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A Face Recognition System Based on Eigenfaces Method

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Abstract

Face recognition systems are built on the idea that each person has a particular face structure, and using the facial symmetry, computerized face-matching is possible. The work on face recognition has begun in the 1960's, the results of which are being used for security in various institutions and firms throughout the world. The images must be processed correctly for computer based face recognition. The face and its structural properties should be identified carefully, and the resulting image must be converted to two dimensional digital data. An efficient algorithm and a database which consists of face images are needed to solve the face recognition problem. In this paper, Eigenfaces method is used for face recognition. In the recognition process, an eigenface is formed for the given face image, and the Euclidian distances between this eigenface and the previously stored eigenfaces are calculated. The eigenface with the smallest Euclidian distance is the one the person resembles the most. Simulation results are shown. Simulations have been done using the Matlab program. The success rate for the large database used is found to be 94.74%.

Keywords: Pattern recognition; Face recognition; Eigenfaces method

1. Introduction

The face recognition system is similar to other biometric systems. The idea behind the face recognition system is the fact that each individual has a unique face. Similar to the fingerprint, the face of an individual has many structures and features unique to that individual. An automatic face recognition system is based on facial symmetry.

Face authentication and face identification are challenging problems. The fact that in the recent past, there have been more and more commercial, military and institutional applications, makes the face recognition systems a popular subject. To be reliable, such systems have to work with high precision and accuracy.

In a face recognition system, the database consists of the images of the individuals that the system has to recognize. If possible, several images of the same individual should be included in the database. If the images are selected so that they account for varying facial expressions, lighting conditions, etc., the solution of the problem can be found more easily as compared to the case where only a single image of each individual is stored in the database.

A face recognition algorithm processes the captured image and compares it to the images stored in the database. If a match is found, then the individual is identified. If no match is found, then the individual is reported as unidentified.

The challenges of face recognition are:

- Shifting and scaling of the image,

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- Differences in the facial look (different angle, pose, hairstyle, makeup, mustache, beard, etc.),
- Lighting,
- Aging.

The algorithm has to work successfully even with the above challenges.

In Table 1, a comparison of some of the methods used for face recognition based on the number of images in the training set and the resulting success rate is provided.

Table 1. Comparison of some work related to face recognition

Method	Number of images in the training set	Success rate	Reference
Principal Component Analysis	400	79.65%	[1]
Principal Component Analysis + Relevant Component Analysis	400	92.34%	[1]
Independent Component Analysis	170	tanh function 69.40%	[2]
	40	Gauss function 81.35%	[2]
Hidden Markov Model	200	84%	[3]
Active Shape Model	100	78.12-92.05%	[4], [5]
Wavelet Transform	100	80-91%	[6]
Support Vector Machines	-	85-92.1%	[7], [8]
Neural Networks	-	93.7%	[9]
Eigenfaces Method	70	92-100%	[10]

2. Eigenfaces Method for the Solution of Face Recognition Problem

The basis of the eigenfaces method is the Principal Component Analysis (PCA). Eigenfaces and PCA have been used by Sirovich and Kirby to represent the face images efficiently [11]. They have started with a group of original face images, and calculated the best vector system for image compression. Then Turk and Pentland applied the Eigenfaces to face recognition problem [12].

The Principal Component Analysis is a method of projection to a subspace and is widely used in pattern recognition. An objective of PCA is the replacement of correlated vectors of large dimensions with the uncorrelated vectors of smaller dimensions. Another objective is to calculate a basis for the data set. Main advantages of the PCA are its low sensitivity to noise, the reduction of the requirements of the memory and the capacity, and the increase in the efficiency due to the operation in a space of smaller dimensions.

The strategy of the Eigenfaces method consists of extracting the characteristic features on the face and representing the face in question as a linear combination of the so called ‘eigenfaces’ obtained from the feature extraction process.

The principal components of the faces in the training set are calculated. Recognition is achieved using the projection of the face into the space formed by the eigenfaces. A comparison on the basis of the Euclidian distance of the eigenvectors of the eigenfaces and the eigenface of the image under question is made. If this distance is small enough, the person is identified. On the other hand, if the distance is too large, the image is regarded as one that belongs to an individual for which the system has to be trained.

The flowchart of the algorithm is shown in Fig. 1.

