A Comprehensive Methodological Analysis of Eigen Face Recognition and Reconstruction

Prabhakar Telagarapu, Gulivindala Suresh, J. Venkata Suman, and N. V. Lalitha

***Abstract*—Face recognition using eigen faces is an approach to the detection and identification of human faces and then recognizes the person by comparing characteristics of the face to those of known individuals is described. This approach treats face recognition as a two-dimensional recognition problem, taking advantage of the fact that faces are normally upright and thus may be described by a small set of 2-D characteristic views. Face images are projected onto a feature space `face space' that best encodes the variation among known face images. The face space is defined by the `eigen faces', which are the eigenvectors of the set of faces. They do not necessarily correspond to isolated features such as eyes, ears, and noses. Eigen faces are obtained from eigenvectors of an image which is a principle component of analysis. The principal component analysis (PCA) is one of the most successful techniques that have been used in image recognition and compression. The main idea of using PCA for face recognition is to express the large 1-D vector of pixels constructed from 2-D facial image into the compact principal components of the feature space. This can be called eigenspace projection. Eigenspace is calculated by identifying the eigenvectors of the covariance matrix derived from a set of facial images. Face recognition has many applicable areas. Moreover, it can be categorized into face identification, face classification, or sex determination. The most useful applications contain crowd surveillance, video content indexing, personal identification (ex. driver's license), and mug Shots matching, entrance security, etc.**

***Index Terms*—Eigen faces, two-dimensional recognition problem, eigenvectors, principal component analysis.**

I. Introduction

Principal component analysis (PCA) algorithm programming steps: calculation of mean, calculation of covariance matrix, and its eigenvalues and eigenvectors [1]. The calculation of covariance matrix eigenvalues greater than the threshold number in descending order of eigenvalue Remove the smaller eigenvalue, Select the appropriate eigenvalues and eigenvectors, computing whitening matrix.

A. Eigen Face Approach

This approach to the face recognition involves the following initialization operations[2]. Acquire an initial set of face images (the training set). Calculate the eigen faces from the training set, keeping only the M images that correspond to the highest eigenvalues. These M images define the face space. As new faces are experienced, the eigen faces can be updated or recalculated.

$$[I_1, I_2, I_3, ...I_M]_{m\times n} \tag{1}$$

Calculate the corresponding distribution in the M dimensional weight space for each known individual, by projecting their face images onto the "face space". These operations can also be performed from time to time whenever there is a free excess computational capacity[3]. Having initialized the system, the following steps are then used to recognise new face images:

1) Calculate a set of weights based on the input image and the M eigen faces by projecting the input image onto each eigen faces.
2) Determine the image is a face at all (whether known or unknown) by checking to see if the image is sufficiently close to the "face space".
3) If it is a face, classify the weight pattern as either a known person or as unknown.
4) Update the eigen faces and/or weight patterns.
5) If the same unknown face is seen several times, calculate its characteristic weight pattern and incorporate into the known faces.

II. Generation of Training Set

Let a face image $I(x, y)$ be a two dimensional m by n array of (8-bit) intensity values. An image may also be considered as a vector of dimension M by M, so that a typical image of size 92 by 112 becomes a vector of dimension 10,304 or equivalently, a point in 10,304 dimensional spaces. Images of faces, being similar in overall configuration, will not be randomly distributed in this huge image space and thus can be described by a relatively low dimensional sub space. The main idea of the principal component analysis is to find the vectors that best account for distribution of face images within the entire image space[4]. These vectors define the subspace of face images, which we call "face space". Each vector is of length N^2, describes an N by N image, and is £ a linear combination of original face images. Because these vectors are the eigenvectors of the covariance matrix corresponding to the original face images, and they are face-like in appearance, we refer to them as eigen faces. Representing image in matrix form, we considered each image to be a $m\times n$ matrix that is an image with m, the number of image rows (vertical pixels) and n the number of columns (horizontal pixels).

