

Human Face Recognition based on Principal Component Analysis and EigenFaces

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Abstract – Recognizing different faces at different times is challenging subject but at the same time it gives rewarding in various areas in society. The police force in solving crime, academic institutes to know students available for lectures, monitoring the in and out movement of people and many more. This paper presents a methodology for face recognition based on Principal component analysis (PCA) techniques. The study aims to implement a model for a particular face and distinguish it from a large number of stored faces. Euclidian distance was used for classification of test images. Reconstruction process simply implied as reversing the eigenface procedure. The proposed method was tested on Olivetti and Oracle Research Laboratory (ORL) face database. Some of such studies gave a result of recognition rate of 96%. There are more others ways of studies that carried out for such study.

Index Terms—**face recognition, Principal component analysis, eigenface, classification.**

I. INTRODUCTION

The face is our primary focus of attention in social intercourse, playing a major role in conveying identity and emotion. Although the ability to infer intelligence or character from facial appearance is suspect, the human ability to recognize faces is remarkable [1].

Face recognition has become an important issue in many applications such as security systems, credit card verification, and criminal identification. A facial recognition system is the application of the computer to automatically identify or verify any person from a digital image or video frame from the video source. One of the ways to achieve this is by comparing selected facial features from images, and a database in the face. The general statement can be formulated to address the problem of recognition (computer vision) as follows: Given a fixed or videotape the scene, identify or verify one or more persons at the scene using a database of faces stored [1].

Face recognition is one of the main fields among other biometric technologies, Biometric technologies include: Face Recognition, Finger Print Identification, Hand Geometry Identification, Iris Identification, Voice Recognition, Signature Recognition, Retina Identification, and DNA Sequence Matching [2].

Face recognition has a wide range of applications. They are mostly used in biometrics, for reliable personal identification. Application of face recognition can be classified into two main types which are: First, finding a face within a large database of faces. In this approach the system returns a possible list of faces from the database. Often only one image is available per person. Secondly, real time face recognition, where face recognition can be used to identify people, and grant access to a building or to identify a person. In this case the face is compared against a multiple training samples of a person. The data used plays a very important role in face recognition [3].

Several research studies in Face recognition system mainly considered the face alignments techniques like Active Appearances Model (AAM) [1] and Active Shape Model (ASM) [1]. Some other face recognition techniques accomplish the face recognition process by using PCA. Several systems were developed for face recognition by exploiting aforementioned techniques.

Most face recognition algorithms fall into one of two main groups: (a) feature-based and (b) image-based algorithms. Feature-based methods explore a set of geometric features, such as the distance between the eyes or the size of the eyes, and use these measures to represent the given face. These features are computed using simple correlation filters with expected templates. These methods are somewhat invariant to changes in illumination and can partially compensate for changes in camera location. However, they are sensitive to aging and facial expressions [4].

On the other hand, Image-based systems are based on ideas like eigenfaces. After a large training set of images has been collected, Principal component analysis is used to compute eigenfaces. Each new face is then characterized by its projection onto this space of Principal eigenfaces. This approach is extremely sensitive to small variations, both external and internal, though it is still one of the most popular methods in industry [5-6].

The study plan is based on information theory, which gives the approach to decompose the images in the face of a small set of characteristic feature images called 'eigenfaces', which are in fact the Principal components in the initial training set of images of the face. This performed to identify by projecting a new image in the space of a partial spread of eigenfaces ('face space') and

then classified by comparing the face and put it in the face of space with the positions of known individuals. The eigenfaces have advantages over other techniques available, on the system's speed and efficiency [5]. Process which uses eigenfaces is very fast, and able to functionally operate on lots of faces in very little time, ease of implementation, no knowledge of geometry or specific feature of the face required, little pre-processing work. It has been noted that the face recognition using eigenfaces has been shown to be quite accurate .

The objective of this study is to implement, test performance of the Eigenfaces using PCA to develop a computer program capable of face recognition. Specifically, the goal of our project was to investigate a mathematical basis and model for face recognition using Principal component analysis with eigenvectors.

