ISTANBUL UNIVERSITY –
JOURNAL OF ELECTRICAL & ELECTRONICS ENGINEERING

YEAR : 2009 (997-1001)
VOLUME : 9
NUMBER : 2

# FACE RECOGNITION AND RECONSTRUCTION USING EIGENFACES

Ganim ALTIOK, Oğuzhan ÖZTAŞ

Istanbul University Engineering Faculty, Computer Engineering Dept., Turkey

ganim@altiok.net, oguzhan@istanbul.edu.tr

## *ABSTRACT*

*In this paper, PCA based face recognition system and reconstruction of faces from principle components of faces are represented. Principle component analysis used for construction of eigenfaces of given training set images. Using the eigenface method, expression of each face's data reduced to a very small integer array. Euclidian distance was used for classification of test images. Reconstruction process simply implied as reversing the eigenface procedure.*

***Keywords:*** *Face Recognition, Face Reconstruction, Eigenface*

## 1.INTRODUCTION

Some governments started to use computer based face recognition systems for tracing criminals and passport checkouts. For security issues face recognition systems expected to maintain flawless process. But there isn't any known face recognition end product that proves to works with 100% correctness. So the human factor should be always in the process of face recognition. For this reason reconstructing of a face image from its principle components takes importance.

There are several approaches for computer based face recognition problem. Eigenface approach extracts principle components of set of face images using statistical methods. Every image can be represented by a simple array of numbers by this method. This allows saving space for keeping face database and also fastens up the classifying process. In this paper we will see how reduced data will shape when reconstructed.

## 2.CALCULATING EIGENFACES

The principle component analysis method, also called Eigenface is the most common algorithm in face recognition solutions. Eigenface method extracts statistical data from all given train images instead of extracting facial features, like nose, mouth or eyes. Eigenface method starts with calculating the average face of entire training image set.

As the FERET database every image has size of 128 by142 becomes a vector of 18,176 dimensions. While there are 5 image samples for every person in FERET database, we use 4 of them as training set images and 1 is for test images. **Lets say I(x,y)** is a two dimensinioal image vector. And **Γ1, Γ2, …, ΓM** represents training set of images. As we have 4 image for each person and we train 10 persons images, we train 40 images.

Here we calculate the average face image:

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i \qquad (1)$$

*Received Date*: 05.09.2008

*Accepted Date: 05.11.2009*

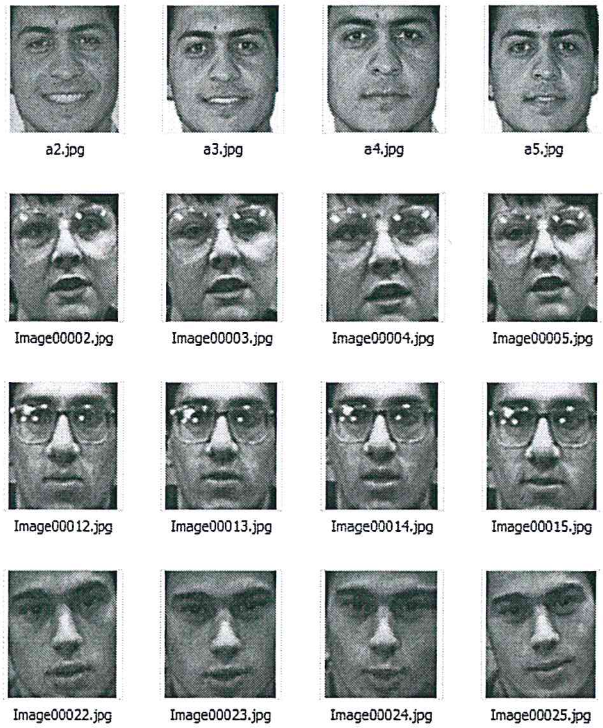


**Figure 1 Sample training set images**

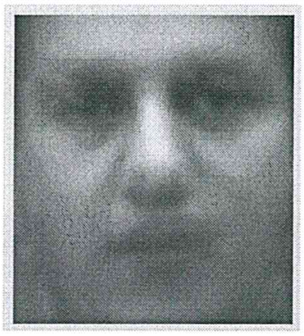

**Figure 2 The average image**

Each image differs from average image and that represents the difference faces. We use difference image vectors so that we reduce the weight of the data while calculating eigenvalues and gather data that each represents only the differences of images. Here we calculate the average image:

