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PERFORMANCE ANALYSIS OF EIGENFACE RECOGNITION UNDER VARYING EXTERNAL CONDITIONS

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Abstract

In the field of image processing and computer vision face recognition is one of the most studied research domain. It has large variety of applications in different areas like security and surveillance systems, identification and authentication etc.

In this paper we propose to analyze the face recognition system based on the eigenface[22] method under different conditions. The eigenface method is a statistical dimensionality reduction method, which obtains the adequate face space, out of a given training database. The idea of observing the performances i.e. the recognition rate in different situations (like presence or absence of important facial features such as glasses or beard) came from the diploma work [20]. The experiments described in this article study the recognition performance of the algorithm, by varying the number of considered feature vectors. Beside of these, we studied the behavior of such a system if the analyzed individual is wearing glasses or beard. Finally, we concentrate on carrying out experiments for noisy images by adding common types of noise like salt & pepper noise, Gaussian noise or Poisson noise to every test image.

Key words: face recognition, Eigenfaces, Principal Component Analysis, performance evaluation

1. Introduction

Object recognition is an important research domain because it can be applied in a wide variety of systems. Especially human face recognition is the most widespread research area, owing to the fact that face is usually in handy it can be recorded easily by different types of visible or hidden cameras, the subject doesn't even notice that he/she is recorded.

Other methods that are more reliable and are used in biometric identification, for example fingerprint recognition, iris recognition, need special devices such as high resolution cameras.

On the other hand, face recognition is the most used identification method wherewith people recognize each other.

Automated facial recognition is a biometric application from a single image or video sequence, comparing the detected face to a large database of faces, from individuals already known.

Several application areas of human face recognition are known, such as: biometrical identification, access control, video surveillance, passport control, security systems, banc verification for ATM, image categorization in films and videos, identification of thefts in open-air cameras.

Face recognition systems can be divided in two classes global aspect based methods and local aspect based methods. The first one is called appearance based method and the second one is also called part-based or feature based method.

This article concentrates only on the eigenface method, the most common face recognition system, which can be included in the global aspect based category. Besides implementing the eigenface method, developed by Turk and Pentland [22], it studies the influence of several external conditions on the recognition performance, such as noise, blurriness, illumination; change of facial features: wearing glasses or presence of facial hear.

The paper is organized as follows: in the first section a short introduction is presented, it follows a summary about the related most important works in the domain. The third section presents the eigenface method and finally some comparative experimental results and detection performances are exposed.

2. Related Work

Many approaches have been developed for face recognition. In this section the most used such systems are summed-up.

Several types of Artificial Neural Networks have been used for face recognition: single layer adaptive network, multilayer perceptron, convolutional networks and probabilistic neural networks for handling partial occlusion or distortion [7].

Elastic Bunch Graph Matching is also used for face recognition. Here a dynamic graph is constructed where vertexes are the features and edges the distances between given features [14].

Face representation in 3D is one of the geometrical representation techniques that are developed as well, they are based on Hidden Markov Models [2].

Despite of the large variety of face recognition systems the most common approach with extremely good results is still the eigenface method. This method is the outcome of the simplest global aspect based method, which takes in account the intensity of pixels. Here, the two dimensional unknown face image is compared to all the other faces from the training database. Comparing faces pixel by pixel works only in limited conditions, under given circumstances. Its major bottleneck is the comparison and classification in a very high dimensional space. Thus, appears the need of dimensionality reduction. One of the most common dimensionality reduction methods is the extraction of Principal Components. Kirby and Sirovich [8] exploit the PCA (Principal Component Analysis) method for face recognition by using the Karhunen-Loève conditions, in order to define the geometry of faces. Turk and Pentland [22] developed a recognition system which tracks the subjects head and recognizes it by comparing the characteristics of it to those of known individuals. The system projects face images onto a feature space named “face space” that spans the significant features from known images. The significant projections are called eigenfaces, because they are eigenvectors of the face space. Su et al. [21] combines PCA and Linear discriminant Analysis (LDA) for extracting multi features and makes the final decision with radial basis function network.

Recently, different types of PCA-based algorithms have been developed by researchers of this domain: weighted modular PCA [9], Kernel PCA [12], diagonal PCA [23], adaptive PCA [3], two-dimensional PCA [11]

Instead of PCA, Bartlett et al. [1] uses Independent Component Analysis, because this method is a generalization of PCA. Liu et al. [10] combined Gabor wavelet transform with Fisher linear discriminant and kernel PCA or Gabor features with fractional polynomial models or Gabor features ICA and PCA.

Nicholl et al. [13] created a face recognition system which automatically selects the coefficient for DWT and PCA.

