

Implementation of Pose Invariant Face Recognition using Eigenface Approach

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Abstract—Face recognition is one among the several techniques for identification and verification of an individual. The approach in the present work transforms face images into a small set of characteristic feature images called eigenfaces, which are the principal components of the initial training set of face images. Recognition is performed by projecting a new image into subspace spanned by eigenfaces, followed by computing the distance between the resultant position in the face space and those of known face classes.

Keywords—Face recognition, face space, eigenface, PCA, image pre processing.

I. INTRODUCTION

Biometric is any automatically measurable, robust and distinctive physical characteristic or personal trait that can be used to identify an individual or verify the claimed identity of an individual. The types of biometrics are iris scanning, retinal scan, voice recognition, finger printing and face recognition. The biometric system is essentially a pattern recognition system that makes a personal identification determining the authenticity of some characteristic of an individual. Falsification of identity cards or intrusion of physical and virtual areas by cracking alphanumeric passwords appears frequently in the media. These problems of modern society have triggered a real necessity for reliable, user-friendly and widely acceptable control mechanisms for the identification and verification of the individual. Face recognition technique is one among the several techniques for the identification and verification of an individual.

Face recognition has been an active area of research with numerous applications since late 1980s. Eigenface approach is one of the appearance-based face recognition methods, which was developed by Turk and Pentland in 1991 [1], [2]. This method utilizes the idea of the principal component analysis (PCA) and decomposes face images into a small set of characteristic feature images called eigenfaces. Recognition is performed by projecting a new face onto a low dimensional linear face space defined by the eigenfaces, followed by computing the distance between the resultant position in the face space and those of known face classes.

Any face can be expressed as linear combinations of the singular vectors of the set of faces, and these singular vectors are eigenvectors of the covariance matrices. Eigenfaces are the eigenvectors which are representative of each of the dimensions of this face space and they can be considered as

various face features [2]. The eigenvectors with higher eigen values represent most significant directions which should be considered in the lower dimensional subspace. The lower eigen values can be neglected as they do not provide significant information about face variation. So it means that all images projected in this direction lie close to each other and so do not represent much face variation [2].

The Eigenface method for human face recognition is remarkably effective and simple. Where, other face recognition methods are forced to attempt to identify features and classify relative distances between them, the eigenface method evaluates the entire image as a whole [1], [2]. These properties make this method practical in real world implementations, outside the laboratory.

Facial recognition holds several advantages over other biometric techniques. It is natural, non-intrusive and easy to use. In a study considering the compatibility of six biometric techniques (face, finger, hand, voice, eye, signature) with machine readable travel documents (MRTD) [3] facial features scored the highest percentage of compatibility as shown in Fig. 1.

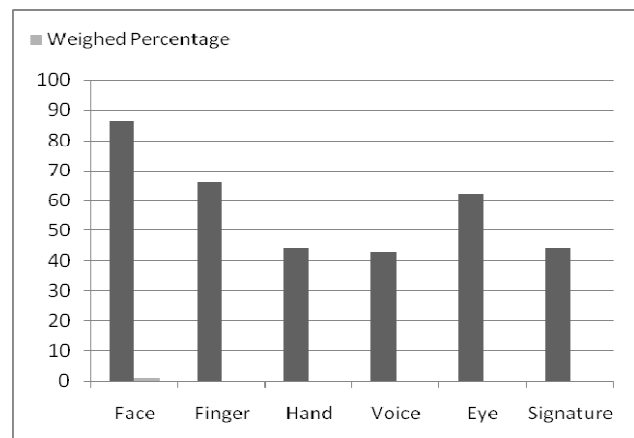


Figure 1. Comparison of MRTD compatibility with six biometric techniques (Hietmeyer, 2000 [3])

Automated facial recognition can be used in various areas other than security oriented applications, such as computer entertainment and customized computer-human interaction. Customized computer-human interaction applications will in

the near future be found in products such as cars, aids for disabled people, buildings, etc. The interest for automated facial recognition and the amount of applications will most likely increase even more in the future. This could be due to increased penetration of technologies, such as digital cameras and the internet, and due to a larger demand for different security schemes.

