Face Recognition by Classification in Eigenspace

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ABSTRACT
Face recognition systems are highly required for variety of applications like user authentication, advanced video surveillance, biometrics etc. Majority of existing systems worked on higher dimensional spaces whereas a human face image (somewhat similar shapes and placement of objects) can be projected on a lower dimensional subspace. This dimensionality reduction is possible by using “Principle Component Analysis” method. PCA approach gives eigenvectors having eigenvalues for a given set of images which represents variations amongst images, creates aneigenspace.

Input image can be identified as a “face” image or a “non-face” image by projecting it on eigenspace and measuring the distance of mean adjusted test image from the face space. If the test image is identified as face image then it can be checked as “known” or “unknown” face image by measuring the distance of its projection on face space with the nearest neighbor face class. So to recognize a input face, two thresholds are required, one for identifying a image as “face” image or a “non-face” image and another for classifying a face image as “known” or “unknown”. This paper also suggests a method to calculate both the thresholds from the set of image database of known images itself.

This method can be used to recognize faces in spite of considerable variations in pose, expression, scale and disguise since the recognition is not based on features but it is based on variations amongst face images. The most important advantage of this method is its lower computational complexity because of working on a lower dimensional workspace.

General Terms
Pattern Recognition, Algorithm, Security.

Keywords
Eigenspace, Eigenfaces, Eigenvectors, Facespace, PrincipalComponentAnalysis (PCA), Pattern Recognition.

1. INTRODUCTION
The scheme is based on an information theory approach that decomposes face images into a small set of characteristic feature images called ‘Eigenfaces’, which are actually the principal components of the initial training set of face images. Recognition is performed by projecting a new image into the subspace spanned by the Eigenfaces (‘facespace’) and thenclassifying the face by comparing its position in the face space with the positions of the known individuals. The Eigenface approach gives us efficient way to find this lower dimensional space. Eigenfaces are the Eigenvectors which are representative of each of the dimensions of this face space and they can be considered as variousface features. Any face can be expressed as linearcombinations of the singular vectors of the set offaces, and these singular vectors are eigenvectors ofthe covariance matrix of known images. There are numerous applications of systems developed for face recognition as criminal identification, security systems, image and filmprocessing, human-computer interaction etc.

1.1 Requirements of Face Recognition
Designing an efficient face recognition system should not merely cover high percentage of correct recognition but must also have high speed, ability to handle large database, ability to recognize faces under varying environments etc. In addition to that, the effectiveness of any face recognizing system depends on how much the recognition is robust to the variations in pose, illumination, expression, accessories etc.

1.2 Related Work
The popular approaches practiced for face recognition are categorized from their way of representing an image[4],[5]. Some of the main categories are feature based representation, template based, and appearance based image representation.

The feature based technique extracts and normalizes a vector of geometric descriptors of biometric facial components such as the eyebrow thickness, nose anchor points, chin corner points, zygomatic breadth, etc. The vector is then matched with the stored model face vectors [1]. This approach is time consuming particularly for large databases, non-frontal parallel poses and varying illuminations.

Template based approaches use pixel-wise 2-D array of entire face or set of their transforms as input and some image based metric,such as correlation is then is used to match the resultingimage with the set of model images.This technique is simple but requires large memory.
An extension to this technique includes low dimensional coding to simplify the image representation and improve the performance of the result matching process and i.e. Principal Component Analysis orEigenface method.
In this approach, we want to extract the relevant information in a face image, encode it as efficiently as possible and compare one face encoding with a database of models encoded similarly. Here, variation in a collection of face images are captured, independent of any judgment of features and this information is used to encode and compare individual face images. Automatically learning and later recognizing new faces is practical within this framework. Recognition under widely varying conditions is achieved by training on limited number of characteristics views with respect to pose, illumination, expressions, etc.

Two thresholds are required in this approach, one for identifying input image as "known" or as "unknown", and another for identifying the image as "face" image or as "non-face" image. Instead of predefining the thresholds by trial and error, better approach is given in this paper and that is to calculate both the thresholds from all the training data available during initialization.