II. HISTORICAL BACKGROUND

In this section, a brief presentation is highlighted on Eigenfaces approach and its properties. In the second part of this section, PCA is presented to be used as main used tool in this study.

A. Eigenfaces approach to facial recognition

In this study principal component analysis method was used as Eigenfaces approach, involving the use of a small group of iconic images to describe the difference between the images of the face.

Eigenfaces is a term known features of a large or principal component of human faces. It is represented as a feature or component eigenvector. These eigenvectors do not correspond to physical entities in the face of (for example, eye, nose, mouth, etc.).

The aim is to find out eigenvectors (eigenfaces) of the covariance matrix distribution, which ran for the training set of images of the face .

Later, the representation of each face image by a linear combination of these eigenvectors. Most of the research is related with Eigenfaces constitute one and rotate images around the center of the image. There is a need to a group of different images from different angles or emotions from the same person to estimate the actual face. The image of a sample more than one person, and will find the best accuracy for the recognition of that person.

Eigenfaces approach for face recognition involves the following operations [5]:

➤ **Initialization:**

- Acquire a set of training images.
- Calculate the eigenfaces from the training set, keeping only the best M images with the highest eigenvalues. These M images define the "face space". As new faces are experienced, the eigenfaces can be updated.
- Calculate the corresponding distribution in M-dimensional weight space for each known individual (training image), by projecting their face images onto the face space.

➤ **Recognizing New Face Images**

Having initialized the system, the following steps are used to recognize new face images:

- Given an image to be recognized, calculate a set of weights of the M eigenfaces by projecting it onto each of the eigenfaces.
- Determine if the image is a face at all by checking to see if the image is sufficiently close to the face space.
- If it is a face, classify the weight pattern as either a known person or as unknown.
- (Optional) Update the eigenfaces and/or weight patterns.

B. The Principal Component Analysis (PCA)

(PCA) is a way of identifying patterns in data, is one of the most successful techniques that have been used in image recognition and compression and expressing the data in such a way as to highlight their similarities and differences[7].

Principal component analysis (PCA) is a technique used to reduce multidimensional data sets to lower dimensions for analysis depending on the field of application. The jobs which PCA can do are prediction, redundancy removal, feature extraction, data compression, etc. Because PCA is a classical technique which can do something in the linear domain, applications having linear models are suitable, such as signal processing, image processing, system and control theory, communications, etc [8].

PCA is mostly used as a tool in exploratory data analysis and for making predictive models. PCA involves the calculation of the eigenvalue decomposition of a data covariance matrix or singular value decomposition of a data matrix, usually after mean centering the data for each attribute. The results of a PCA are usually discussed in terms of component scores and loadings [8].

PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. PCA is theoretically the optimum transform for a given data in least square terms [9].

PCA can be used for dimensionality reduction in a data set by retaining those characteristics of the data set that contribute most to its variance, by keeping lower-order principal components and ignoring higher-order ones. Such low-order components often contain the "most important" aspects of the data. However, depending on the application this may not always be the case. The other main advantage of PCA is that once you have found these patterns in the data ie, by reducing the number of dimensions, without much loss of information. PCA is a powerful tool for analyzing data [9].

PCA is a method in which is used to simplify the problem of choosing the representation of eigenvalues and corresponding eigenvectors to get a consistent representation. This can be achieved by diminishing the

dimension space of the representation. In order to obtain fast and robust object recognition, the dimension space needs to be reduced. Moreover, PCA also retains the original information of the data. Eigenface based algorithm applies the PCA basis.

This next session of the chapter describe the steps you needed to perform a Principal Components Analysis on a set of data.

