Abstract

Principal Component Analysis has been used since 1990 [1] in many recognition algorithms to get a face feature representation and to exploit the dimensionality reduction characteristic of the Principal Component Analysis (PCA). The way to determine the optimal dimension of the reduced space is still not available. Another critical point when working with PCA is the influence of the training set, denoted here as PCA construction set.

In this paper we are working on the behaviour of the signal/residual information of the PCA-eigenspectrum in order to determine an optimal threshold that could be used for the dimensionality reduction. We also study the influence of different sets used to construct the PCA representation. Our experiments are done on the FRGCv2 database, using the BEE PCA baseline software. We also use images from the BANCA database for the construction of the PCA representations.

1. Introduction

Face recognition research in biometrics, and as well as in computer vision is witnessing a growing interest. Even though there are new algorithms being developed, the original face recognition method based on the Principal Component Analysis (PCA) is still widely used as a dimensionality reduction method of face images. An important and unsolved problem is the choice of the dimension of the reduced representation space. As already pointed out by [2], among other authors, the choice of the dimension but also of the set chosen to construct the face manifold is critical. Usually the same database or a subset of it is used for the construction of the PCA face representation and for the evaluation of the face recognition algorithms. In this paper we compare baseline PCA face verification results with results obtained when new data coming from different databases and are used to construct the reduced face space. We have chosen to evaluate our results in mismatched train-test conditions. The idea is to study the influence of adding data from different databases in order to construct more representative face space representations.

2. PCA Representations of the Face Space Manifold for Face Recognition

Principal component analysis (PCA) has been widely used for face analysis [1],[3]. This technique is based on the statistical representation of a random variable. The main idea of the PCA is to reduce the dimensionality of the dataset while retaining the maximum variations in it.

Starting with an N-dimensional observation vector

\[ X = (x_1, x_2, \ldots, x_N) \]  

the main goal of the PCA technique is to build an orthonormal basis, that maximizes the variance of the dataset X. The basis vectors are obtained by solving the algebraic eigenvalue problem

\[ C_X = \Omega \Sigma \Omega^T \]  

where \( C_X \) is the covariance matrix of the observation vector \( X \), \( C_X = XX^T \), \( \Sigma \) diagonal is the matrix of eigenvalue, and \( \Omega \) is the eigenvectors matrix of \( C_X \).

In the following we will consider a set of frontal images from the BANCA database.
normalized face images\(^2\). An ensemble of \(T\) faces is denoted by \(\{I^x(x)\}_{x=(1,1)}^T\), with \(I^x(x)\) the vector of the image intensity centered by \(I_{\text{mean}}\) (the mean face of the ensemble). The PCA approach is applied on \(\{I^x(x)\}\) by solving the eigenvalue problem (2).

The **PCA representation** of an arbitrary face \(\varphi(x)\) projected on the \(r\)-th eigenface \(\psi_r\) is given by (3):

\[
\sigma_r, a_r = \frac{1}{V} \sum_x \varphi(x) (\varphi(x) - I_{\text{mean}}) \quad (3)
\]

where \(\{\sigma_r^2\}\) (in non-increasing order) are the *eigenvalues* of the correlation matrix and \(V = \text{dim}(I^x(x))\). The average signal power of the ensemble is given by (see [4] for more details):

\[
PW = \frac{1}{TV} \sum_{x,n} I^x(x)^2 = \sum_{r=1}^{N} \sigma_r^2 \quad (4)
\]

Considering \(N\)-dimensional subspaces (\(N<T\)), the respective reconstruction and error of \(\varphi(x)\) are:

\[
\varphi_r^N = \sum_{r=1}^{N} a_r \sigma_r \psi_r; \quad \varphi_{r-N}^N = \varphi - \varphi_r^N \quad (5)
\]

The PCA approach is used in face recognition as a mean of space reduction. For the matching step the distance between 2 images (\(\phi^1, \phi^2\)) is given by the measure of distance between feature values, by projecting the faces, by the transformation matrix \(\Omega_N^T\) where \(\Omega_N = \{\psi_r\}_{r=1,N}\). This distance is denoted as \(d(\phi^1, \phi^2) = \|\phi^1 - \phi^2\|\quad (6)\); where \(\phi^1\) and \(\phi^2\) are feature values and \(\|\cdot\|\) is an appropriately selected metric norm such as L1, L2, angle or Mahalanobis.