2. THE EIGENFACE APPROACH

2.1 Principal Component Analysis

Principal component analysis (PCA) is a useful statistical technique that has found application in fields such as face recognition and image compression and is a common technique for finding patterns in data of high dimensions [8].

Let a face image be a 2-D, N by N array of (8 bit) intensity values. This image may be considered as a vector of dimension N^2. For example, a 112x92 image can be considered as a vector of dimension 10304. Suppose, we have 'M' number of face images (samples) then our dataset can be considered as,

$$X = [\Gamma_1 \Gamma_2 .... \Gamma_M] \text{---- (2.1.1)}$$

Where, Γ_i = column vector of size N^2 for i=1,2…M.

Fig, (2.1) shows images of 20 individuals used for training with total 100 images (each individual having 5 varied images).

Fig.(2.1): Training Set

Mean of these sample dataset is denoted by,

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \quad \text{----(2.1.2)}$$

Mean or average image of given training set is as shown in Fig,
(2.2).

Fig.(2.2):Average face of Training Set.

And Covariance matrix of the dataset is,

$$C_\Gamma = \frac{1}{M}\sum_{n=1}^{M}[\Gamma_n - \Psi][\Gamma_n - \Psi]^T \text{ ---- (2.1.3)}$$

The components of C_Γ, denoted by C_{ij}, represent the covariance between random variable components Γ_i and Γ_j. The component C_{ii} denotes variance of component Γ_i, variance indicates spread of the component value around its mean value. If Γ_i and Γ_j are uncorrelated components then, $C_{ij}=C_{ji}=0$. Hence, by definition covariance matrix is always symmetric.

Each face differs from the mean by a vector, $\Phi_i=\Gamma_i-\psi$. Hence, data matrix of centered face images can be written as,

$$A = [\Phi_1 \Phi_2 .... \Phi_M] \text{----(2.1.4)}$$

Hence equation, (2.1.3) becomes,

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n \Phi_n^T \text{ Or, } C = AA^T \text{ ---- (2.1.5)}$$

For this symmetric covariance matrix C, we can calculate an orthogonal basis by finding its eigenvalues and eigenvectors. The eigenvectors, $v_i$with the eigenvalues, $\lambda_i$are the solutions of the equation,

$$Cv_i = \lambda_i v_i \text{ for, i =1, 2,……, N}^2 \text{ ---- (2.1.6).}$$

These eigenvectors (principal components) calculated forms an orthogonal basis which best describes the distribution of the data and the corresponding eigenvalues indicates how much percentage the principal component represents the total tendency of variation. Hence, by ordering the eigenvectors in the order of descending eigenvalues, one can create an ordered orthogonal basis with the first eigenvector (with largest eigenvalue) having direction in which the data set has the most significant amount of energy and largest variance.

2.2 Reducing Order of Calculation

Above literature clearly indicates that we have to solve for the covariance matrix, C of size N^2XN^2 determining N^2 eigenvectors and eigenvalues which is quite a cumbersome task.

Fortunately if number of samples (no. of data points in space) is less than number of pixels in aimage (no. of dimensions of space) or, if $M<<N^2$ then we can solve for N^2dimensional eigenvectors by first solving for eigenvectors of *MXM* matrixand then taking appropriate linear combinations of face images Φ_i, as per [2] .

If we find out eigenvectors,$v_i$of matrix$A^TA_{(MXM)}$such that,

$$A^T Av_i = \lambda_i v_i \text{ for, i=1,2,……,M ---- (2.2.1)}$$

Pre-multiplying both sides by A, we get

$$AA^T Av_i = \lambda_i Av_i \quad \text{----(2.2.2)}$$

Comparing above equation with basic eigenvalue problem,$Cv=\lambda v$, we observe that Av_i are the eigenvectors of $C=AA^T$.