- Mathematics of PCA [10]

Step 1: Get some data:

In this step, the faces will be taken through a training set (Γ^i) to used for preparing for processing. Let the training set of face images be $\Gamma_1, \Gamma_2, \Gamma_3, \dots, \Gamma_M$

Step 2: Subtract the mean:

The average matrix, Ψ , is to be calculated, then subtracted from the original faces (Γ^i) and the result stored in the variable Φ^i :

The average face of the set if defined by

$$\Psi = \frac{1}{M} \sum_{n=1}^M \Gamma_n \quad (1)$$

Each face differs from the average by the vector

$$\Phi_n = \Gamma_n - \Psi \quad (2)$$

Step 3: Calculate the covariance matrix:

In this step, the covariance matrix C is calculated according to

$$C = \frac{1}{M} \sum_{n=1}^M \Phi_n \Phi_n^T = AA^T \quad (3)$$

where the matrix $A = [\Phi_1 \Phi_2 \dots \Phi_M]$. The matrix C, however, is N^2 by N^2 , and determining the N^2 eigenvectors and eigenvalues is an intractable task for typical image sizes. A computationally feasible method is needed to find these eigenvectors.

If the number of data points in the image space is less than the dimension of the space ($M < N^2$), there will be only $M-1$, rather than N^2 , meaningful eigenvectors (the remaining eigenvectors will have associated eigenvalues of zero). Fortunately, we can solve for the N^2 -dimensional eigenvectors in this case by first solving for the eigenvectors of M by M matrix—e.g., solving a 16 x 16 matrix rather than a 16,384 x 16,384 matrix—and then taking appropriate linear combinations of the face images Φ_n . If A is a square matrix, a non-zero vector v is an eigenvector of A if there is a scalar λ (eigenvalue) Consider the eigenvectors v_n of $A^T A$ such that:

$$A^T A v_n = \lambda_n v_n \quad (4)$$

Pre multiplying both sides by A, we have

$$AA^T A v_n = \lambda_n A v_n \quad (5)$$

from which we see that $A v_n$ are the eigenvectors of $C = AA^T$.

Following this analysis, we construct the M by M matrix $L = A^T A$, where $L_{mn} = \Phi_m^T \Phi_n$, and find the M

eigenvectors v_n of L. These vectors determine linear combinations of the M training set face images to form the eigenfaces μ_n :

$$\mu_n = \sum_{k=1}^M v_{nk} \Phi_k = A v_n, n = 1, \dots, M \quad (6)$$

The advantage of this method is that one has to evaluate only M numbers and not N^2 . Usually, $M < N^2$ as only a few principal components (eigenfaces) will be relevant. The amount of calculations to be performed is reduced from the number of pixels ($N^2 \times N^2$) to the number of images in the training set (M).

Step 4: Calculate the eigenvectors and eigenvalues of the covariance Matrix:

In this step, the eigenvectors (eigenfaces) and the corresponding eigenvalues λ_i should be calculated. The eigenvectors (eigenfaces) must be normalized so that they are unit vectors, i.e. of length 1. The description of the exact algorithm for determination of eigenvectors and eigenvalues is omitted here, as it belongs to the standard arsenal of most math programming libraries.

Step 5: Select the principal components:

From M eigenvectors (eigenfaces), only M' should be chosen, which have the highest eigenvalues. The higher the eigenvalue, the more characteristic features of a face does the particular eigenvector describe. Eigenfaces with low eigenvalues can be omitted, as they explain only a small part of characteristic features of the faces. After M' eigenfaces are determined, the "training" phase of the algorithm is finished.

III. METHODOLOGY

The aim of this study is to create a system of facial recognition to identify a person by comparing his/her image with that of data of other people's information that already stored in database. After research that has conducted, about the technique that will utilize in this study is the Eigenfaces. This technique PCA is a method in which is used to simplify the problem of choosing the representation of eigenvalues and corresponding eigenvectors to get a consistent representation. In order to obtain fast and robust object recognition, the dimension space needs to be reduced. Moreover, PCA also retains the original information of the data. Eigenface technique is based algorithm applies the PCA.

First, an experiment was performed using the first five image samples per class for training, and the remaining images for testing.