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

We calculated each difference image vector and we get a vector $A=[\Phi_1, \Phi_2,...,\Phi_M]$ sized 18276 by 40. As the PCA algorithm we should get the covariance of the $A$ matrix to extract the rise out differences.

$$C = \frac{1}{M}\sum_{i=1}^{M} \Phi_i \Phi_i^T \quad (3)$$

$$= AA^T$$

We get a matrix 18276 by 18276 and with this sized matrix we will have 18276 eigenvalues and eigenvectors of only 40 images, which is not feasible at all. If the number of pixels for an image is greater than number of images then eigenvectors as much as number of images will be enough. In this case considering $A^TA$ rater than $AA^T$ will be more judicious.

$$A^T A v_i = \mu_i v_i \quad (4)$$

Premultiplying both sides with $A$, we have

$$AA^T A v_i = \mu_i A v_i \qquad (5)$$

As we can see $Av_i$ is the eigenvector of the covariance matrix of **C**.

With this analysis we get a M by M **L=A$^T$A** matrix. L will have M eigenvectors. These eigenvectors attracts linear combinations of M training set images and also used by the formula $u_l$ creating the eigenfaces.

$$u_l = \sum_{k=1}^{M} v_{lk} \Phi_k \,, \qquad l = 1..M \qquad (6)$$

As you can see in Figure.3 eigenface 1 has the highest and distinctive value and the images becomes darker and not figures any clear feature of face in eigenface 6 and so.

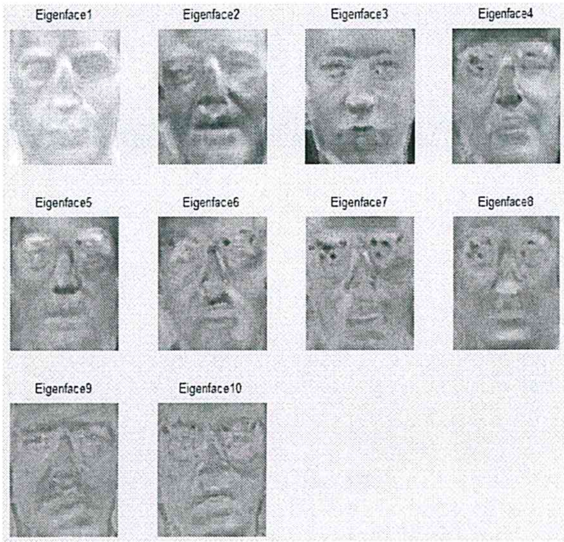


**Figure 3 Top 10 eigenfaces**

## 3.CLASSIFY A FACE IMAGE USING EIGENFACES

Given new test image **Γ** is implied to formula (7) and image's eigenface components will be extracted (projected into 'face space').

$$w_k = u_k^T(\Gamma - \Psi) \,, \quad k = 1,2,\dots,N \qquad (7)$$

This **$\Omega^T$=(w1,w2,...,wN)** weight vector represents the weights between given test image and eigenfaces. We can use this weight vector for which image describes this image the most from the training set images. The simplest way to find which face class describes the input $\Omega_k$ class the most is Euclidian Distance method.

$$\varepsilon_k = \|\Omega - \Omega_k\| \qquad (8)$$

The value ε describes the distances between given test image and training images. Selecting the minimum valued distance would give the correct face space. While we can determine a threshold Θ to not accept values bigger than the chosen value.

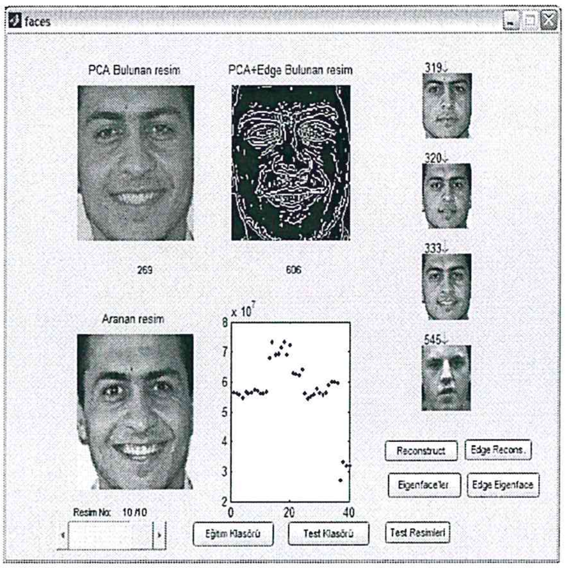


**Figure 4 Classifying**

As you can see in Figure 4, we implied Eigenface algorithm with grayscale images and also edged images of in the same time. In the screenshot bottom left image represents the test image, the slider under image changes the test image and also runs the algorithm again. The up left image is the image corresponds to found minimum value Euclidian distance of eigenface and near of it is the edged found image. Right four images represents next minimum valued images. And the middle graphic points every training image in scalar. As you can see there are four points, which have minimum values of the same person.