The use of Eigen-analysis has found considerable favor in the area of face recognition, although it has been applied to optical character recognition and voice recognition. For the task of searching through a database of faces to recognize a person, eigen-analysis has been found to be particularly effective and efficient. There are many challenges in face recognition which are tried to overcome in the current work, such as, illumination effect on the face images, pose of the person in the image and facial expressions. The other challenges in face recognition are in the area of biomedical to recognize the faces before and after the surgical procedures on the face, such as facial aesthetics/prosthetics and facial implants. Like human faces, the images obtained by CT/MRI/x-ray of human body such as brain, kidney, liver, chest etc., exhibit a great deal of variation under normal and pathological conditions. The examining of these images for diagnostic purpose is a real challenge. Recent studies concluded that there is a significant difference between the interpretations/diagnostics of these images taken in emergency situations by radiology specialists and those by non-specialists [4]. Therefore recognizing the image as normal or abnormal will reduce the incidence of misdiagnosis. Eigen based image analysis and recognition approach can be used in identifying these images as normal or pathological.

II. LITERATURE REVIEW

Humans always had the innate ability to recognize and distinguish between the faces, and the computers have recently shown the same ability. In the mid 1960s, scientists began work on using the computer to recognize human faces. Since then, facial recognition has come a long way. Techniques for face recognition were proposed by Francis Galton as early as 1888 [6]. This method focused on detecting important facial features or key-points. Typical key-points include eye corners, mouth corners, nose tip, and the chin edge. By comparing the relative distances between these facial key-points a feature vector can be constructed to describe each face to the feature vectors from a database of known faces, the closest match can then be determined. This technique is extremely sensitive to changes in facial orientation and fails to perform accurately even under controlled conditions.

The most intuitive way to carry out face recognition is to look at the major features of the face and compare these to the same features on other faces. Some of the earliest studies on face recognition were done by Darwin [5] and Galton [6]. Darwin's work includes analysis of the different facial expressions due to different emotional states, where as Galton studied facial profiles. However, the first real attempts to develop semi-automated facial recognition systems began in the late 1960's and early 1970's, and were based on

geometrical information. Here, the landmarks were placed on photographs locating the major facial features, such as eyes, ears, noses, and mouth corners. Relative distances and angles were computed from these landmarks to a common reference point and compared to reference data. Goldstein and Harmon [7] created a system of 21 subjective markers, such as hair color and lip thickness. These markers proved very hard to automate due to the subjective nature of many of the measurements still made completely by hand.

A more consistent approach to do facial recognition was done by Fischer et al. [8] and later by Yuille et al. [9]. These approaches measured the facial features using templates of single facial features and mapped these onto a global template. Most of the developed techniques during the first stages of facial recognition focused on the automatic detection of individual facial features. However, even today facial feature detection and measurement techniques are not reliable enough for the geometric feature-based recognition of a face and geometric properties alone are inadequate for face recognition [10]. Due to drawback of geometric feature-based recognition, the technique has gradually been abandoned and an effort has been made in researching holistic color-based techniques, which has provided better results. Holistic color-based techniques align a set of different faces to obtain a correspondence between pixels intensities, a nearest neighbour classifier can be used to classify new faces when the new image is first aligned to the set of already aligned images [11].

The appearance of the Eigenface technique [2], a statistical learning approach, has notably enhanced the performance of face recognition. Instead of directly comparing the pixel intensities of the different facial images, the dimension of the input intensities were first reduced by a PCA in the Eigenface technique. One of the current techniques is Fisherfaces [12]. It combines the Eigenfaces with Fisher Linear Discriminant Analysis (FLDA) to obtain a better separation of the individual faces. In Fisherfaces, the dimension of the input intensity vectors is reduced by PCA and then FLDA is applied to obtain an optimal projection for separation of the faces from different persons. The use of Eigen-analysis has found considerable favour in the area of face recognition. Like faces, chest radiograph images exhibit a great deal of variation in normal and disease condition. A method employed for face recognition can be extended to analyse a set of chest x-ray images [4].