### 3. Eigenspace Dimensionality and Data Generalization

Penev and Sirovich [5] used a perceptual criterion and argued that the dimensionality of the PCA subspace necessary for adequate representation of the identity information in relatively tightly cropped faces is in the 400-700 range. In our experiments we studied face verification results, as a function of the PCA dimensions. We are also interested in the Eigenface signal and residual power, as well as their ratios on the subsets with which we construct the eigenface spaces, calculated according to the following formulas [5].

\[
S_r = \frac{\sigma_r^2}{\sum_{n=1}^{N} \sigma_n^2} \quad (8)
\]

\(S_r\) is the ratio of the \(r\)-th eigenface power and the total power of the system, and the ratio of the residual power by the total power is given by:

\[
R_r = \left(\frac{\sum_{n=1}^{N} \sigma_n^2 - \sum_{n=1}^{N} \sigma_r^2}{\sum_{n=1}^{N} \sigma_n^2}\right) \quad (9)
\]

We consider the ratio signal by residual [fig 4]:

\[
\frac{S_r}{R_r} = \frac{\sigma_r^2}{\left(\sum_{n=1}^{N} \sigma_n^2 - \sum_{n=1}^{N} \sigma_r^2\right)} \quad (10)
\]

### 4. Databases and Experimental Protocols

In order to study the influence of the training set used to construct the PCA eigenspaces we have used images originating from FRGCv2 and BANCA databases. We have constructed sets coming from the FRGCv2 and BANCA databases as explained below.

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\(^2\) We used the BEE normalisation module on the images of FRGC v2 and BANCA databases, the normalised images are frontal and 150x130 size with 70 pixels between eyes centres, with histogram normalisation.
4.1. FRGC (Face Recognition Grand Challenge)

We have used the FRGC v2 database [6] split in training set (222 subjects) and evaluating set (466 subjects). We focus our work on the mismatched train/test Experiment 4, where for the enrolment (Query Set) simple controlled still images are used. During the test phase single uncontrolled still images are used. The baseline PCA method and code given in the BEE framework of FRGCv2 [6], are used for the face verification algorithm.

4.2. BANCA Database

The BANCA database [7] is composed of 52 subjects (26 males and 26 females). The total number of images in BANCA is 6240. For our work only 1020 images will be used to construct the eigenspace as explained in table 1.

4.3. Database Subsets

Intuitively more data is always better, but which data: more subjects, more expressions, different illuminations?

For our study we used only some subsets of the FRGC large training set, we have used 3 different subsets, F1, F2 and F4. Each subset was chosen for a specific purpose. F1 is a subset that contains the maximum of variability (in term of lighting and expressions) for only 18 subjects. F2 has the same properties as F1 with a double number of images (1024 for F1 vs 2048 for F2). For the subset F4 the variability of persons was advantaged: 222 subjects with only 10 images by subject.

The BANCA subset was chosen in order to see the performance of the face verification algorithm when the PCA eigenspace is constructed by a completely different data. We could also see the influence of combining data from different databases when constructing the PCA eigenspace.

<table>
<thead>
<tr>
<th>DataBase</th>
<th>Subset</th>
<th># of Images</th>
<th># of Subjects</th>
<th>Controlled/Uncontrolled/Degraded</th>
</tr>
</thead>
<tbody>
<tr>
<td>FRGCv2</td>
<td>F1</td>
<td>1024</td>
<td>18</td>
<td>50% / 50% / 0%</td>
</tr>
<tr>
<td></td>
<td>F2</td>
<td>2048</td>
<td>35</td>
<td>50% / 50% / 0%</td>
</tr>
<tr>
<td></td>
<td>F4</td>
<td>2220</td>
<td>222</td>
<td>50% / 50% / 0%</td>
</tr>
<tr>
<td>BANCA</td>
<td>E3</td>
<td>1020</td>
<td>52</td>
<td>40% / 40% / 20%</td>
</tr>
</tbody>
</table>

Table 1: characteristics of subsets used to construct the eigenspaces.

