1 # Face Recognition Based on Eigeneyes[1]

P. Quintiliano* and A. Santa-Rosa**

** Federal Police Department, Brasilia, Brazil*
e-mail: quintiliano.pqs@dpf.gov.br
*** University of Brasilia, Brasilia, Brazil*
e-mail: nuno@cic.unb.br

Abstract—Face recognition is a subject of emergent research that offers great challenges, mainly in adverse conditions. This paper proposes still a larger challenge: to perform face recognition from fragments of face
1 images with approximately 20% of the face, based on eigeneyes techniques. This approach can work with partly occluded or nonideal illuminated images as well as in the cases when a person is disguised or wear a scarf, sun glasses, or mask. Even working with fragments of image, we achieved the recognition rate of 87%. Images were extracted from the Yale Face Database.

INTRODUCTION

Recognition of the known faces has a fundamental importance in our social relationships, being a trivial function for our brain, however, extremely important for our simple daily activities. Usually, we establish an interaction with people only if face recognition occurs.

Face recognition is a part of a larger context, that
2 is biometrics, that gives us the notion of life measure.
2 Biometrics can be defined as the physiologic or psychological characteristics that can be used to verify
2 the person's identity. The most used biometrics are: face, voice, fingerprint, signature, hand geometry,
2 iris, and retina [1]. Biometrics systems are subjected to the *principle of threshold*. According to it, a face is recognized if its features lie inside an acceptance range. This principle defines some uncertainty degree in results that imply obtaining more than one answer as a searching result, eventually, requiring human intervention for the correct alternative choice. Based on this principle, the results presented in this paper consider to be correct the matches ranked even on the third place.

3 Our work is based on the first eigenface approaches by Kirby and Sirovich [2] and Turk and Pentland [5, 6]. Many approaches tried to perform face recognition in adverse conditions and to
4 improve eigenfaces [3, 4].

STATEMENT OF THE PROBLEM

We perform automated face recognition from the fragments of face images. It can work with half-occluded images or with fragments of images. Thus, the eigenfaces concepts are expanded to eigeneyes, 4 1
because the algorithm developed on the base of only on eigenfaces badly performs when working with half- 4
occluded or incomplete images. The technique presented here can be quite useful in police applications, where it is necessary to recognize people with several disguises, covering part of the face, what usually happens in crimes scenes. Using these techniques, automatic face recognition becomes possible with the use of small parts of a face.

Eigeneyes algorithms are similar to the eigenface 1 3
algorithms. However, they are supposed to have an "additional intelligence" for verifying which eye is the best to be automatically submitted to recognition. We also have to maintain a much more complete database, with specific information of eigenfaces and eigeneyes, 4 1
about all worked classes. The same established criterion is supposed to be used in the training and match steps and in the choice of the eigeneye to be used. In 5
this approach, each class is represented by a different people.

We used the "withglasses," "happy," "noglasses," 6 7
"normal," "sad," "sleepy," "surprised," and "wink" images from the Yale Face Database, supplied by Yale University. So, we used only images obtained in well-illumination conditions. Figure 1 shows the 15 classes of the database characterized by different facial expressions and illumination conditions. This database, whose images have 243 × 320 pixels, offers several good challenges to any face recognition approach. For evaluation and tests, we extracted 64 × 64 pixel fragments from the face images, around the eyes.

As the aim of this work is not the detection of faces, but just recognition, we would not tell about the algorithms used for face detection to extract the 64 × 64 eye images.

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Fig. 1. Some images of the training set.

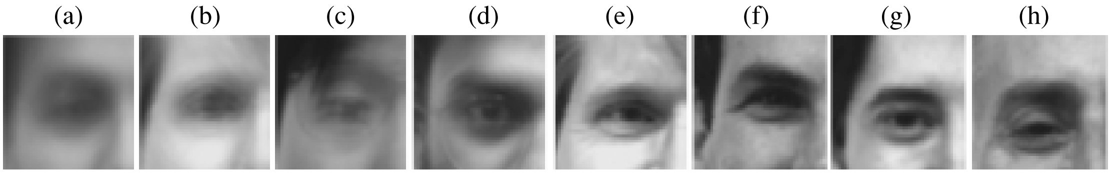


Fig. 2. (a) The average eye from entire training set, (b–d) average eyes from its classes, and (e–h) some examples of images from the training set.