After development of the Fisherface technique, many related techniques have been proposed. Techniques like Kernel Fisherfaces [13], Laplacianfaces [14] or discriminative common vectors [15] can be found among these approaches.

III. FACE RECOGNITION

The problem of face recognition is a classic pattern recognition problem. With an increasing emphasis on security, automated personal identification and verification based on biometrics, pattern recognition has been receiving extensive attention over the past decade. Pattern recognition principles



are extensively applied in many fields. Any pattern recognition system has two modes of operation as shown in Fig.2. They are training mode and classification mode. In the training mode, the model is trained with a set of test patterns. Here the aim is to make the model to learn about the input patterns. In the classification mode the learned model is used to classify the given input pattern.

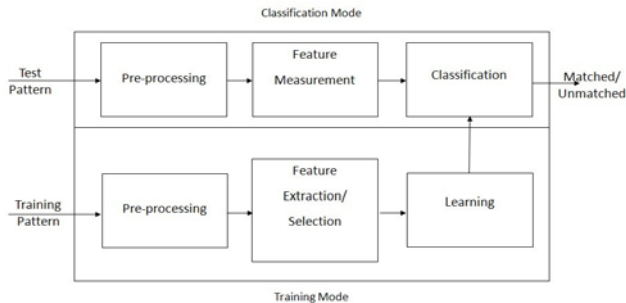


Figure 2. Two modes of operation of pattern recognition system

The simplest method for face recognition can be based on comparison approach in which the new face image can be compared with each of the existing images in the database to check for match. This is very simple approach as it takes the dot product of two images that means comparing images pixel by pixel. If the pixel intensity values of both images match then this new image is said to be a known face. As the database size is large and contains redundant information in high dimensional space, the performance is improved by using PCA [1], [2], a technique used for dimensionality reduction in computer vision particularly in face recognition. PCA techniques choose a dimensionality reducing linear projection that maximizes the scatter of all projected samples.

There are many interesting problems that remain in the area of face recognition. One problem is image pre-processing prior to the application of the Eigenface method. It may be possible to gain better accuracy in classification, if one segments the spectrum of people into different spaces. Since appearance based method use image intensities directly they are inherently sensitive to variations in illumination. Changes in pose and expressions, drastic changes in illumination such as between indoor and outdoor scenes cause significant problems for appearance based face recognition algorithms. The proposed algorithm will overcome the challenges in face recognition such as changes in pose and expressions and small changes in illumination.

The objective of the present work is to develop an efficient automatic face recognition system/algorithm using PCA technique to compare the face image captured and classify this new image into either as a face of a known person whose face images are in the database or unknown face image. To develop an algorithm to work for faces with scar and expression or pose variations this plays an important role in security systems and face implant surgeries.

IV. METHODOLOGY

The training set of images is given as input to find eigenspace. Using these images, the average face is computed. The difference of these images is represented by a co-variance matrix. This is used to calculate eigenvectors and eigenvalues. These are the eigenfaces which represent various face features. The eigenvalues are sorted and higher of them is considered since they represent significant features. This becomes eigenspace spanned by the eigenfaces which has lower dimension than original images. Now a given test image is projected on this eigenspace to give the feature vector also known face key for that image.

The Euclidean distances between test feature vector and all training image feature vectors are calculated. If the minimum Euclidean distance is below some threshold value, then two images are said to be matching that means they belong to same person. Depending on this result, false acceptance ratio (FAR) and false rejection ratio (FRR) are found. These are used to change the value of threshold. In this way face recognition is carried out using Eigenface approach.

