Effect of Eigenfaces Level On The Face Recognition Rate Using Principal Component Analysis

Dr. Eyad. I. Abbas
Electrical Engineering Department, University of Technology/Baghdad.
Email: eyad_electdep@yahoo.com

Received on:11/2/2014 & Accepted on:2/4/2015

ABSTRACT

This paper presents an approach to study the effect of the different eigenfaces levels on the faces recognition rate using principal component analysis. The increase in the strength of the variables and the lighting in the facial geometry to represent the human face , has been using the principal component analysis (PCA) on the image of the whole face . The principal component analysis is a statistical measurement method , which works in the field of linear and can be used to reduce the dimensions of the image and thus serve to reduce the calculations significantly to the image database . It is a method gives better accuracy and a higher rate of recognition . The experiment was conducted on 50 images from the database of faces (ORL), using 40 images for the training set and 15 images for the test group (five images in common with the training set and the remaining 10 images are different in expression and corner) . The results proved that the proposed method is effective and successful in obtaining recognition rate up to 100% in the third level when using ten eigenfaces.

Keywords: Face recognition, PCA, Eigenfaces

تأثير مستويات الايكنفيس على معدل تمييز الوجوه باستخدام تحليل المكون الاساسي

الخلاصة

يقدم هذه البحث مدخلا لدراسة تأثير مستويات مختلفة من الايكنفيسس على معدل تمييز الوجوه. ان زيادة متانة المتغيرات والاضائة في هندسة الوجه لتمثيل الوجه الإنساني ، تم باستخدام تحليل المكون الاساسي (PCA)على صورة الوجه كله . ان تحليل المكون الاساسي هو أسلوب للقياس الإحصائي ، والذي يعمل في مجال الخطية ، والذي يمكن استخدامه لتقليل من أبعاد الصورة وبالتالي يعمل على تقليل العمليات الحسابية بشكل ملحوظ لقاعدة بيانات الصور. وهذه الطريقة تعطي دقة أفضل ومعدل التمييز اعلى . تم إجراء التجربة على 50 صورة من قاعدة البيانات للوجوه (ORL) ، وذلك باستخدام 40 صور لمجموعة التدريب و 15 صورة لمجموعة الاختبار (خمس صور مشتركة مع مجموعة التدريب و 10 صور المتبقية هي مختلفة في التعبير والزاوية) . اثبتت النتائج أن الطريقة المقترحة هي فعالة وناجحة في الحصول على معدل للتمييز تصل الى نسبة 100٪ في المستوى الثالث عند استخدام عشرة من الايكنفيسس.

INTRODUCTION

Human Face is a complex multidimensional structure and needs good computing techniques for recognition. It plays an important role in biometrics base personal identification. The need for reliable recognition and identification of interacting users is obvious. The biometrics recognition technique acts as an efficient method and wide applications in the area of information retrieval, automatic banking, and control of access to security areas and so on. This paper was introducing the definition of principal component analysis (PCA) and how can be used in pattern recognition. PCA is a classical feature extraction and data representation technique widely used in pattern recognition and computer vision [1]. Sirovich and Kirby first used PCA to efficiently represent pictures of human faces [2]. They argued that any face image could be reconstructed approximately as a weighted sum of a small collection of images that define a facial basis (eigenimages) and a mean image of the face. Since eigenpictures are fairly good at representing face images, one could consider using the projections along them as classification features for recognizing human faces. Within this context, Turk and Pentland presented the well-known eigenfaces method for face recognition in 1991 [3]. They developed the well-known face recognition method, where the eigenfaces correspond to the eigenvectors associated with the dominant eigenvalues of the face covariance matrix. The eigenfaces define a feature space, or "face space," which drastically reduces the dimensionality of the original space, and face detection and identification are carried out in the reduced space [4]. Principal Component Analysis (PCA) has been widely adapted as the most promising face recognition algorithm. Yet still, PCA has its limitations: poor discriminatory power and large computational load.

Principal Component Analysis

Principal component analysis transforms a set of data obtained from possibly correlated variables into a set of values of uncorrelated variables called principal components [5]. It is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the luxury of the graphical representation is not available, PCA is a powerful tool for analyzing data.

The other main advantage of PCA is that once you have found these patterns in the data, and you compress the data, i.e. reducing the number of dimensions without much loss of information.

Here are five steps to get the PCA for a given data [6]

§ **Step-1 Prepare the given data**

The data is an image which is represented by 2D-matrix.