Hence, we construct matrix, $L=A^TA_{\ (MXM)}$ and find M eigenvectors v_l of L. These eigenvectors determine linear combinations ofM training set face images to formeigenfaces μ_l as,

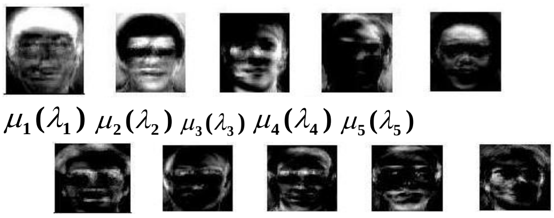
$$\mu_l = \sum_{k=1}^{M} v_{lk}\Phi_k \text{ ---- (2.2.3)}$$

With this analysis, the calculations are greatly reduced from the order of number of pixels in the images *(N^{2})* to the order of number of images in the training set *(M)*.

2.3UsingEigen faces to Classify Face Image

The eigenfaces seem adequate for describing face images under very controlled conditions, hence decided to investigate their usefulness as a tool for face identification[8]. In practice, as evaluated by Sirovich and Kirby [3] and [6], a smaller *M'* is sufficient for identification, since accurate reconstruction of the image is not a requirement. The eigenfaces span a M' dimensional subspace of the original N^2 image space by choosing *M*' eigenvectors with highest associated eigenvalues out of M eigenvectors of matrix *L*.

Ten most prominent eigenfaces (*M*'=10) of the given training set are as shown in Fig, (2.3). This group of *M*' eigenfaces forms the "facespace" on which to operate for face recognition.



$\mu_1(\lambda_1)$ $\mu_2(\lambda_2)$ $\mu_3(\lambda_3)$ $\mu_4(\lambda_4)$ $\mu_5(\lambda_5)$

$\mu_6(\lambda_6)$ $\mu_7(\lambda_7)$ $\mu_8(\lambda_8)$ $\mu_9(\lambda_9)$ $\mu_{10}(\lambda_{10})$

Fig.(2.3): Ten Eigenfaces of given Training Set

A new face image, (г) is transformed into its eigenface components (projected onto face space) by a simple operation,

$$\omega_k = \mu_k^T(\Gamma - \Psi) \text{ -(2.3.1)for k=1, 2,………, M'.}$$

The weights form a vector, $\Omega = [\omega_1, \omega_2, \ldots\ldots\omega_{M'}]$ describes the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images.

The method for determining which predefined face class provides the best description of an input face image is to find the face class 'k' that minimizes the Euclidian distance,

$$\varepsilon_k^2 = \|(\Omega - \Omega_k)\|^2 \text{ ---- (2.3.2)}$$

The Ω_k is a vector describing the k[th]face-class. The face classes Ω_k are calculated by averagingthe results of the eigenface representation over asmall number of face images of each individual i.e, each class indicates each training individual.

A face is classified as belonging to class 'k' when ε is minimum for class vector, $\Omega_k$and labeled as 'known' if this minimum $\varepsilon_k$is less than threshold,**T2**(maximum allowable distance from any face class). During training by considering each training image as a test image (г),**T2** can be obtained as a maximum out of M minimum ε of each training image. And if$\boldsymbol{\varepsilon_k}$ **>T2** , the face is classified as 'unknown', and optionally used to create a new face class.

2.3.1: Calculation of threshold, T2:

T2defines maximum allowable distance from "face class".

For this, firstly calculate the Euclidian distance,

$$f_{i,k}^2 = \|(\Omega_k - \Omega_i)\|^2 \text{ ---- (2.3.1.1)}$$

by considering the pattern vector, Ω_k of each training image as input for '*k*' number of times (k=1,2,….,*M*).

Hence, each *k*'th training image is most similar to the class (individual) to which its distance is least. So now we have to calculate for,

$$l_k = \min(f_{i,k}) \text{ ---- (2.3.1.2)}$$

fori =1,2,…….,No. of classes in training set.

Then threshold, **T2** is obtained as the maximum value amongst alll_k's that is,

$$\mathbf{T2} = \max(l_k) \text{---- (2.3.1.3)}$$

2.4 Classifying Image as Face or Non-Face

To classify any input image as a face image or anon-face image, Euclidian distance between mean adjusted input image, Φ = г - ψ and measure of its "face class" property, $\Phi_f = \sum_{i=1}^{M'} \omega_i \mu_i$ can be calculated as:

$$\varepsilon^2 = \|\Phi - \Phi_f\|^2 \text{ ---- (2.4.1)}$$

This, ε if less than a threshold, **T1**(maximum allowable distance from face space, calculated from training set) then, test image is considered as a "face" image.