A. Algorithm

The basic steps involved in face recognition using Eigenface approach in the present work are as follows:

(i) Database creation and initialization:

1. Read all the training images in the training set.
2. Apply pre-processing techniques to all the training images.
3. Form training data matrix by first converting 2D image matrices into 1D image vectors and then concatenating them.
4. Compute average face image by calculating mean of all 1D image vectors in training data matrix.
5. Calculate difference images by subtracting average image vectors from 1D image vectors. This forms Covariance matrix.
6. Form Surrogate matrix of the Covariance matrix.
7. Calculate Eigen values and Eigenvectors of Surrogate matrix.
8. Calculate Eigenvectors of the Covariance matrix, which are called Eigenfaces.
9. Generate feature vectors for all images in training set by projecting centered images into facespace by multiplying in Eigenface basis.
10. Store feature vectors, Eigenfaces and mean face as database.

(ii) Face Recognition:

11. Read Test face.
12. Apply pre-processing techniques to the Test face.
13. Form 1D image vector from 2D image matrix of Test face.
14. Calculate difference Test image by subtracting mean face image vector from 1D Test image vector.

15. Generate feature vector of Test face by projecting difference Test image into face space using eigenfaces.
16. Compute the distances between test feature vector and all training feature vectors.
17. Classify the test face as a well known face or an unknown face.

Database creation and initialization:

The Camera used for taking train and test images is “i ball Twist Cam 12.0” with image sensor resolution of 1.3 Megapixels.

1. Read Training set of images: Let the training set consists of P images. Each of these images can be represented as matrix of size M x N x 3. Let these images be I₁, I₂, ..., I_P.
2. Apply pre-processing techniques: Image pre-processing involves changing the nature of an image in order to either: (i) improve its pictorial information for human interpretation, or (ii). render it more suitable for autonomous machine perception. The proposed system uses following three pre-processing techniques, RGB to GRAY conversion, histogram equalization and noise removal.

If the image is acquired from the digital camera then median filtering will be very appropriate for removing the noise from the image. Median filtering is similar to using an averaging filter, in that each output pixel is set to an average of the pixel values in the neighborhood of the corresponding input pixel. However, with median filtering, the value of an output pixel is determined by the median of the neighborhood pixels, rather than the mean. The median is much less sensitive than the mean to extreme values called outliers. Median filtering is therefore better able to remove these outliers without reducing the sharpness of the image.

3. Formation of training data matrix:

The pre-processed gray scale training 2D image matrices of dimension M x N are first converted into 1D image vectors of dimension M*N x 1. Let these 1D image vectors be Γ₁, Γ₂, ..., Γ_P. All these 1D image vectors are concatenated to form 2D training data matrix of dimension M*N x P.

4. Computing average face image:

$$\Psi = (1/P) \sum_{i=1}^P \Gamma \quad (4.1)$$

5. Formation of covariance matrix:

$$\Phi_i = \Gamma_i - \Psi \quad (i=1, 2, \dots, P) \quad (4.2)$$

$$A = [\Phi_1 \Phi_2 \Phi_3 \dots \Phi_M] \quad (4.3)$$

Using matrix A, the covariance matrix C is formed.

$$C = A A^T \quad (4.4)$$

6. Formation of Surrogate matrix:

As the dimension of covariance matrix is M*N x M*N, which means it will result in M*N eigen values and M*N eigenvectors. Since the value of M*N is very large, it would be better to reduce this overhead by considering matrix

$$L = A^T A \quad (4.5)$$

This matrix is called Surrogate matrix and it has a dimension P x P.

7. Eigen values and Eigenvectors of Surrogate matrix:

We have the equation,

$$(L - \lambda I) X = 0 \quad (4.6)$$

This is a homogeneous system of equations and a nontrivial solution exists if and only if

$$\det(L - \text{eigen value} * I) = 0 \quad (4.7)$$

where det () denotes determinant. When evaluated, becomes a polynomial of degree P. Since L is P x P, then there are ‘P’ solutions or ‘P’ roots of the characteristic polynomial. Thus there are ‘P’ eigen values of L satisfying the equation,

$$L x_i = \lambda_i x_i \quad (4.8)$$

Thus we have P eigen values and P eigen vectors.