Poon et al. [15, 16] analyze the performance of PCA recognition for different datasets, varying the image size, alignment, training set, blurriness, illumination condition and noise. Shermina [19] presents a method based on multi linear principal component analysis.

Rady [17] compares different distance classifiers with the same eigenface method. Dabhade [4] combines Haar Detection, Gabor feature extraction and Eigenface recognition in the achieved system.

For more details about other techniques and recent advances in face recognition consult the survey articles [6, 18]

3. The Eigenface method

The idea of retrieving relevant features from a set of training images can be obtained by the extraction of principal components. These features are not necessarily evident, perceptible features such as facial feature parts, but they characterize the common part of a given set.

If we consider every gray-scale pixel of $n \times m$ image, a feature space of this is obtained. Nowadays, the number of pixels of an image is more hundred thousand, even million. These dimensions can hardly be applied in any classification algorithm, therefore comes the necessity of dimensionality reduction.

The Principal Component Analysis is a statistical method for dimensionality reduction, while minimizing the mean square reconstruction error [16, 5].

The PCA is able to extract only the relevant information of a given space and transform every element of it in a considerably lower dimensional space.

Let us consider L images each of them having the same dimension $n \times m$.

$$S_{training} = \{I_1, I_2, \dots I_L\} \tag{1}$$

Each image is vectorized and we obtain an N dimensional column vector, where $N = n \times m$.

The PCA is a linear algebra concept based on the eigenvectors and eigenvalues of a matrix.

The eigenvector is a vector which is scaled by a linear transformation. When a matrix acts on it, the direction of the vector does not change, only the magnitude.

$$Av = \lambda v \tag{2}$$

In equation (2) the A is the analyzed matrix, v the eigenvector and the scalar λ is the corresponding eigenvalue of the eigenvector v.

Equation (2) can be rewritten as the characteristic equation of the matrix A.

$$\left(A - \lambda I\right)v = 0 \tag{3}$$

Nontrivial solution of the characteristic equation exists if and only if

$$\det\left(A - \lambda I\right) = 0 \tag{4}$$

The characteristic equation is an $N \times N$ linear homogeneous equation system, with N equations and N unknowns. The solutions of the N degree characteristic polynomial (4) are the eigenvalues of the A matrix. Because the degree characteristic polynomial is N, we obtain N roots. These N roots are not necessarily distinct. If all the eigenvalues are distinct, the corresponding eigenvectors are linear independent and form an N dimensional basis.

The matrix for which the eigenvalues are computed is the covariance matrix of the input space denoted by $S_{training}$ in equation (1).

The covariance matrix of two random variables e.g. images is

$$\Sigma = cov(I_i, I_j) = E[(\mathrm{I}_i - \mu_i)(\mathrm{I}_j - \mu_j)] \tag{5}$$

where E is the expected value.
The matrix form of the covariance matrix of the whole set of images $S_{training}$ can be rewritten as

$$\Sigma = cov(I) = E[(\mathrm{I} - E[I])(\mathrm{I} - E[I])^T] \tag{6}$$

here I is the training set of images and $\mu = E(I)$ is the mean image. The mean image is a column vector of N pixels, as well.

$$\mu = E(I) = \frac{1}{L}\sum_{i=1}^{L} I_i \tag{7}$$

If the eigenvalues and eigenvectors of the covariance matrix Σ are computed the "eigenfaces" are obtained. This name comes from the parents of the Eigenface method Turk and Pentland [22], they call it so because the obtained eigenvectors are similar to faces in appearance.
The covariance matrix is an $N^2 \times N^2$ matrix, which can be simply formulated as

$$\Sigma = \frac{1}{L}\sum_{i=1}^{L}\left(I_i - \mu\right)\left(I_i - \mu\right)^T = AA^T \tag{8}$$

where A is an $N^2 \times L$ matrix column-vise formed of the differences of each image and the mean image, the i th column is the i th difference.

$$A = [I_1 - \mu \; I_2 - \mu \ldots I_L - \mu] \tag{9}$$

The problem is the dimension of the covariance matrix Σ which became $N^2 \times N^2$. Fortunately, we can obtain the same eigenvalues by computing them for another covariance matrix. This covariance matrix is

$$\Sigma' = A^T A \tag{10}$$

The dimension of this Σ' matrix is $L \times L$, where L is the number of images. The order of magnitude of N^2 is million, but the order of L is thousand ($L << N^2$). Thus, instead of computing eigenvalues of a huge matrix (8) we compute the eigenvalues of a such smaller matrix (10).
Consider the eigenvectors of Σ' such that

$$\Sigma' v_i = \lambda_i v_i \tag{11}$$

$$A^T A v_i = \lambda_i v_i \tag{12}$$

Left multiplying both sides with A we obtain

$$AA^T A v_i = \lambda_i A v_i \tag{13}$$

We denoted $\Sigma = AA^T$
Equation (13) becomes

$$\Sigma A v_i = \lambda_i A v_i \tag{14}$$

Let us denote $u_i = Av_i$

$$u_i = \sum_{l=1}^{L} v_{il}\left(I_i - \mu\right) \tag{15}$$

then we obtain the eigenvalues λ_i and eigenvectors u_i of the Σ covariance matrix.