The training image set is designated as each image is converted into a column matrix for the simplification purposes and to have a better implementation of PCA. This is done by taking column one below another and so on for all the n columns. Thus we result with the column matrices of all the M images and are represented as

$$[\Gamma_1 \Gamma_2, \Gamma_3, \cdots, \Gamma_M]_{mn\times 1} \tag{2}$$

Manuscript received October 3, 2011; revised January 10, 2012.

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A. Mean Image

Let the training of face images are $\Gamma_1 \Gamma_2, \Gamma_3, \cdots, \Gamma_M$. The average face of the set is defined as

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \tag{3}$$

B. Normalization of Training Set

Each face differs from the average by the vector. This process is called normalization[5]. The normalization of all the faces in the training set is done to remove any brightness in the background i.e. highlighting the pixels in the center and it is expressed mathematically as follows

$$\phi_i = \Gamma_i - \Psi \tag{4}$$

C. Generation of Eigen Faces

Each face differs from the average by the vector. $\phi_i = \Gamma_i - \Psi$. This set of very large vectors is then subject to principal component analysis, which seeks a set of M orthonormal vectors U_n which best describes the distribution of the data. The Kth vector U_k is chosen such that is a maximum subject to -

$$U_l^T U_k = \delta_{lk} = \begin{cases} 1, & \text{if } l = k \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

The vectors U_k and scalars λ_k are the eigenvectors and eigenvalues, respectively, of the covariance matrix

$$C = \frac{1}{M}\sum_{n=1}^{M}\phi_n \phi_n^{\,T} = AA^T \tag{6}$$

where the matrix $A = [\phi_1\ \phi_2 \cdots \phi_M]$. The matrix C, however, is N^2 by N^2 eigenvectors and eigenvalues is an intractable task for typical image sizes. We need a computationally feasible method to find these eigenvectors. If the number of data points in the image is less than the dimension space ($M < N^2$), there will be only M–1, rather than N^2, meaning full eigenvectors (the remaining eigenvectors will have associate eigenvalues of zero). Fortunately we can solve for the N^2 dimensional eigenvectors in this case by first solving a 16 by 16 matrix rather than a 16,384 by 16,384 matrix and then taking appropriate linear combinations of face images Φ_i, consider the eigenvectors V_l of A^T.A such that

$$A^T A v_i = \mu_i v_i \tag{7}$$

Pre multiplying both sides by A, we have

$$AA^T A v_i = \mu_i A v_i \tag{8}$$

From which we see that Av_i, are the eigenvectors of $C = AA^T$. Following this analysis, we construct the M by M matrix $L = A^T A$, where $L_{m\times n} = \phi_m^T \phi_n$, and find the M eigenvectors, V_l, of L. These vectors determine linear combinations of M training Set face images to form the eigen faces u_l.

$$u_l = \frac{1}{M}\sum_{k=1}^{M}\phi_k v_{lk}\ ,\quad 1 = 1,2,\cdots,M \tag{9}$$

With this analysis the calculations are greatly reduced, from the order of the number of pixels in the images (N^2) to the order of the number of images in the training set (M). In practice the training set of face images will be relatively small ($M<N^2$), and the calculations become quite manageable. The associated eigenvalues allow us to rank the eigenvectors according to their usefulness in characterizing the variation among the images.

D. Eigen Face Recognition

To summarize, the eigen faces approach [6]-[13] to face recognition involves the following steps.

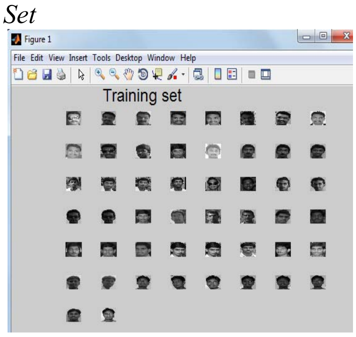
- Collect a set of characteristic face images of the known individuals. This set should include a number of images for each person, with some variation in expression and in the lighting. (Say four images of ten people so M=40).
- Calculate the (40×40) matrix L, find its eigenvectors and eigenvalues, and chose the M' eigenvectors with the highest associated eigenvalues. (Let M'=10 in this example).
- Combine the normalized training set of images (according to (6)) to produce the (M'=10) eigen faces U_k.
- For each known individual, calculate the class vector Ω_k by averaging the eigen face pattern vectors Ω (from (8)) calculated from original (four) images of the individual. Choose a threshold