The experimental results reported in this paper are done according to experimental protocol according to Experience 4, from the FRGCv2 database. In this experiment there are 98,336 intra-class matching and 27,608,616 inter-class matching.

5. Experimental Results

We first report in figure 1 some eigenfaces examples coming from the PCA construction set corresponding to E3. It shows the transition from face to face details and noisy images. If we concentrate on E3 eigenfaces (E3 images are from the BANCA databases), we can observe the first eigenface that represents the “typical BANCA face” seems to represent a person watching downsides. Effectively the recordings are done when the subjects were asked to read a text. The second eigenface seems to represent the lightening mode associated with this position also, and this could explain the results (Table 2 & figure 2), in the sense that BANCA is not adapted to the testing database.

![EER evolution with eigenface percentage (exp4)](image)

Figure 2: EER is reported in function of the eigenspace percentage.

<table>
<thead>
<tr>
<th>EER (20%)</th>
<th>29%</th>
<th>24.6%</th>
<th>23.6%</th>
<th>24%</th>
<th>26.8%</th>
</tr>
</thead>
<tbody>
<tr>
<td>EER (40%)</td>
<td>28.2%</td>
<td>23.4%</td>
<td>22.9%</td>
<td>23.4%</td>
<td>26.9%</td>
</tr>
</tbody>
</table>

Table 2: results for EER at 2 different points, corresponding to 20% and 40% of the eigenspace size.

The experiments reported in figure 2, confirm the point that face verification performance using PCA algorithm is tightly related to the training sets.

As explained in paragraph 4.3 comparable results are obtained with F1, F2, F1+E3 and E3. The sets were chosen in order to give representation of expressions, illumination and subjects’ variability.
In the $F_4$ set, we have chosen a set with a big variability in the number of persons (222) compared to the 18/35/52 subjects present in $F_1$, $F_2$ and $E_3$. Adding the BANCA set to train the PCA improves slightly the results. The subjects’ variability seems to be less critical than the expression and illumination variability, as suggested by comparing face verification results using $F_1$, $F_2$ and $F_2$. 20% of eigenspace constructed from $F_1 + E_3$ seems to perform similar to 20% of $F_1$ (with the half dimension).

The best verification results (reported on the evaluation set) are observed for the $F_1 + E_3$ PCA construction set. Surprisingly, the $F_4$ set, which is characterized by a bigger variability as far as the subjects are concerned (222 subjects, 10 images per subject), gives poor performances, compared to an equivalent (in number of images set) but with much less subjects (35 subjects and about 60 images per subject $F_2$). This difference in performance could be explained by the difference in the variability of light and expressions that the $F_2$ could give rather than the $F_4$ (with much more subject variability but less expressions and light changeability). This result confirms the fact that in an open protocol where the training set is different from the testing set, the modeling of the environment parameters is more important than the modeling of the intrinsic subjects’ characteristics of the training set.

We also observe that the performances for all databases are stable in some interval (starting at 20% of the eigenspace) followed by an exponential degradation of the results.

The power/residual ratio for the same PCA construction subsets are reported in Figure 4: a stable region is observed, corresponding to 20%-60% of eigenspace. This stability region corresponds to the stability regions of the EER rates of figure 2. This stable region could be used to determine the optimal PCA space size to get the optimal performance of the algorithm.

6. Conclusion

In this paper we have focused our attention to the influence of training set for the constructions of the PCA eigenface representations, as well as on predicting a threshold for the dimensionality reduction with good generalization properties, based on the signal/residual power information of the eigenspaces. This method is interesting in the sense that it is independent from the validation or evaluation database. Our experiments show also that it seems to be more important to have the variability as present in the evaluation concerning expression and lightening conditions data rather than a variability of subjects.

![Figure 4: representation of the ratio of the signal power by the residual signal power, as a function of the eigenfaces space index.](image)

7. References