$$\Sigma u_i = \lambda_i u_i \tag{16}$$

Thus, if we compute the eigenvalues of Σ', the same are the eigenvalues of Σ and in the same way, if we compute the eigenvectors v_i of corresponding eigenvalues for Σ', we obtain the eigenvectors u_i of Σ using the equation (15).
After computing all the L eigenvalues, we have to select the most representative P eigenvalues. This value of P is less the hundred.
From the largest P eigenvalues the corresponding P eigenvectors are computed, and a P dimensional span is obtained, which is called by the authors of [22] the "facespace".
The training step is the computation of the facespace, based on a set of input images (see eq.(1)).

In the test phase the input image has to be projected into the facespace. Each of the selected P eigenvectors will have a corresponding weight. These weights are, in fact, the eigenface components of the input image, and are computed by a simple dot product.

$$w_p = u_p^T\left(I_{in} - \mu\right) \tag{17}$$

From these vectors putting column-wise we can form a matrix W.

$$W = [w_1, w_2, ..., w_p] \tag{18}$$

If the eigenvectors form a basis then the input image can be reconstructed using the following linear combination:

$$I_{rec} = w_p u_p \tag{19}$$

In order to determine which person resembles the input image best, so an error has to be computed. This error is the means square error of two W matrixes [22]. W_{in} is the weight matrix of the input image and W_{pers} is the average weight matrix of more images for a given person.

$$MSE = \left\|W_{in} - W_{pers}\right\|^2 \tag{20}$$

The minimum of this mean square error will determine the most alike person.
If the error is greater than a threshold we can say that the input image is an unknown person.
In order to find out that input image is not a face image another distance has to be computed, the distance between the average reconstructed image and the difference between the input image and the mean image ($A_{in} = I_{in} - \mu$).

$$MSE_{face} = \left\|A_{in} - Avg_{Irec}\right\|^2 \tag{21}$$

If this value is less than a threshold it means that the input image is a face, otherwise it is an unknown object the projection of which in the facespace is useless.

4. Results and Experiments

In our experiments we have used the Yale database [24] specially developed for face recognition and facial expression recognition. This database has 165 grayscale images of 15 individuals and 11 different photos about each individual. These 11 poses to a facial expression: normal, happy, sad, sleepy, surprised and wink. Different configuration refers to center-light, left-light, right-light. Besides, each subject appears also with and without glasses.

At the same time we generated another condition and put beard to each subject.

We have to underline that these images are not aligned and are in different illumination conditions. In order to form an acceptable training set we have normalized the images (see fig 1 original image and normalized image). As we can observe the normalization brings uniform illumination conditions. It seems that this procedure messes up uniformly lighted "normal" image, but repairs the left-lighted and right-lighted image in some way. Further we will see that different illumination conditions have a great impact on recognition with this eigenface method.

Fig. 1: a).Yale database sample image [24]

b). Normalized sample image

c). Left light d). Normalized left light

The second step after normalization is obtaining the mean image of the training data set. Because the images are not properly aligned the mean image shows only a blurred head shape formed of several contours. Regarded to the covariance and resemblance this image is the common part of each image, that is why it has to be subtracted from each image in the training set (see fig. 2 a). and b).)

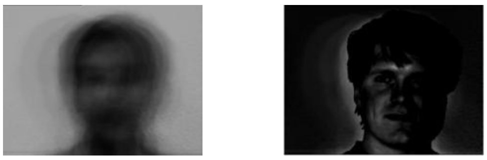

Fig. 2: a). Mean image denoted by μ

b). Difference image

After obtaining the difference images, comes the computation of covariance matrix and out of it we obtain the eigenvalues and eigenvectors.

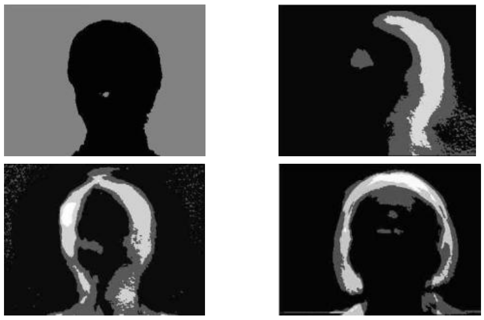

Fig. 3: First four eigenfaces

In our experiments we studied the influence of number of used eigenvectors. As shown in fig. 3 the eigenvectors corresponding to the most representative (first four) eigenvalues are the strong contours of the head, the first eigenvector is the shape of an average head.