As shown in the Figure 1, the face recognition system can be separated into two main processes: the pre-processing, and the classification. The input image is first pre-processed to remove unwanted noise from lighting and the environment. Second the classifier recognizes the input face.

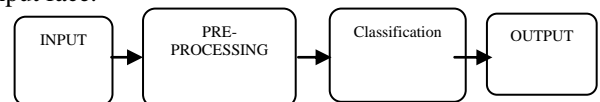


Figure 1. Face recognition system

Figure 2 shows the summary of face recognition process in details.

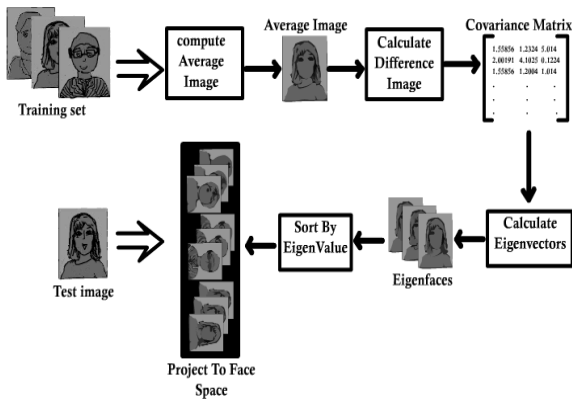


Figure 2. Summary of Overall Face Recognition Process

To conduct experiments and testing the system, Olivetti Research Laboratories (ORL) database of faces was used [6]. This face database provides 10 sample images of each of 40 subjects. Five sample images of one person from the ORL database are shown in Fig.3. The different images for each subject provide variation in views of the individual such as lighting, facial features (such as glasses), and slight changes in head orientation. We chose to use this face database because it seemed to be a standard set of test images used in much of the literature we encountered dealing with face recognition.



Figure 3. Five sample images of one subject in the ORL face database.

The algorithm for the facial recognition using eigenfaces is basically represented with help of flow diagram in Figure 4.

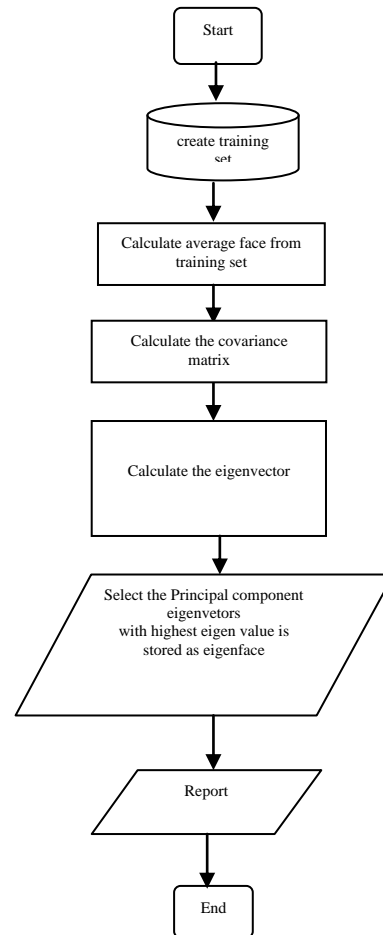


Figure 4. Flow diagram of the proposed face recognition system.

A. Classifying The Faces

When a face classification system is given a test input image, one of three possible classifications can result not a face, unknown face or recognized face.

- *Not a Face:* The “Not a face” classification is useful in situations where face detection is done automatically.
- *Unknown Face:* The “unknown face” classification indicates that a test image contains a face, but the face is not recognized by the classification system. This classification is used to indicate that the face presented to the classification system does not closely match any face images on which it has been trained. In the eigenface system, “unknown face” is interpreted as a point in face-space that is not close enough to any cluster of points for a known individual, yet it is close enough to the cluster of all face images so that the image is still classified as a face.

The process of classification of a new (unknown) face to one of the classes (known faces) proceed, the new image is transformed into its eigenface components. The resulting weights form the weight vector.