8. Eigen values and Eigenvectors of Covariance matrix:

The M*N eigen values obtained from C are same as P eigen values with remaining (M*N – P) eigen values equals zero. Also if x is eigen value obtained from C, then the eigenvectors of L are given by

$$y = A^T x \quad (4.9)$$

The eigenvectors for C (Matrix U) are obtained from eigenvectors of L (Matrix V) as given below:

$$U = A V \quad (4.10)$$

9. Projecting centered image vectors into face space:

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:

$$\Omega_i = U^T (\Gamma_i - \Psi) \quad \text{where } i=1, \dots, P. \quad (4.11)$$

As the projection on the Eigenfaces space describes the variation of face distribution, it is possible to use these new face descriptors as feature vectors.

10. Store feature vectors:

Store the training image feature vectors, eigenfaces and average face as database.

Face recognition:

11. Read test face:

A new face image for testing the algorithm is read from a file.

12. Apply pre-processing techniques:

The same pre-processing techniques which are applied during database creation are applied to test image. Now a pre-processed image of dimension M x N is obtained.

13. Formation of test data matrix:

The pre-processed gray scale 2D image matrix of dimension M x N is first converted into 1D image vector of dimension M*N x 1. Let this 1D image vector be Γ.

14. Calculate centered test image vector:

$$\Phi = (\Gamma - \Psi) \quad (4.12)$$

15. Projecting centered test image vector into facespace:

Each of such new face submitted to the face recognition is projected into the facespace, obtaining the feature vector, also known as face key for this image, by using the equation

$$\Omega = U^T \Phi \quad (4.13)$$

16. Compute Euclidean distances:

$$\epsilon^2_i = \| \Omega - \Omega_i \|^2 \quad (4.14)$$



17. Classification of input image:

If the distance found among Ω and any Ω_i is inside threshold and is the smallest found distance then there is a facial recognition of belonging to training image i .

This type of classification is called Nearest Neighbour classification

B. Error Rates

The percentage of images which are accepted as known face images although they are unknown is called as False Acceptance Rate (FAR). This value represents error rate for acceptance of unknown images. The percentage of images which are rejected as unknown face images although they are known is called as False Rejection Rate (FRR). This value represents error rate for rejection of known images.

If a new face image is given for face recognition, then the Euclidean distances between the face key vectors of all training images and test feature vector are calculated. If the minimum distance is below some threshold value, then two images are said to be matching i.e. they belong to same person. Depending on this result, FAR and FRR are found. These are used to change the value of threshold. In this way face recognition is carried out using Eigenface approach.

C. Significance of Eigenface Approach

An algorithm based on standard Eigenface approach for face recognition is developed. Now it is important to choose only P' eigenvectors from these P eigenvectors, such that P' is less than P , to represent face space spanned by images. This will reduce the face space dimensionality and enhance speed for face recognition. As the higher eigen values represent maximum face variation in the corresponding eigenvector direction, it is important to consider this eigenvector for face space representation.

The most important point here is to reduce the value of P' so that it does not result in high error rates for face recognition process. The P' should be chosen such that error does not increase much and are acceptable depending on application for face recognition.

V. SOFTWARE IMPLEMENTATION IN MATLAB

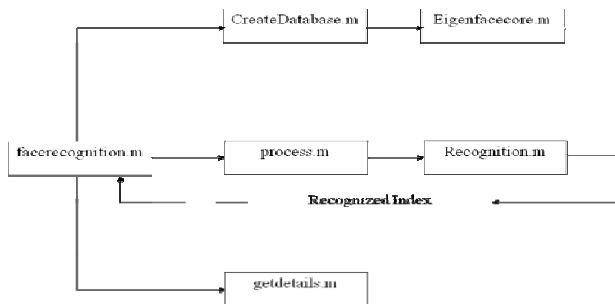


Figure 3. Functional block of Software Implementation

Displaying Personal Details in GUI

The task here is to create a database file using Microsoft Access containing personal information of all authorized persons and establishing a connection between Matlab GUI and this database file. The personal information contains fields such as Name, Address, Date of Birth, Age and Sex.