## 4.RECONSTRUCTION OF FACES

While creating eigenfaces we reduced the data of covariance matrix eigenvectors. This means eigenfaces contains less information then real image. To see what is it look like and to see if reconstructed face will be recognizable by human we implied the formula 9.

$$X = \left(V * u^T\right) + \Psi \quad (9)$$

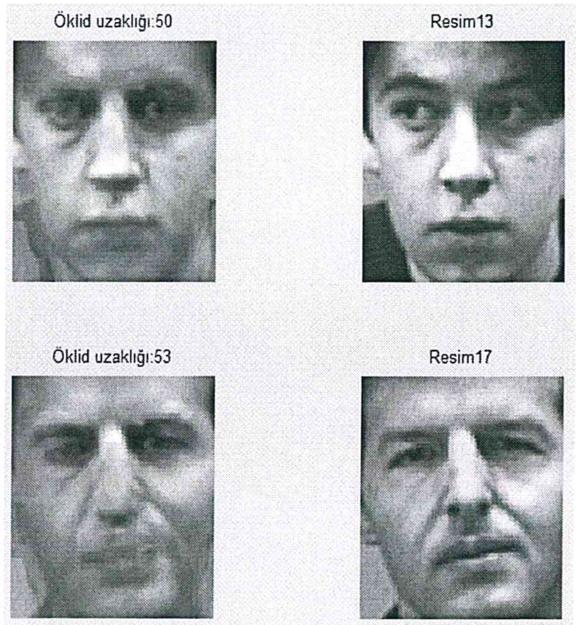


**Figure 5 Original (right) and Reconstructed (left) images**

Left images are reconstructed images and right ones are originals. We can see that reconstructed images are deformed. But still we can recognize the person. This allows us for human attraction and if the found face space corresponds the same person.

## 5.CONCLUSION

We implied very basic PCA algorithm and made classification simply with Euclidian distance method. This way we get %~60 accurate result. If the training set images preprocessed like normalizing, classifying result would be more accurate. Also getting average image of each person's separately and giving the training set as the average images would increase the result either.

Representing each image with 10 elements integer array respectably reduces image information. While loosing remarkable image information we can still classify faces with computer also by reconstruction and human interaction. This allows us to store less data for each person and keep data for more people with same storage. Reconstruction process lets human approval for classifying.

## REFERENCES

[1] Matthew Turk and Alex Petland, *Eigenfaces for Recognition*, 1991

[2] Hyonjoon Moon, P. Jonathon Phillips, *Computational and performance aspects of PCA-based face-recognition algorithms*, 2000

[3] Javier Ruiz-del-Solar, *Eigenspace-Based Face Recognition: A Comparative Study of Different Approaches*, 2005

[4] Young-Gil Kim, Young-Jun Song, Un-Dong Chang, Dong-Woo Kim, Tae-Sung Yun, Jae-Hyeong Ahna, *Face recognition using a fusion method based on bidirectional 2DPCA*, 2008

[5] R. Jenkins* and A. M. Burton, *100% Accuracy in Automatic Face Recognition,* 2008

[6] Kevin W. Bowyer, *Face Recognition Technology: Security versus Privacy*, 2004

**Ganim Altıok** was born in Sarıyer Istanbul in 1984, completed elementary school in Adana and completed Anatolian Technical High School in Istanbul Macka Akif Tuncel Lycee. Graduadet in first degree from Cukurova University Computer Programming Vocational High School. Now graduated from Istanbul University Computer Engineering and working in a company.

**Oguzhan OZTAS** was born in Izmir, Turkey, 1966. He received B.Sc. Degree in Mathematical Engineering from the Faculty of Science and Letters, Istanbul Technical University, Turkey in 1989. He received M.Sc. Degree in System Analysis, from the Institute of Science and Technology of the same University in 1992. He received Ph.D. Degree in Computer Engineering, from the Institute of Science and Technology, Istanbul University in 2001. He has been teaching computer science courses in the Computer Engineering Department of Istanbul University. His research interests include computer graphics, fuzzy systems, multimedia and database systems. He is married and has one son.