2.4.1: Calculation of threshold, T1:

T1 defines maximum allowable distance from face space.

For this, we have to calculate for the projection of normalized training images on "face space" as:

$$\Phi_{f,j} = \sum_{i=1}^{M'} \omega_i \mu_i \text{ ---- (2.4.1.1)}$$

for i=1,2,…….,*M*' and j=1,2,…….,*M*.

Then Euclidian distance between$\Phi_j$and Φf,jis calculated as:

$$\theta_j^2 = \|\Phi_j - \Phi_{f,j}\|^2 \text{ ---- (2.4.1.2)}$$

Where, $\Phi_j = г_j - \psi$.

The above calculations have to be done by considering each training image $г_j$and $\theta_j$are calculated for i=1, 2… *M*.

Then, the threshold **T1** is obtained as the maximum value amongst all θ_j's.

$$\mathbf{T1} = \max(\theta_j)\text{.---- (2.4.1.3)}$$

2.5 Learning to Recognize New Faces

During testing, when any image is recognized as "Unknown", that image and its vector are temporarily stored. If images are classified continuously as "Unknown" for 'x' numbers of times then the stored pattern vectors are checked for similarity by requiring that the distance from each image to the mean of the unknown images is less than a predefined threshold. If the images pass the similarity test then, those images of an individual are stored as a separate dataset.

Occasionally user may opt to learn some frequently subjected new faces. So if opted, the training set is updated with images of new faces and the whole system is reinitialized thus, ready to learn the updated new faces.

3. IMPLEMENTATION SUMMARY

The complete process of face recognition is broadly divided into three stages as:

- **Training or Initialization: Fig.(3.1).**
- **Testing or Recognizing Input Face: Fig.(3.2).**
- **Learning to Recognize New Faces (Optional).**