The euclidean distances of point of the input image with the points of training set are then computed. The training set image with minimum distance from the input image should be the best match.

The Euclidean distance of the weight vector of the new image from the face class weight vector can be calculated as formula 7.

$$\mathcal{E} = \left\| \Omega - \Omega_k \right\| \quad (7)$$

where Ω_k is a vector describing the kth face class. The face is classified as belonging to class k when the distance ε_k is below some threshold value $\theta\varepsilon$. Otherwise the face is classified as unknown. Also it can be found whether an image is a face image or not by simply finding the squared distance between the mean adjusted input image and its projection onto the face space.

$$\mathcal{E}^2 = \left\| \Phi - \Phi_f \right\| \quad (8)$$

where Φ_f is the face space and $\Phi = \Gamma_i - \Psi$ is the mean adjusted input.

With this we can classify the image as known face image, unknown face image and not a face image.

A distance threshold may be defined for the maximum allowable distance from any face class, which is half of the distance between the two most distant classes;

Distance Threshold

$$\theta_\varepsilon = \frac{1}{2} \max \left(\left\| \Omega_{\psi_i} - \Omega_{\psi_j} \right\| \right) \quad (9)$$

After this we have to distinguish between face and nonface images, by applying these conditions on our calculated result. The conditions are:

If $\mathcal{E} \geq \theta_\varepsilon$, then the image is not a face.

If $\mathcal{E} < \theta_\varepsilon$, then it's a new face.

If $\mathcal{E} < \theta_\varepsilon$, $\varepsilon = \min \{ \varepsilon_k \} < \theta_\varepsilon$, then it's a known face.

IV. RESULTS AND DISCUSSIONS

This section describes the experiments that performed on this study and their results to investigate a mathematical basis and model for face recognition using Principal component analysis with eigenvectors. and create a system of facial recognition to identify a person by comparing his/her image with that of data of other people's information that already stored in database. In eigenface approach, the threshold value is a very important factor for performance of face recognition. Even the images with large eigen values, if the threshold value is chosen 0.8 times maximum of minimum Euclidean distances of each image from all other images, it will greatly improve the recognition 96%. Likewise the reorganizations of the faces are based on threshold value and also user can have option to setting this value. The figure 5, show the results with different values of threshold factor. However the user should understand the minimum and maximum limit of this value

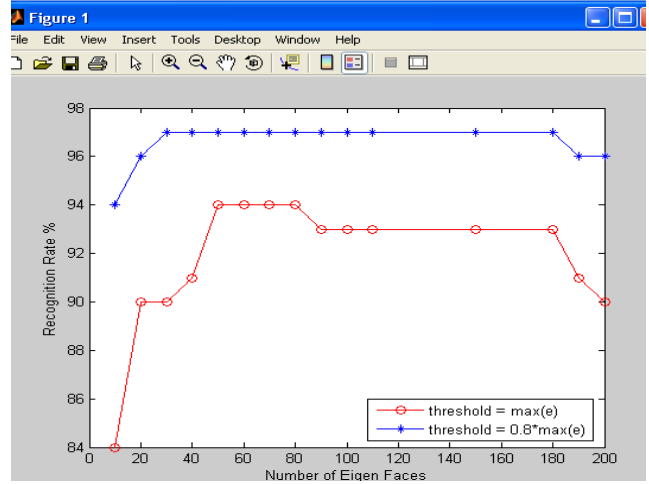


Figure 5. Choosing the threshold.

For Using Training and Test Images, ORL database has different 10 images per different individual. The effect of different number of training and test image combinations are tested. The tests are performed using PCA method. Figure 6 shows the optimized results of this study (proportion of faces using PCA). The reorganization level is increase when the numbers of images in training or test sets are decrease.