§ **Step-2 Subtract the mean**

For PCA to work properly, It has to subtract the mean from each of the data dimensions. The mean subtracted is the average across each dimension. The mean of each column is computed as:

$$\overline{X} = \frac{\sum_{i=1}^{n} X_i}{n} \qquad \dots(1)$$

§ **Step-3 Calculate the covariance matrix**

Covariance can be calculated as:

$$\mathrm{cov}(X,Y) = \frac{\sum_{i=1}^{n}(Xi-\overline{X})(Yi-\overline{Y})}{n-1} \qquad \dots(2)$$

§ Step-4 Calculate the eigenvalues and the eigenvectors of the covariance matrix

To calculate the eigenvalues and eigenvectors of a matrix (A) , using the following condition

$$\det|A - \lambda I| = 0 \qquad \ldots(3)$$

Where A is the matrix, λ is the eigenvalue, and I an identity matrix. Now, by solving this equation will produce the eigenvalues and eigenvectors.

§ Step-5 Choose components and form a feature vector

Here is where the notion of data compression and reduced dimensionality comes in. In fact, the eigenvector with the highest eigenvalue is the principal component of the data set. In general, once eigenvectors are found from the covariance matrix, the next step is to order them by eigenvalues, highest to lowest. This gives the components in order of significance. Now, the decision will be taken to ignore the number of components values for less significance. In this case, it will lose some information. However, anywise the leave out some components make the final data set will have fewer dimensions than the original. To be precise, if you originally have n dimensions in your data, and you calculate n eigenvectors and eigenvalues and then choose only the first p eigenvectors which are less than n dimensions, then the final data set has only p dimensions.

Face Recognition

The eigenfaces (EF) method is perhaps the most common method based on a holistic approach for face recognition. It employs PCA, in order to analyze the distribution of the points in the image space, and to express their variation in a number of principal components [7]. The main idea is to decompose face images into a set of eigenfaces (a small set of characteristic feature images), which are the principal components of the original images. These eigenfaces function as the orthogonal basis vectors of linear subspace called face space. The face recognition strategy involves projecting a new face image into the face space and then comparing its position in the face space with those of known faces [8]. The basic steps involved in face recognition using eigenfaces approach are as follows[5]:

Ø Training Set of Images

Let the training set consists of M images representing M image classes. These images are taken from ORL database. Let these images be $\Gamma_1,\Gamma_2,\ldots\Gamma_M$. The average face ($\psi$) of the set is obtained from eq (1) by rewriting it as below

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma i \qquad i=1,2,\ldots\ldots,M \qquad \ldots(4)$$

Each face image differs from the average face of the distribution, and this distance is calculated by subtracting the average face from each face image. This gives us new image space (Φ_i).

$$\Phi i = \Gamma i - \Psi \qquad \ldots(5)$$

Ø Formation of Covariance Matrix

From this new image space of Φ_i images (Each with dimension N x 1), the matrix A is formed with dimension N x M by taking each of image vectors Φ_i and placing them in each column of matrix A.

$$A = [\Phi_1 \;\; \Phi_2 \qquad \Phi_M] \qquad \ldots(6)$$

Using matrix A, it is important to set up the Covariance matrix C. This can be given by the product of matrix A with matrix A^T. The dimension of such covariance matrix will be N x N

$$C = \frac{1}{M}\sum_{i=1}^{M} \Phi i \; \Phi i^T = AA^T \qquad \ldots(7)$$

Ø Calculation of Eigenvalues (Ev) and Eigenvectors

The matrix C has an order of N, and, therefore can have N eigenvectors. In practice, we have to calculate a very large number of big dimension eigenvectors, which is an intractable problem. For example, if we consider images of size 100x100 we have to calculate 10,000 eigenvectors. It was proved in that there are only M-1 non-zero eigenvalues of an MxM matrix, where M is the number of the faces in the image space, and, in general, the size of the training set is significantly smaller than N.
Let us consider the eigenvectors v_i of matrix $D=A^TA$ so that

$$A^TAv_i=\mu_iA_i \qquad \ldots(8)$$

multiply both sides at left by matrix A, give us:

$$AA^TAv_i=A\mu_iA_i \leftrightarrow (AA^T)Av_i=\mu_i(Av) \qquad \ldots(9)$$

From this; it is observed that Av_i are in fact the eigenvectors of matrix C of eq (7) because μ_i are scalars.
let show that, first it can calculate M number of eigenvectors of matrix $D=A^TA$ and then get the eigenvectors u_i of the covariance matrix C by a linear combination of the eigenvectors v_i:

$$u=Av \leftrightarrow u_i=Av_i \;,\; i=1,..,M \qquad \ldots(10)$$

The eigenvectors of a large matrix C are equal to the eigenvectors of a smaller matrix D, pre-multiplied by A. By this observation, the complexity of the algorithm reduces significantly, from calculating M eigenvectors instead of N.
This is reducing the dimensionality of the image space from N to M; in other words, from the number of pixels in the image to the number of eigenfaces. The M eigenvectors u_i are column vectors of dimension N.