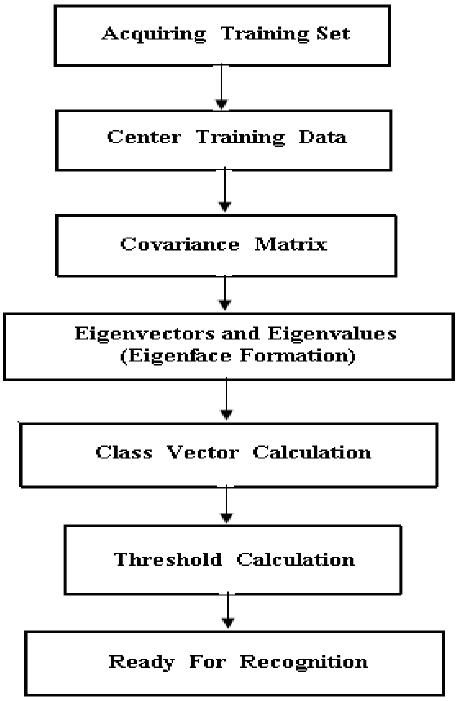


Fig.(3.1): Training or Initialization

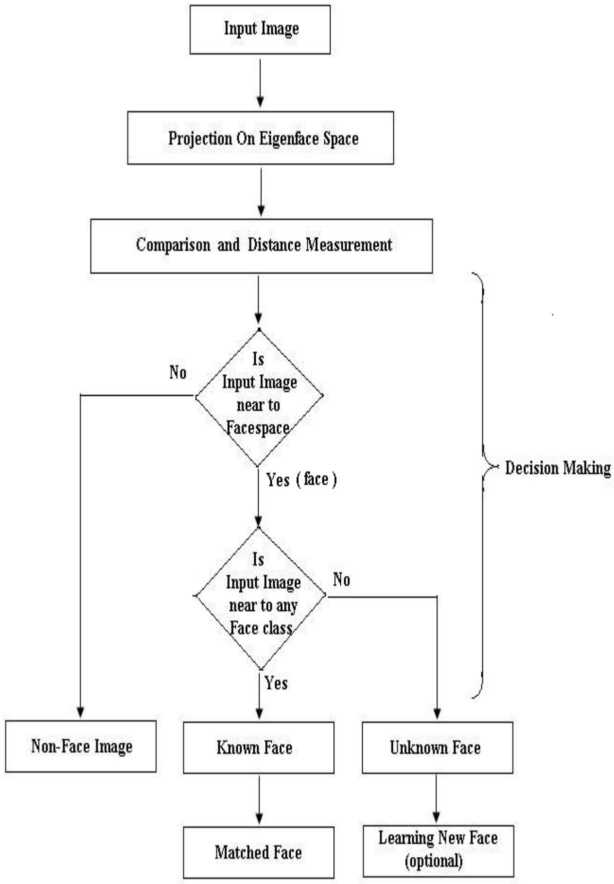


Fig.(3.2): Testing

4.EXPERIMENTS AND RESULTS

Experiments were performed using the ORL (Olivetti Research Laboratory) database. This database includes ten different images of 40 distinct subjects. For some of the subjects, the images were taken at different times, plus there are variations in facial expression (open/closed eyes, smiling/non-smiling), scale, lighting, and facial details (glasses/no glasses). The original face images were all sized 112x92 with a 256-level gray scale.

To experiment for classifying images as "known" or as "unknown", the database is divided into two categories. First category is a "known" category which is composed of 200 images of 20 individuals (each individual with 10 varying images). This category is termed as "known" since training is provided to the system with 100 images of the same 20 individuals (5 images per person) from this "known" category of images. Actually, the 200 images of "known" category are subdivided into two non-overlapping sets with 5 training images and 5 test images per person to calculate for the efficiency in recognizing known persons as "known" as well as recognizing them correctly to show the matched image from training set. By randomly selecting the training and test sets for several times, the average efficiency of 91% is obtained for "known" category.

Results are shown in fig (4.1), fig (4.2), fig (4.3), fig (4.4), and fig (4.5) for variations in pose, expression, glasses/non-glasses, illumination, and scale respectivelyfor known persons with the corresponding distances available for the test images.

Obtained values of thresholds are,**T2 = 7293.3**, **T1 = 5389**

M_d =Distance between projection of test image on face space and the closest class projection. (Minimum distance)

T_d = Distance between centered test image and projection of its weights on eigenface.

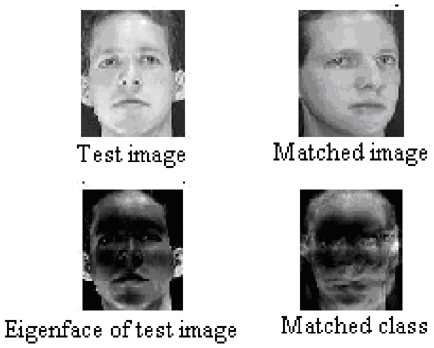


Fig. (4.1): Pose invariant recognition of known person.

M_d = 6247, T_d = 3995.

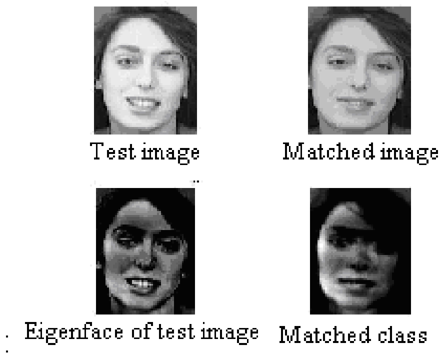


Fig. (4.2): Expression invariant recognition of known person.

M_d = 5039, T_d = 4098.9.

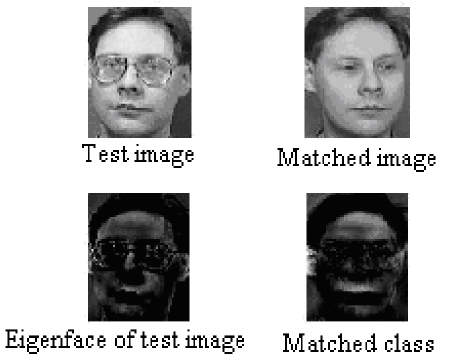


Fig. (4.3): Recognition of known person with glasses.

M_d = 5190.5, T_d = 3235.