VI. RESULTS AND DISCUSSIONS

The training database consists of 56 images of 14 persons with 4 images of each. The test images used for the experiments are as shown in Fig. 4

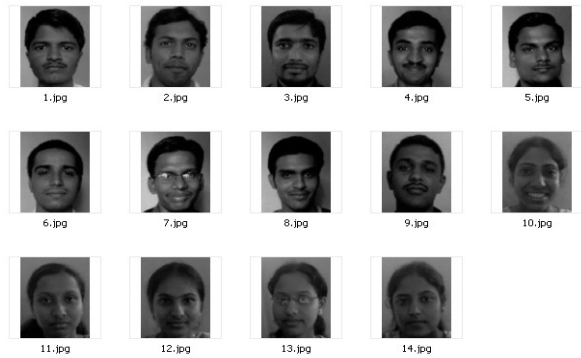


Figure 4. Test images

Experiment 1:

The purpose of this experiment is to project test image 1.jpg into facespace and finding Euclidean distances.

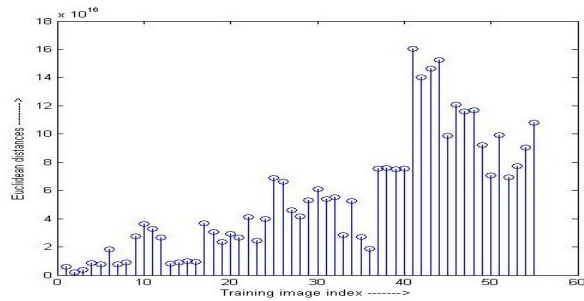


Figure 5. Plot of Euclidean distances

From the plot in the Fig. 5 we observe that the Euclidean distance between the test image 1.jpg and 2nd image in the training set is minimum. The test image and the matched image are as shown in Fig. 6.



Figure 6. Test image and Equivalent image



Experiment 2:

The purpose of this experiment is to project test image 13.jpg into face space and finding Euclidean distances.

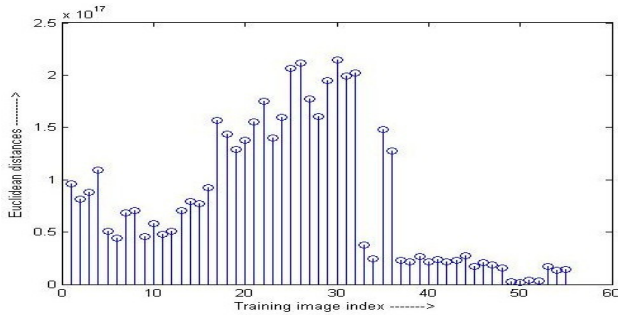


Figure 7. Plot of Euclidean distances

From the plot in the Fig. 7, we observe that the Euclidean distance between the test image 13.jpg and 50th image in the training set is minimum. The test image and the matched image are as shown in Fig. 8.



Figure 8. Test image and Equivalent image

The table below shows the variation of False Acceptance Ratio (FAR) and False Rejection Ratio (FRR) values with respect to threshold levels:

TABLE 1.
FAR AND FRR FOR TRAINING AND NON-TRAINING IMAGES

Threshold values (x10 ¹³)	10	100	200	300	400	500	600	700	800	900
FAR	0	0	0	0	0	0	0	1	4	10
FRR	14	13	6	4	2	1	0	0	0	0

From the above table we can conclude that a suitable value of threshold between 500 x 10¹³ and 700 x 10¹³ can be selected, for better results.

VII. CONCLUSIONS

The present work is implementation of an algorithm for face recognition using eigenfaces. The considered model is sufficiently robust in the recognition of facial images obtained in controlled conditions of illumination, varied face expressions and with transparent eyeglasses. Thus, the proposed approach can be extended to recognise an individual in cases of facial aesthetics/prosthetics and facial implants.

The work will be further extended in the diagnosis of diseases based on medical images.

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