Ø Projecting Face Images

All the images from the training set are projected to this eigenspace. These can be represented by linear combination of the eigenfaces, which have a new descriptor as a point in a great dimensional space. This projection is constructed in the following way

$$W_i=u_i(\Gamma_i-\Psi) \qquad \ldots(11)$$

As the projection on the eigenfaces space describes the variation of face distribution, it is possible to use these new face descriptors to classify them [5].

Reconstruction of the training set can be obtained by using the following formula:

$$\Gamma_i^T=\Psi+uW\leftrightarrow\Gamma_i^T=\Psi+\sum_{i=1}^{M'} u_i W_i \qquad \text{….(12)}$$

The procedure is similar for any test image to be recognized. first reshape the image as a column vector, denoted by Γ_T and extract the mean image of the training set(Ψ).

$$Y_T=\Gamma_T-\Psi \qquad \text{…(13)}$$

And project Y_T on the face space by..

$$W_T=u^T Y_T \qquad \text{…(14)}$$

And it can be reconstructed by:

$$\Gamma_T^R=\Psi+uW_T\leftrightarrow\Gamma_T^R=\Psi+\sum_{i=1}^{M'} u_i\, W_i^T \qquad \text{…(15)}$$

Where

W_T^i is the projections of the test image Γ_T in the face space [8].

Ø Matching

For recognition, the similarity measurement will be used, the similarity measurement between the test images and the training set in the database to determine whether the test image matches any image in the training set. The process of classification of a test image to one of the classes training images proceeds in two steps.

First, the new image is transformed into its eigenface components. The resulting weights form the weight vector Ω_{test}^T

$$w_k = u^T(\Gamma_{test}-\psi) \qquad k = 1 \ldots\ldots\ldots M' \qquad \text{…(16)}$$

$$\Omega_{test}^T = [w_1\ \ w_2 \ldots\ldots\ldots w_{M'}] \qquad \text{…(17)}$$

Second, the Euclidean distance between two weight vectors $d(\Omega_{Test},\Omega_i)$ provides a measure of similarity between the corresponding test image (Γ_{test}) and Training images(Γ_i). If the Euclidean distance between Γtest and other faces exceeds - on average - some threshold value θ, one can assume that Γtest is no face at all. $d(\Omega_{Test},\Omega_i)$ also allows one to construct"clusters" of faces such that similar faces are assigned to one cluster. The equation of the Euclidean distance is[6]:

$$d = \sqrt[2]{\|\Omega_{test}-\Omega_i\|} \qquad \text{…(18)}$$

The flowchart for this proposed algorithm was shown in Figure (1).

Face Database

The Olivetti and Oracle Research Laboratory (ORL) face database is used in order to test our propose method in the presence of head pose variations. There are ten different images of each of 40 distinct subjects. For some subjects, the images were taken at different times, varying lighting, facial expressions (open / closed eyes, smiling / not smiling), facial details (glasses / no glasses) and head pose (tilting and rotation up to 20 degrees). All the images were taken against a dark homogeneous background. There are a set of 40 individuals 10 images per person from the ORL database. The images are grey scale with a resolution of 112×92[9].

Experimental Results

The experiment was done on the 50 images are selected from ORL dataset as shown in the
Figure (2) in order to determine the performance and accuracy for different eigenfaces levels of the system. There are two groups: the first is the training set consists of 40 faces (the first eight images from each row) done to obtain eigenfaces of the database images and second is testing group, which consists of 15 images (the last 3 images from each row) done to test images of different orientations whether it match with the database images. Figure(3) shows all 40 descending sorted eigenvalues, that are coming from training images. Each eigenvalue corresponds to a single eigenvector and determins how much images from training bases vary from the mean image in that direction. There are about 10 of vectors have significant eigenvalues, while the remaining vectors are approximately equal to zero and do not carry important information about the image. Figure(4) shows all 40 eigenfaces that are ranked according to descending sorted eigenvalues. The eigenvectors corresponding to the covariance matrix define the eigenface which has a ghostly face like appearance and a match is found if the new face is close to these images. The results of three level of eigenfaces are doing according to the significant eigenvalues as shown in the Table(1). The first level is one eigenface (the first eigenface in the corner of left top in Figure (4)) which gives recognition rate equal to 66.66% corresponding to the testing images. The second level is eight eigenfaces (the first row from eigenfaces in Figure (4)) which gives recognition rate equal to 86.66% corresponding to the testing images. While the third level is the most signification 10 eigenfaces in the Figure(4) which gives recognition rate equal to 100% corresponding to the testing images. The reasoning of these results is with the increase of the eigenfaces will lead to increase in the features of training images that is used in eigenfaces, therefore the increasing will be obtained in the recognition rate. Also in the third level of eigenfaces in spite of testing images include of ten images (the last two images from each row shown in Figure(2))) has different facial expression and orientation, the recognition rate reach 100%.

