Face Recognition: Reduced Image Eigenfaces Method

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Abstract – *A new algorithm for automatic face recognition is presented: Reduced Image Eigenfaces (RIE), based on the Eigenface mode, improvements in the recognition percentage. The original Eigenfaces method has been implemented in order to compare the results obtained by the new method under various conditions, such as quantity of people and quantity of photos of each of them. In the experimentation, we have used a limited-image data base which is internationally normalized. With RIE, two important advantages are achieved in relation to the previous model: improvement of the percentage of success in the recognition, and possibility of enhancing the set of images used for training.*

Keywords – *Face recognition –Image Reduction– Pattern Recognition – Eigenfaces.*

1. INTRODUCTION

There exist several applications requiring automatic face recognition, such as access security systems for physical or electronic places, people recognition in files or real time, and combinations of face recognition and other methods that require more time - such as fingerprints – so as to reduce the set of possible candidates. To achieve this, it is necessary a system that allows maximizing the number of successes, or minimizing the number of failed recognitions, depending on the application.

For any of the uses, the aim consists in obtaining an automatic face recognition system that is tolerant to different variations in the images, such as pose, expression, and illumination. It should work both for high security applications (minimizing faults) and for those useful to reduce the set of possible candidates (maximizing successes).

Face recognition involves the following stages:

- **Training:** it consists in using some mechanism allowing the system to "learn" the faces that make up the training set. The training type used for the learning will depend, to a large extent, on the methodology applied for the recognition.
- **Recognition**: it consists in filling the system with different images of people, expecting to obtain as result a univocal codification way which allows to identify who the person is, or else to determine that the face is not in the knowledge base.

For the implementation of this type of systems, independently on the technique or methodology implemented, two sets of data are involved. The first is used during the learning stage, which is generally called *training set.* The second face set is used during the recognition stage, and is called *testing set.*

One of the mostly used face recognition models is the Principal Component Analysis (PCA) or *Eigenfaces* [1][2][3][4][5], which is based on the mathematical properties of the digitized image and captures the invariant characteristics of faces. It is interesting to study and analyze this technique for the following reasons:

- Simplicity of the implementation and good results in large data bases.
- It is a technique tolerant to the previously mentioned variations.
- It is carried out under a purely automatic process.

This paper presents a new method called Reduced Image Eigenfaces (RIE), based on the Eigenfaces model (PCA) to achieve a better performance in faces recognition. Results are compared to those of the PCA model in order to show such improvement.

The rest of the paper is organized as follows: section 2 describes PCA (2.1) and RIE (2.2) algorithms; section 3 is dedicated to the experiments carried out and their results; and in the last section, the conclusions are presented.

2. PRINCIPAL COMPONENT ANALYSIS (PCA) – "EIGENFACES"

The success of a face recognition methodology highly depends on the elements used to represent

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images for its later classification. The pattern representing an image should be composed by its most outstanding elements, allowing to reduce the quantity of data used in the classification process and increase the differences between them so that it can act as a powerful discriminant or classifier. One of the techniques mostly used to select a subset of elements fulfilling these conditions is the Principal Component Analysis (PCA), which generates a set of orthonormal vectors that maximize the scatter of all the projected samples, reducing at the same time its dimension. The first in using this methodology to represent face images were Kirby and Sirovich [2], and for face recognition, Turk and Pentland [1][3].

2.1. Eigenfaces Original Algorithm

In the first place, a face recognition system based on the basic *Eigenfaces* algorithm [5][6] was developed. Both the training stage and the recognition stage use a face base made up of a set $I_1, I_2, \dots, I_M$ of images of size NxN.