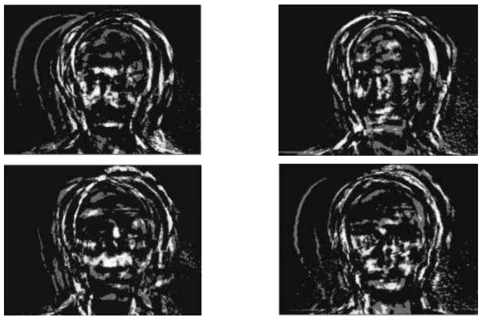

Fig. 4: 47th, 48th, 49th, 50th

As we compute more and more eigenvectors corresponding to smaller values we can observe that these represent the fine contours. Overall, we have to use several eigenvectors corresponding to strong contours. These give the basis of the shape. But at the same time we have to consider some fine contours as well.

We noticed that if the number of eigenvectors is increased, the recognition accuracy becomes better, until a certain amount, where it saturates.

In Table 1 we measured the recognition rate using 25, 50, 100, 112 eigenvectors.

The best detection rate is 99.38% for the considered training data set. Table 1 shows that after 100 eigenvectors the increase of the number of such significant vectors taken in account is useless.

Table 1: Number of most representative eigenvalues

Number of Eigenface features	Recognition Rate
25	92.72%
50	96.36%
75	98.18%
100	99.39%
112	99.39%

In the testing phase each image is compared to the existing classes in the training set. Each class corresponds to a certain individual. For each image in the training set we compute its weight. This weight is the dot product between difference image and the eigenvectors (equation (17)). After computing the weight-vector for the training set we compute the average of it for each individual. This average weight is compared to the weight obtained for the tested image (equation (20)). The similarity measure in this case is the means square error between these two vectors measured by the Euclidean distance.
As more eigenvectors we have considered as higher is the dimensionality of the obtained weight-vector (equation (18)). This means that we have more components, so the vectors contain more information based on which the error is more precise. This statement can be also verified visually by computing the reconstructed image. Comparing the reconstructed images out of 10, 50, 100 and 112 eigenvectors we can confirm that the more eigenvectors are used the accurate the reconstruction is.

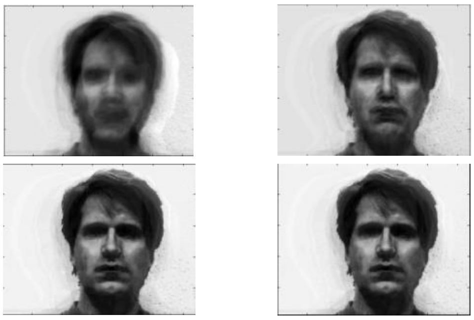

Fig. 5: Reconstructed image 10, 50, 100, 112 eigenvectors

Our second experiment studied the recognition rate of the person if he/she wears glasses or he is bearded. In this case the training set does not contain images with these disturbing factors. As we have observed from the measurements the reconstruction rate of people with glasses is 86.66% and those with beard was 92.85% (table 2).

Table 2: Effect of different facial features

Noise type	Detection Rate
Glasses	86.66%
Beard	92.85%

Our final experiment observed the effect of noise in the recognition process. We have tested three types of different noises. The salt & pepper noise, the Gaussian noise and the Poisson noise and other illumination changes.
Considering our experiments we draw the following conclusions: illumination changes have a great impact on the recognition rate, mainly if the illumination is not uniform and the source comes from different directions. In the Yale database we compared the center-light, left-light and right-light poses(figure 1c).
Gaussian noise is white noise with mean 0 and covariance 1 (figure 6a).
Salt & pepper noise is a noise with white black pixels with density 5% of the total pixels. (figure 6b)
The Poisson noise is separately computed for each pixel with the Poisson mean which is equal to the value of the pixel (figure 6c). The recognition rates for these types of images are presented in table 3.

Table 3: Effect of noise

Noise type	Detection Rate
Salt & Pepper	98.36%
Gaussian	98.21%
Poisson	98.76%

Fig. 6: a).Gaussian b). Salt & Pepper c).Poisson

5. Conclusion and future work

Eigenface recognition is one of the most used face recognition system, but it has to respect certain conditions like geometric aligning of faces, uniform illumination conditions. In the presented article we analyzed these types of external conditions, putting an accent on varying characteristic facial features such as glasses or beard. We have observed that the number of considered descriptive features increases the recognition rate. The increase of image noise slightly decreases the recognition accuracy. Occlusion, facial features have little effect on recognition, while illumination or light sources from different directions have a great effect on the recognition performance. Overall, these observations can be helpful in designing future recognition systems.

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