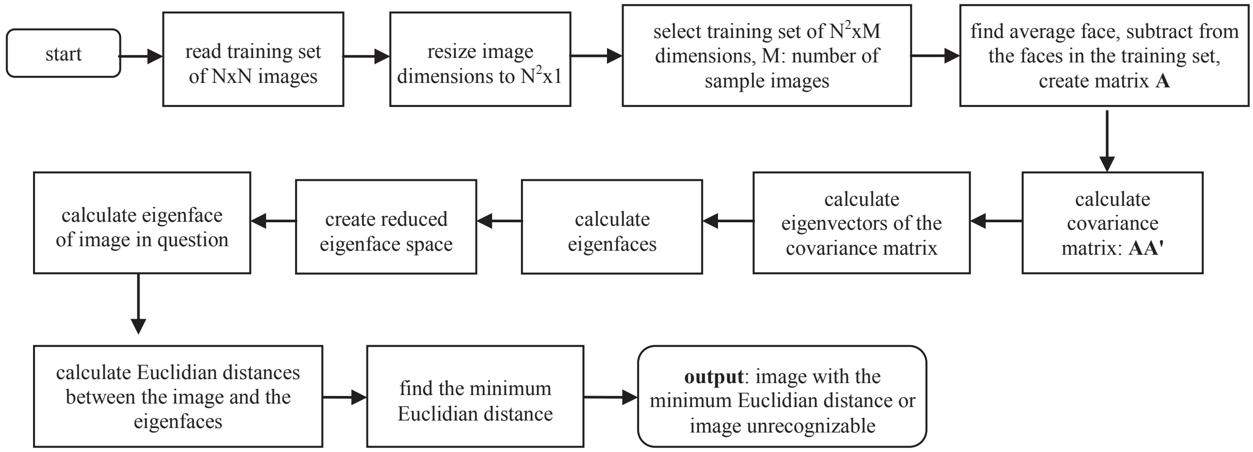

Fig. 1. Flowchart of the algorithm of the Eigenfaces method

As a starting point, the training images of dimensions N*N are read and they are converted to N^2*1 dimensions. A training set of N^2*M dimensions is thus created, where M is the number of sample images. The average of the image set is calculated as:

$$\boldsymbol{\psi} = \frac{1}{M}\sum_{i=1}^{M}\boldsymbol{\Gamma}_{\mathbf{i}} \quad (1)$$

where $\boldsymbol{\psi}$: average image, M: number of images, $\boldsymbol{\Gamma}_{\mathbf{i}}$: image vector.

The eigenfaces corresponding to the highest eigenvalues are retained. Those eigenfaces define the face space. The eigenspace is created by projecting the image to the face space formed by the eigenfaces. Thus the weight vectors are calculated. Dimensions of the image are adjusted to meet the specifications and the image is enhanced in the preprocessing steps of recognition. The weight vector of the image and the weight vectors of the faces in the database are compared.

Average face is calculated and subtracted from each face in the training set. A matrix (**A**) is formed using the results of the subtraction operation. The difference between each image and the average image is calculated as

$$\boldsymbol{\phi_i} = \boldsymbol{\Gamma_i} - \boldsymbol{\psi}; \quad i = 1, 2, \dots, M$$

where $\boldsymbol{\phi_i}$ is the difference between the image and the average image.

The matrix obtained by the subtraction operation (**A**) is multiplied by its transpose and thus covariance matrix **C** is formed:

$$\boldsymbol{C} = \boldsymbol{A^T A}$$

where **A** is formed by the difference vectors, i.e.,

$$\boldsymbol{A} = [\boldsymbol{\phi_1}, \boldsymbol{\phi_2}, \dots, \boldsymbol{\phi_M}]$$

The dimensions of the matrix **C** is N*N. M images are used to form **C**. In practice, the dimensions of **C** is N*M. On the other hand, since the rank of **A** is M, only M out of N eigenvectors are nonzero.

The eigenvalues of the covariance matrix is calculated.

The eigenfaces are created by using the number of training images minus number of classes (total number of people) of eigenvectors.

The selected set of eigenvectors are multiplied by the A matrix to create a reduced eigenface subspace.

The eigenvectors of smaller eigenvalues correspond to smaller variations in the covariance matrix. The discriminating features of the face are retained. The number of eigenvectors depend on the accuracy with which the database is defined and it can be optimized. The group of selected eigenvectors are called the eigenfaces. Once the eigenfaces have been obtained, the images in the database are projected into the eigenface space and the weights of the image in that space are stored. To determine the identity of an image, the eigencoefficients are compared with the eigencoefficients in the database.

The eigenface of the image in question is formed.

The Euclidian distances between the eigenface of the image and the eigenfaces stored previously are calculated.

The person in question is identified as the one whose Euclidian distance is minimum below a threshold value in the eigenface database. If all the calculated Euclidian distances are larger than the threshold, then the image is unrecognizable.

The reasons for selecting the eigenfaces method for face recognition are:

- Its independence from the facial geometry,
- The simplicity of realization,
- Possibility of real-time realization even without special hardware,
- The ease and speed of recognition with respect to the other methods,
- The higher success rate in comparison to other methods.