The ***training*** consists in the following stages:

a) Each image I_i ($\forall i\ \varepsilon[1,M]$) is reorganized as a vector Γ_i of size N^2 whose value is constructed as the concatenation of each of the image rows, thus composing a matrix of N^2xM.

b) The average face Ψ is obtained according to the formula

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \qquad (1)$$

c) The obtained average face Ψ is subtracted from each of the images Γ_i thus obtaining a new set of vectors

$$\Phi_i = \Gamma_i - \Psi \qquad (2)$$

which composes matrix $\Lambda = [\Phi_1, \Phi_2, \dots, \Phi_M]$ of N^2xM.

d) At this point, the eigenvectors of the covariance matrix of Λ are looked for

$$C = \frac{1}{N^2}\Lambda\ \Lambda^T \qquad (3)$$

of size N^2xN^2. These eigenvectors are the orthonormal vectors used to built up the images representation. The size of matrix C makes this stage impossible (due to the required space and time); this is why an approximation of such vectors is obtained.

d.1) The reduced covariance matrix is obtained

$$L = \frac{1}{M}\Lambda^T\Lambda \qquad (4)$$

of dimension MxM.

d.2) The eigenvectors of L are obtained, which, ordered from greater to lesser according to their corresponding eigenvalues, make up matrix v.

d.3) Eigenvectors C are approximated through u

$$u = \Lambda\ v \qquad (5)$$

where each column of u represents an eigenvector.

e) A pattern of image i is obtained ($\forall i\ \varepsilon[1,M]$) $\Omega_i^T = [\omega_1, \omega_2, \dots, \omega_M]$ where

$$\omega_k = u_k^T(\Gamma_i - \Psi) \qquad (6)$$

Given a new face image, the ***recognition*** process tries to find in the image base the one corresponding to the given face, for which its pattern Ω is computed using the same proceeding previously described, and the minimum distance is looked for

$$\min(\|\Omega - \Omega_i\|^2) \quad \text{for } \forall i\ \varepsilon[1,M] \qquad (7)$$

Once the minimum distance is found, the corresponding image is indicated.

2.2. Reduced Image Eigenfaces

As specified in stage d) of the original algorithm, the covariance matrix eigenvectors are searched for. Due to their large sizes, these should be approximated through the eigenvectors of the reduced covariance matrix.

This paper proposes a new method consisting in transforming face images into smaller ones in order to allow working directly with the covariance matrix instead of using an approximation of it.

The ***training*** consists in the following stages:

a) Each image I_i ($\forall i\ \varepsilon[1,M]$) is divided into blocks of PxP pixels each, P being the reduction level. Each of them is averaged and an new image I_i' of DxD is computed, with $D=N/P$, which is obtained by replacing each block with its average.

b) Each image I_i' ($\forall i\ \varepsilon[1,M]$) is reorganized as a vector Γ_i of size D^2 whose value is built up as the concatenation of each row of the image, thus composing a matrix of D^2xM.

c) The average face Ψ is obtained according to the formula

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \qquad (8)$$

d) The obtained average face Ψ is subtracted from each of the images Γ_i thus obtaining a new set of vectors

$$\Phi_i = \Gamma_i - \Psi \qquad (9)$$

which compose matrix $\Lambda = [\Phi_1,\Phi_2,\ldots,\Phi_M]$ of D^2xM.

e) The covariance matrix is obtained

$$C = \frac{1}{D^2}\Lambda\Lambda^T \qquad (10)$$

of dimension D^2xD^2.

f) The eigenvectors of C are obtained, which, ordered from greater to lesser according to their corresponding autovalues, make up matrix u.

g) A pattern of image i is obtained ($\forall$i $\varepsilon[1,M]$) $\Omega_i^T = [\omega_1, \omega_2,\ldots, \omega_{D^2}]$ where

$$\omega_k = u_k^T(\Gamma_i - \Psi) \qquad (11)$$

The ***recognition*** process is similar to that of the previou model: given a new face image, its pattern Ω is computed using the same proceeding previously described, and the minimum distance is looked for

$$\min(\|\Omega - \Omega_i\|^2) \quad \text{for } \forall i\ \varepsilon[1,M] \qquad (12)$$

3. EXPERIMENTAL RESULTS

This paper includes two types of experiments in order to compare the proposed method (2.2) with the original implementation (2.1), and to determine its behavior under different conditions. For all the tests carried out, we have used the standard "ORL Face Data Base" [8], which contains a set of 40 people, with 10 photos of the face of each, taken between April 1992 and April 1994 in the AT&T Lab of Cambridge. The images of this base are in gray levels, and were modified to turn them into a 100x100 pixel size.
In all of the cases, a subset of photos were used as *Training Set*, and the rest of the images as *Testing Set*.