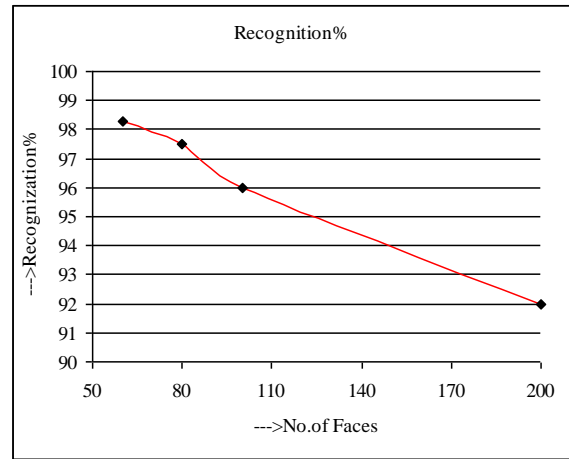


Figure 6. Recognition rate of faces

Table 1, shows another result set for large image set.

TABLE 1 : THE SUCCESS RATES USING DIFFERENT NUMBER OF TRAINING AND TEST IMAGES.

Total Number of Images	Number of Training Images (per individual)	Number of Test Images (per individual)	Success Rate (%)
400	1	9	69,7
400	5	5	96,0
400	9	1	87,5

It has 200 samples (5 for each individual) for training. The remaining 200 samples are used as the test set.

It was one of the first successful approaches for face recognition and it showed better results. Eigenfaces approach excels in its fast to implement, definitely robust and simplicity and delivers good recognition performances under controlled conditions. It provides a practical solution to the recognition problem. Much complex geometry is not involved. Training is done in an unsupervised manner.

Experimental results show that, eigenfaces approach is very sensitive to face background and head orientations. Illumination and presence of details are reasonably simple problems for the proposed face recognition system.

It smaller representation of the database to store images that we are only training in the form of projections on the basis of a discounted rate. It is also to reduce noise because we have to choose the basis of the maximum difference and thus features such as the background with a small difference is automatically ignored.

REFERENCES

- [1] M Janga Reddy, "A survey of face recognition techniques," *International Journal of research in Computer Applications and Robotics*, vol. 2, pp. 47-55, 2014.
- [2] Anil K Jain and Stan Z Li, *Handbook of face recognition*: Springer, 2011.
- [3] Jay Prakash Maurya, Akhilesh A Wao, PS Patheja and Sanjay Sharma, "A survey on face recognition techniques," 2013.
- [4] Rabia Jafri and Hamid R Arabnia, "A survey of face recognition techniques," *Jips*, vol. 5, pp. 41-68, 2009.
- [5] Marijeta Slavković and Dubravka Jevtić, "Face recognition using eigenface approach," *Serbian Journal of Electrical Engineering*, vol. 9, pp. 121-130, 2012.
- [6] Reecha Sharma and MS Patterh, "Face recognition using face alignment and PCA techniques: a literature survey," *IOSR Journal of Computer Engineering (IOSR-JCE)*, vol. 17, pp. 17-30, 2015.
- [7] Sweta Thakur, Jamuna Kanta Sing, Dipak Kumar Basu, Mita Nasipuri and Mahantapas Kundu, "Face recognition using principal component analysis and RBF neural networks," In *Proceeding of the Emerging Trends in Engineering and Technology*, 2008. ICETET'08. First International Conference on, 2008, pp. 695-700.
- [8] Nawaf Hazim Barnouti, Sinan Sameer Mahmood Al-Dabbagh and Muhammed Hazim Jaafer Al-Bamarni, "Real-Time Face Detection and Recognition Using Principal Component Analysis (Pca)-Back Propagation Neural Network (Bpnn) and Radial Basis Function (Rbf)," *Journal of Theoretical and Applied Information Technology*, vol. 91, p. 28, 2016.
- [9] Ali Javed, "Face recognition based on principal component analysis," *International Journal of Image, Graphics and Signal Processing*, vol. 5, p. 38, 2013.
- [10] Manpreet Kaur and Ajay Kumar Singh, "Performance Analysis of Face Recognition using Feed Forward Neural Network and PCA," *Journal of Image Processing and Artificial Intelligence*, vol. 2, 2016.