APPROACH AND TECHNIQUES

We used a set of $M = 120$ face images, identified as i ($i = 1, \ldots, M$), for verification and testing. The extracted fragments of images are $N \times N$ square matrices, with $N = 64$. At first, all those M eye images, as is shown in Figs. 2e–2h, are transformed into a column vector, with the $N^2 \times 1$ dimension, with the same N_2 pixels. This conversion is performed taking every lines and concatenating them, one after another, building the column vector in the following way:

$$\Gamma_{i,1} = \Gamma'_{i,1} \quad (i = 1, \ldots, N^2; \ j, k = 1, \ldots, N) \tag{1}$$

Then, we calculate the average image of all image set, adding all the images and dividing the result by the amount of images (see Fig. 2a) in the following way:

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i \tag{2}$$

Once calculated the average eye Ψ, we set up a new group of images Φ, obtained from the difference between each image of the training set and the average features. Thus, each image Φ differs from the average image of the distribution. Each individual distance is calculated by subtracting them from average image, this deriving a new space of images in the following way:

$$\Phi_i = \Gamma_i - (i = 1, \ldots, M) \tag{3}$$

From the new set of M images, we set up the $N^2 \times M$ matrix A, by taking each M vectors of Φ and by placing them in each column of A, in the following way:

$$A_{i,j} = \Phi_{j;\,i,1} \tag{4}$$

The covariance matrix C, with dimension $N^2 \times N^2$ is:

$$C = AA^T \tag{5}$$

As the dimension of that matrix is very big, it is more suitable to work with $M \times \mathrm{M}$ matrix L:

$$L = A^TA \tag{6}$$

The eigenvectors of C are calculated from the eigenvectors of L. They are obtained through linear combination of the original image space with the eigenvectors of L (matrix V) in the following way:

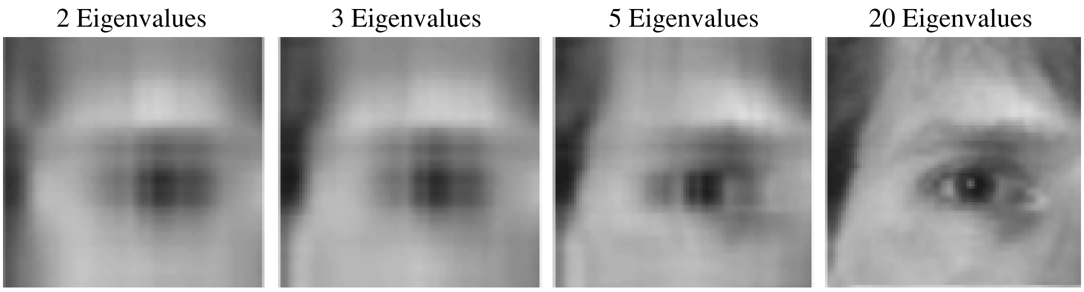
$$U = AV \tag{7}$$

$N^2 \times M$ matrix U contains all eigenvectors of C, $M \times M$ matrix V contains M eigenvectors of L, and $N^2 \times M$ matrix A is the space of images. After eigeneyes are 1
extracted from the covariance matrix of faces set, the training stage takes place. We used only one artificial image to represent each class in order to train the approach. Those training images are generated from average of four images of each class, as shown in Figs. 2b–2d. We used all the $M = 120$ training images for verification and test.

We know that only the eigenvectors with the larger eigenvalues are necessary for the face recognition. So we used just ($M' < M$) eigenvectors, with $M' = 5$, 10, 20, 30, or 50. Every artificial image from each class is projected into the "eye space" in the following way:

$$\Omega_i = U^T(\Gamma_i - \Psi), \ i = 1, \ldots, Nc. \tag{8}$$

The matrix i, with dimension ($M^{\tau} \times Nc$), contains the Nc eigenvectors, with dimension ($M\tau \times 1$), from matrix L, and it is used for comparison with the new faces presented for comparison effect and recognition. Nc is the number of classes in the training set.