3.1. Tests with a photo per person

Tests were carried out where the quantity of people in the *training sets* was varied (5, 10, 20 and 40), using a photo per person. For the case of the proposed algorithm (2.2), tests were carried out with the reduction level (P) equal to 5 (block size) determined as optimum for this set of images [9].
For each of the tested sizes (except for 40 people), 30 different combinations were used in the training set.
The training set of each experiment consisted of the 9 remaining images of each person belonging to the training set.

Table 1 briefly presents the results, indicating the average percentage of successes achieved for each size of the Training Base. Data show the increase of the success percentage achieved when using the RIE method in comparison to the original eigenfaces algorithm (OE). This is stressed when the quantity of people is increased in the Training Base. **Figure 1** shows the bar diagram of the same results.

Table 1. Summary of success percentages

QIB	QIT	OE	RIE
5	45	87	91
10	90	79	86
20	180	69	78
40	360	61	70

QIB: Quantity of images in the Training Base
QIT: Quantity of images in the Testing Base
OE: Success average percentage for the original algorithm.
RIE: Success average percentage for the proposed algorithm.

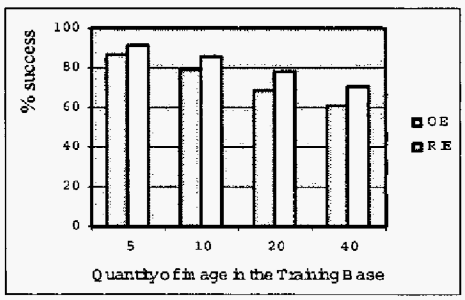

Figure 1. Success average percentage.

3.2. Tests with several photos per person

In these tests, more than one photo was used for each person of the training set (2, 3, 4, 5, 6, 7, 8 and 9).
Tests were oriented to the set of biggest size (40 different people), which were the most troublesome. In all the cases (except in 9 of the photos per person) 20 tests were carried out for each algorithm with different image combinations, which vary in the orientation of the face.

For the case of the algorithm "*Reduced Image Eigenfaces*" (2.2), tests were carried out with the reduction level (P) equal to 5 as in the tests (3.1).
For the testing set, all the remaining images were used.
With the tests containing 5 or more photos per person, only the algorithm "Reduced Image Eigenfaces" could be calculated, since the excessive memory required in the other implementation (2.1) made its running impossible.

Table 2 presents a summary of the average success percentages obtained by each type of test according to the quantity of images of each person in the Training Base. Results show how the success percentage increases as more images of each person are used in the training base. The same data are presented graphically in **Figure 2.**

Table 2. Summary of success percentages

QIP	QIT	OE	RIE
1	360	61	70
2	320	74	83
3	280	84	90
4	240	85	94
5	200	--	95
6	160	--	96
7	120	--	98
8	80	--	98
9	40	--	100

QIP: Quantity of images by person in the Training Base
QIT: Quantity of images in the Testing Base
OE: Success average percentage for the original algorithm.
RIE: Success average percentage for the proposed algorithm.

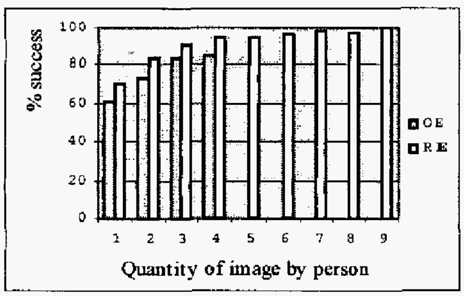

Figure 2. Success average percentage.

4. CONCLUSIONS

The results obtained with the first type of experiments allow us to conclude that the proposed method provides an important improvement in relation to the original algorithm. This difference is even more greater as the quantity of people increases in the training set.
With the tests carried out in the second part, we can notice an increase in the recognition percentage in both algorithms as the quantity of photos per person used for the training is increased.

We conclude that with the proposed method better results are obtained than with the original eigenfaces-based recognition algorithm. Besides, this method allows us to work with more images in the training, with which there exists an even greater improvement in the results.
On the other hand, there appears an increase of the time necessary to carry out the learning stage, which leads us to study the parallelization of the algorithm in order to run it over a logically shared and physically distributed memory architecture as that of Clementina II (SGI Origin 2000 with 40 processors). [10][11][12][13].

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