , 8] | [0 , 6] |
| Scaling (%) | ± 7 % | ± 6 % |
| Blurring (σ) | [0 , 5,5] | [0, 4] |
| Additive white noise (σ) | [0 , 90] | [0 , 90] |
| Scarf (% of total height) | 31 % | 15 % |
| Glasses (β) | [0 , 1] | [0 , 0.15] |

Fig.3(e) shows that 2D-PCA is much more robust to blurring, with a tolerance of 5.5, than the eigenfaces method for which tolerance is only 4.

Fig.3(f) shows that both techniques are very robust to additive white noise. Recognition rates for both techniques are very close to 100% with $\sigma$ varying from 0 to 90, which corresponds to a strong additive noise, as shown in Fig.1(h).

From Fig.3(h-i) we can conclude that 2D-PCA is significantly more robust to partial occlusions than the eigenfaces approach. While 2D-PCA tolerates a 47 pixel scarf, the eigenfaces only tolerate a 22 pixel occlusion (improvement of about 114%). Concerning glasses, from 9 2D-components to 20, the recognition rates are 100% when $\beta$ is varied from 0.05 to 1, while the tolerance range of the eigenfaces method is at most 0.15, with the optimal number of 90 eigenfaces.

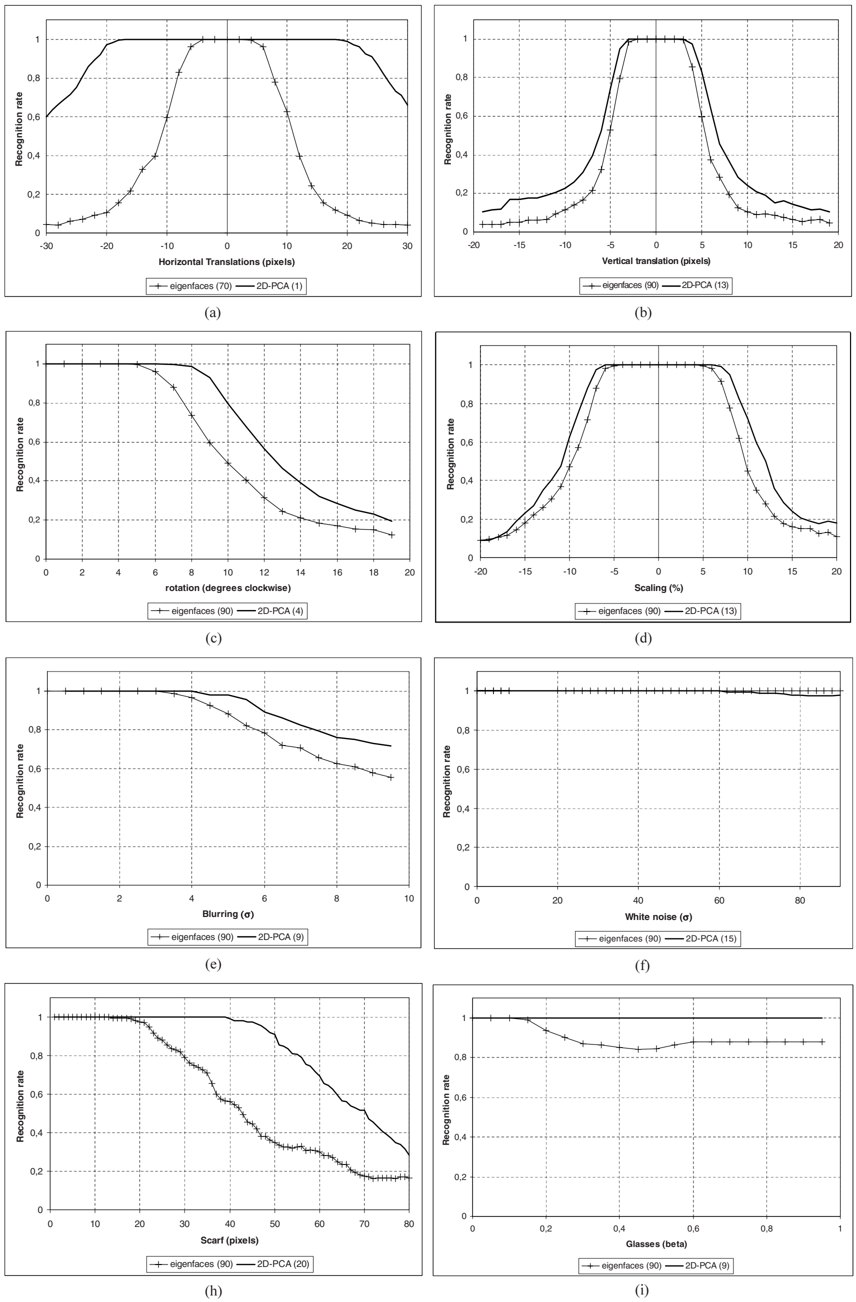



**Fig. 3.** Compared recognition rates of 2D-PCA and eigenfaces when each parameter is tuned independently.

## 5 Conclusion

Two-Dimensional PCA has proven to be efficient for the task of face recognition as well as computationally more efficient than the eigenfaces method [3]. However, like every statistical projection technique, it requires several preprocessing steps, that can generate various artifacts. Our aim was to determine the minimum accuracy required for 2D-PCA to provide efficient recognition. The robustness of 2D-PCA was compared to the robustness of the classical eigenfaces method, on a subset of the well-known FERET database.

Experimental results have shown that 2D-PCA is more robust than the eigenfaces method over a wide range of normalization artifacts, overall translations, rotation of the face in the plane of the image, scaling, blurring and partial occlusions of the face. Some of our very recent experiments tend to show that 2D-PCA is also more robust to in-depth rotations than the eigenfaces method (recognition rates are improved of about 9% until a 30 degree rotation). Therefore, assuming that the efficiency of the preprocessing algorithm is within the tolerance ranges given in this paper, 2D-PCA can be applied successfully to face recognition in an unconstrained environment such as video indexing or video surveillance.

## References

1. Turk, M., Pentland, A.: Eigenfaces for recognition. Journal of Cognitive Neuroscience **3** (March 1991) 71–86.
2. Zhao, W., Chellappa, R., Phillips, P.J., Rosenfeld, A.: Face recognition: A literature survey. ACM Computing Survey, **35(4)** (2003) 399–458.
3. Yang, J., Zhang, D., Frangi, A.F.: Two-Dimensional PCA: A New Approach to Appearance-Based Face Representation and Recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence **26(1)** (January 2004) 131–137.
4. Yang, M.H., Kriegman, D., Ahuja, N.: Detecting Faces in Images: A Survey. IEEE Transactions on Pattern Analysis and Machine Intelligence **24(1)** (2002) 34–58.
5. Garcia, C., Delakis, M.: Convolutional Face Finder: A Neural Architecture for Fast and Robust Face Detection. To appear in IEEE Transaction of Pattern Analysis and Machine Intelligence (2004).
6. Reisfeld, D., Yeshurun, Y.: Preprocessing of Face Images: Detection of Features and Pose Normalization. Computer Vision and Image Understanding **71(3)** (September 1998) 413–430.
7. Lemieux, A., Parizeau, M.: Experiments on Eigenfaces Robustness. Proc. International Conf. on Pattern Recognition (ICPR) (2002).
8. Martinez, A.M., Benavente, R.: The AR Face Database. CVC Technical Report **24** (June 1998).
9. Phillips, P.J., Wechsler, H., Huang, J., Rauss, P.: The FERET Database and Evaluation Procedure for Face Recognition Algorithms. Image and Vision Computing **16(5)** (1998) 295–306.