1 **Fig. 3.** Some eigeneyes of the average eye, from eigenvectors with larger eigenvalues.

1 If we use all eigeneyes to represent the eyes of the
faces, those groups of initial images can be completely
1 reconstructed. The eigeneyes are used to represent or to code any face that we tried to compare or to recognize. Figure 3 shows images reconstructed from the
1 eigeneyes with highest eigenvalues. We should use
1 eigeneyes with higher eigenvalues in the reconstruction, because they provide much more information about the variation of the eyes of the faces.

Face recognition is performed by extracting the descriptors of the new image submitted to recognition. These descriptors are compared with the descriptors of the classes stored in the database, calculated in the same way, using the Euclidean distance. Thus, each image submitted to face recognition is projected in the eye space obtaining the vector Ω in the following way:

$$\Omega = U^T(\Gamma - \Psi) \tag{9}$$

We found up to ten thresholds for each analyzed class, in order to achieve a better performance in face recognition. The thresholds *i* ($i = 1, \ldots, Nc$) define the maximum distance allowed between the new face submitted to recognition and every class. If the distance found between the new image and one of the classes is inside the threshold of the set class, then the face is recognized. *Nc* thresholds are calculated in the following:

$$\theta_i = \frac{1}{k}\max\{\|\Omega_i - \Omega_j\|\} \quad (i, j = 1, \ldots, Nc) \tag{10}$$

We use factor k in a scale from 1 to 10. If it is little (near to 1), we have a big false-positive rate and a little false-negative rate. Otherwise, if it is big (near to 10), we have a little false-positive rate and a big false-negative rate. In this approach we used $k = 1$ to produce the results presented.

RESULTS

In order to compare the eigenfaces and eigeneyes 4 1
algorithms, we applied both algorithms to the same 120 images, obtained in good illumination conditions. All presented results were obtained with one processing for each amount of eigenvectors (5, 10, 20, 30, and 50). Table 1 presents the results obtained with the
eigenfaces algorithm and Table 2 presents the results 4
obtained with the eigeneyes algorithm working with 1
the same 120 well illuminated images.

INTERPRETATION

Based on the *principle of threshold*, the recognition is acceptable when the found Euclidean distance is ranked up to the third place and is inside the predefined threshold. This principle is quite acceptable because of the great complexity of face representation and the proximity of the found results, until the third place and inside the predefined threshold.

3 **Table 1.** Eigenface results

Eigenvec	Errors		Success	
	quant	rate, %	quant	rate, %
05	28	23.3	92	76.6
10	13	10.8	107	89.1
20	6	5.0	114	95.0
30	2	1.6	118	98.3
50	2	1.6	118	98.3

Table 2. Eigeneyes results 1

Eigenvec	Errors		Success	
	quant	rate, %	quant	rate, %
05	21	17.5	88	77.3
10	16	13.3	101	84.1
20	17	14.1	100	83.3
30	16	13.3	101	84.1
50	18	15.0	105	87.5

CONCLUSION

3 The verified eigenface approach is quite robust in the treatment of face images with varied facial expressions and transparent glasses use. However, it is very sensitive in the treatment of face images to the of disguise, scarf, sun glasses, and masks.

Our approach can perform face recognition under these complicated conditions. In spite of the fact that
1 eigeneyes algorithm uses only about 20% of face images, its performance is only a little worse than
3 eigenface algorithm that uses whole face images, as is shown in the tables.

1 3 Eigeneyes algorithm has the advantages of eigenface algorithm, it is also quite efficient and simple in the training and recognition stages, dispensing from low level processing to verify the face geometry or the distances between the facial organs and their dimensions.

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SPELL: 1. eigeneyes, 2. biometrics, 3. eigenface, 4. eigenfaces, 5. eigeneye, 6. withglasses, 7. noglasses