Conclusions

The recognition rates, with different number of eigenfaces and PCA system, are implemented. The algorithm successfully recognized the human faces and worked better in different conditions of face orientation. Its seem from the results with increasing the number of eigenfaces led to increasing the recognition rate, and reached up to 100% at the third level of eigenfaces which represents a quarter from the total eigenfaces.

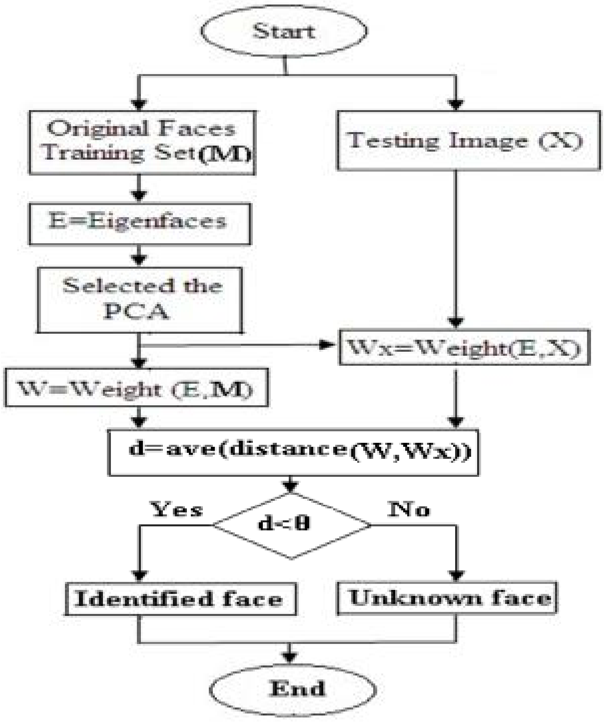
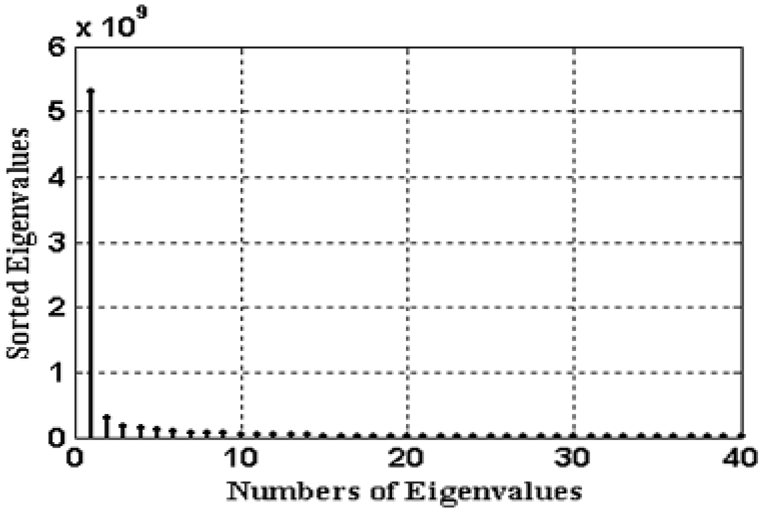
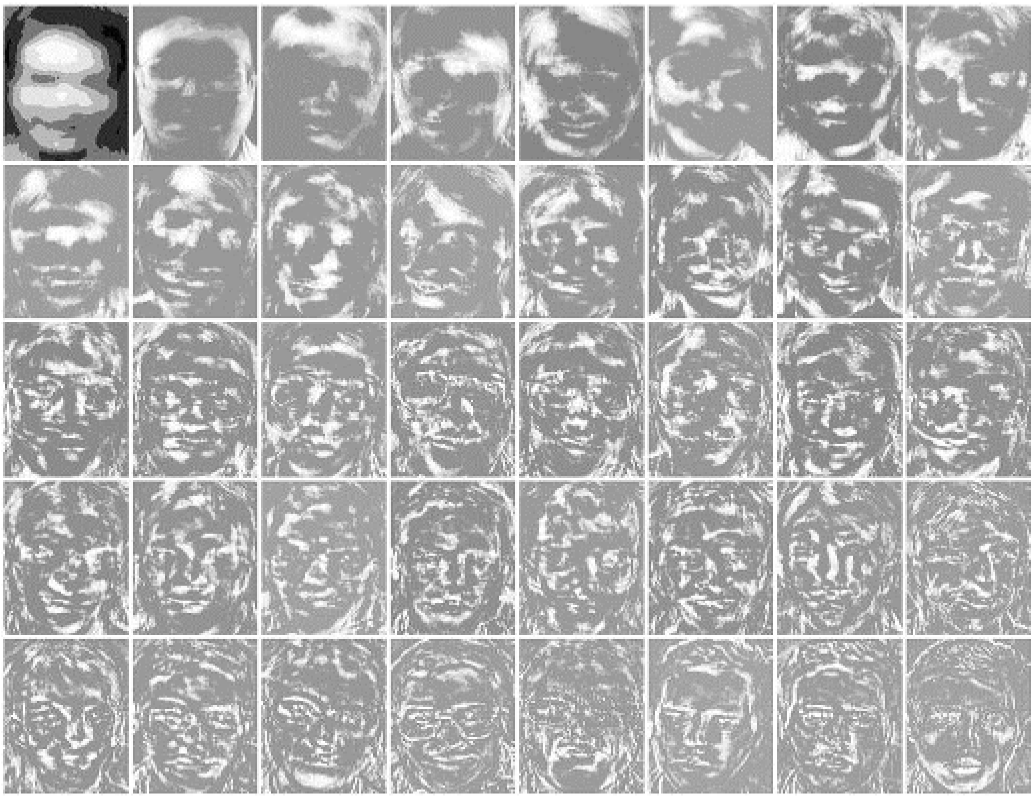