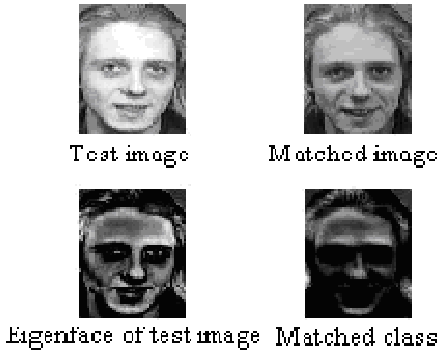


Fig. (4.4): Illumination invariant recognition of known person.

M_d = 6728.9, T_d = 3468.3.

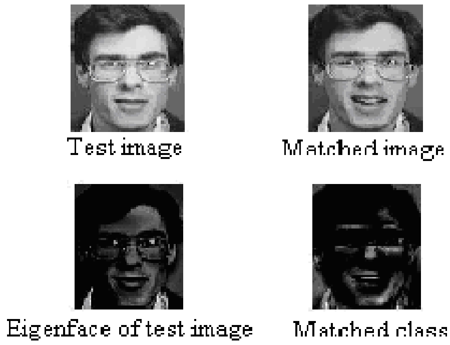


Fig. (4.5): Scale invariant recognition of known person.

M_d = 6825.3, T_d = 4402.8.

For all the above shown examples, we can observe that:

T_d <T1thus, "face images" and

M_d<T2 thus, "known" images**.**

The second category is an "Unknown" category which is composed of remaining 200 images in the database (all unknowns) of other 20 persons. Testing is carried out on these "unknown" category images to calculate for the efficiency in recognizing them as "Unknown". Average efficiency of 95% is obtained in this category.

Example result for unknown category is as shown in fig. (4.6) We can observe with the distances obtained that:

T_d < T1, thus it is "face" image, But

M_d > T2, thus it is considered as "unknown".

Result for non-face image is shown in fig. (4.7). Here, obtained T_d >T1hence, decided to be a "non-face" image.

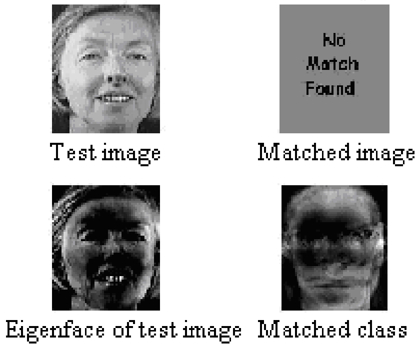


Fig. (4.6): Recognition Result for unknown person

M_d =8575.8, T_d = 4133.7.

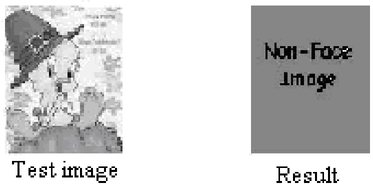


Fig. (4.7): Recognition Result for non-face image.

T_d =9323.8.

Experiments were performed for classifying images as "face" or as "non-face" using the complete ORL database to test for "face" image results and variety of non-face, grayscale images are collected, resized to the size of original database image (112x92) to test for the "non-face" image results. Result is shown in fig(10) for non-face image which shows T_d less than threshold T1**.**

5. CONCLUSION

The central theme of eigenface approach for face recognition is getting a small set of image features that best approximates the set of known face images, without requiring that they correspond to our intuitive notions of facial parts and features. Although it is not an elegant solution to the general recognition problem, the approach does provide a practical solution.

Little preprocessing work is needed, raw intensity data are used directly for learning and recognition without any significant low-level or mid-level processing.No knowledge of geometry and reflectance of faces are required in this method.Ease of implementation, Recognition is simple and efficient compared to other matching approaches. Hence it is comparatively simple.

This technique is quite sensitive to scarring, head scale changes, light levels changes above some limits and to extreme changes in pose, expression and disguise. Approach is not suitable for extreme non-frontalviews.Good performance is available under controlled background; this condition may not be satisfied in most natural scenes.

There are number of fields where face recognition systems are widely in use as: Information security, law enforcement and surveillance, smart cards, access control etc.

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