The challenge of the eigenfaces face recognition method is the computation time. If the database is large, it may take a while to retrieve the identity of the person under question.

3. Simulation Results with Eigenfaces Method

The database used in this work consists of 20 images of 152 people. A total of 3040 images are used [13]. The average face is calculated using the training set. In Fig 2 some images of the training set are shown.

Fig. 2. Samples from the training set

In Fig. 3, images belonging to the same person are shown. Twenty pictures with various facial expressions, distances and lighting conditions are taken. The program processes all of them to recognize the person.

Fig. 3. Sample for the twenty images of one person

The average face is calculated according to (1), and the result for the database used is shown in Fig. 4.

Fig. 4. Average face

Ten eigenfaces with the highest eigenvalues are calculated using the training set. They are called the ghost faces. Those are shown in Fig. 5. For some databases, the ghost faces turn out to be sharper. For some others, they are blurred, like the ones in this case. The sharpness depends on the backgrounds and the other details of the images. Here the images are very detailed and the background, the facial expressions, and the lighting conditions are quite varying. Thus the sharpness is sacrificed.

Fig. 5. Ghost faces

Each face can be represented as a linear combination of the eigenfaces. Each face can also be estimated using the 'best' eigenfaces, which have the largest eigenvalues and represent the largest variations in the face image database. The images of each person are stored in individual folders. If a person is selected as the input to run the program, then the folder belonging to that person is selected.

Some simulation results are shown in Fig.s 6 and 7. In Fig 6, the input has the challenge in the form of beard. Yet the result is found correctly. The calculations are summarized in the chart (Fig. 6a), where the person in question is found to match the image number 272. In the chart, the y axis shows the calculated Euclidian distance, and the x axis shows the image number in the database. The image number is identified as the plus sign at the minimum Euclidian distance.

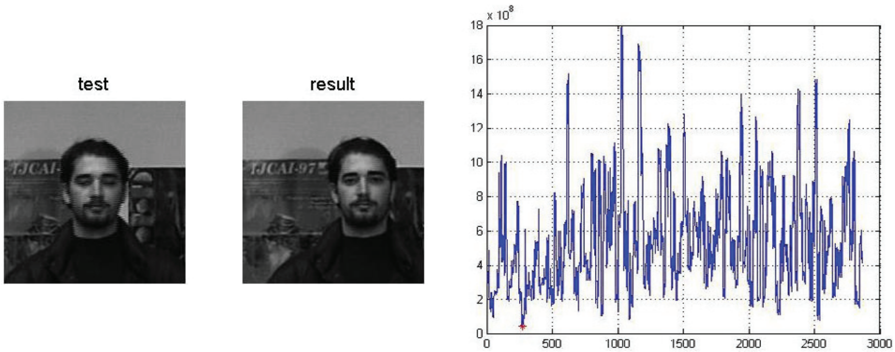

Fig. 6. (a) the image output of the program for the first sample; (b) recognition chart for the first sample

In Fig 7, the input has the challenge in the form of eye-glasses. Yet the result is found correctly. The calculations are summarized in the chart (Fig. 7a), where the person in question is found to match the image number 195.

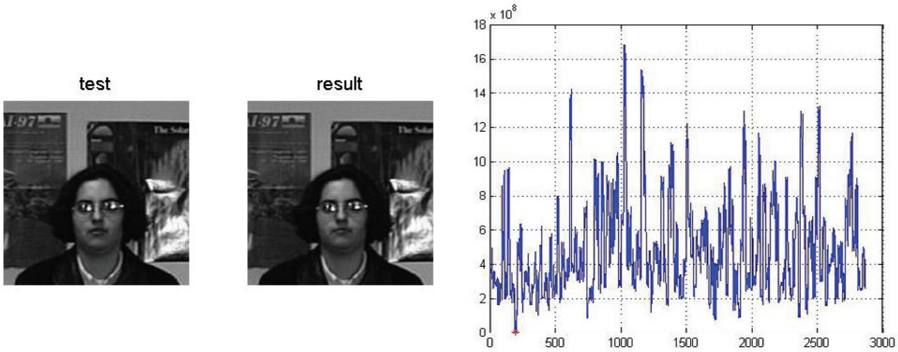

Fig. 7. (a) the image output of the program for the second sample; (b) recognition chart for the second sample

4. Conclusion

The Eigenfaces method is applied to a very large database consisting of 3040 images. The challenging details, such as background, eye-glasses, beard, mustache are dealt with. Simulation results show that sometimes failure occurs. The success rate is calculated as 94.74%. To increase the success rate, the eigenfaces method can be fortified with the use of additional information, such as the face triangle. The future work will focus on increasing success rate for very large databases.

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