Figure (1) Flowchart for proposed algorithm

Figure (2) The AT&T Lab of Cambridge University ORL database



Figure(3) The eigenvalues



Figure(4) Eigenface ranked according to descending sorted eigenvalues

Table(1) The recognition rate for different eigenfaces level

Number of EF / Iimages test	1	8	10
	Matching	Matching	Matching
Image 1-8	Yes	Yes	Yes
Image 1-9	Yes	Yes	Yes
Image 1-10	Yes	Yes	Yes
Image 2-8	Yes	Yes	Yes
Image 2-9	No	Yes	Yes
Image 2-10	No	Yes	Yes
Image 3-8	Yes	Yes	Yes
Image 3-9	Yes	Yes	Yes
Image 3-10	Yes	Yes	Yes
Image 4-8	No	Yes	Yes
Image 4-9	No	No	Yes
Image 4-10	Yes	Yes	Yes
Image 5-8	Yes	Yes	Yes
Image 5-9	Yes	Yes	Yes
Image 5-10	No	No	Yes
Recognition Rate	66.66%	86.66%	100%

References

[1]. R. Kumar, and S. Singh," Face Recognition using Principle Component Analysis for Biometric Security System", International Journal of Engineering Trends and Technology (IJETT) , Volume 4, Issue 9, Sep 2013.

[2]. M. Kirby, and L. Sirovich, "Application of the KL Procedure for the characterization of human faces.", IEEE Transactions on Pattern Analysis and Machine Intelligent, Vol.12,No.1, pp 103-108,1990.

[3]. M.Turk,and A.Pentland, "Eigenfaces for recognition", Journal of Cognitive Neuroscience,Vol.3,No.1,pp 71-86,1991.

[4]. J. Zhang, "Face recognition: Eigenface, elastic matching, and neural nets." Proceedings of the IEEE, Vol. 85, No.9, 1997.

[5]. M. Slavković1, and D. Jevtić1," Face Recognition Using Eigenface Approach", Serbian journal of electrical engineering, Vol. 9, No. 1, February 2012.

[6]. D.Zang, X.Jing, and J.Yang, "Biometric Image Discrimination Techniques", Idea Group Inc. 2006.

[7]. A. Mihaila, "Person Identification from Video using Facial and Speaker Features", M.Sc thesis, Department of Computer Science, University of Joensuu, 2005.

[8]. T.Acharya, and A. K. Ray, "Image Processing Principles and Application", John Wiley & Sons, Inc., 2005.

[9]. AT&T Laboratories, Cambridge, U.K., "The ORL Face Database", Available at : http:// www.orl.co.uk/facedatabase.html.