$\theta\varepsilon$ that defines the maximum allowable distance from face class, and threshold $\theta\varepsilon$ that defines the maximum allowable distance from face space according to (9)

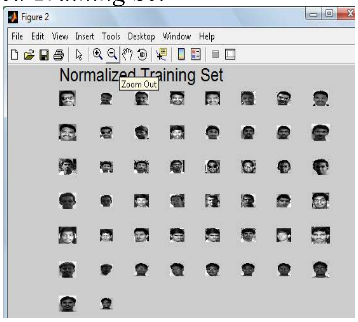
For each new face image to be identified, calculate its pattern vector Ω, the distance ε_i to the face space. If the minimum distance $\varepsilon_k < \theta\varepsilon$ and the distance $\varepsilon < \theta\varepsilon$ classify the input as face as the individual associated with class vector Ω_k, if the minimum distance $\varepsilon_k < \theta\varepsilon$ but the distance $\varepsilon < \theta\varepsilon$, then the image may be classified as "unknown" and optionally used to begin a new face class. If the new image is classified as a known individual this image may be added to the original set of familiar face images and eigen faces may be recalculated[14]-[17]. This gives the opportunity to modify the face space as the system encounters more instances of known faces.

III. Results

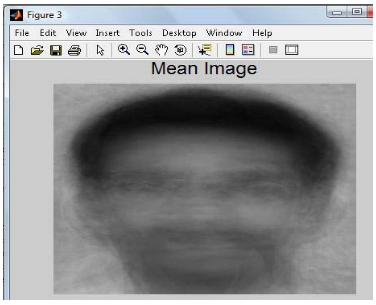
A. Training Set



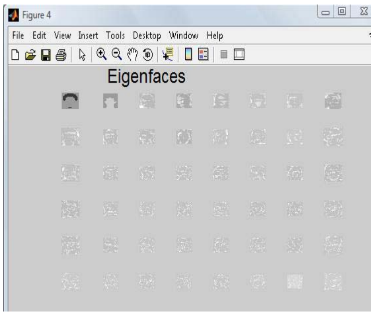
B. Normalized Training Set



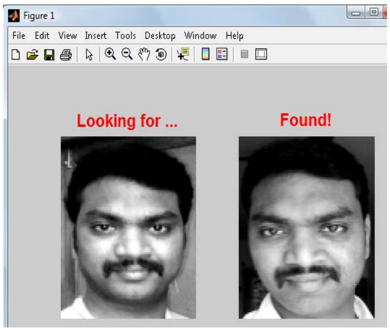
C. Mean Image

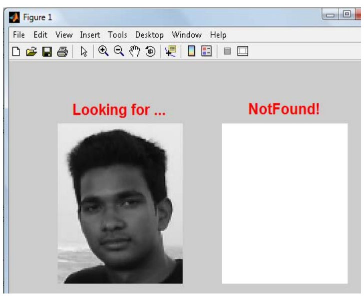


D. Eigen Faces



E. Recognition





IV. Conclusion

Early attempts at making computers recognize faces were limited by the use of impoverished face models and feature descriptions, assuming that a face is no more than the sum of its parts, the individual features. Attempts using parameterized feature models and multi-scale matching look more promising still face severe problems before they are generally applicable. Current connectionist approaches tend to hide much of the pertinent information in the weights that makes it difficult to modify and evaluate parts of the approach. The eigen face approach to face recognition was motivated by information theory, leading to the idea of basing face recognition on a small set if image features that best approximate 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 eigen face approach does provide a practical solution that is well fitted to the problem of face recognition. It is fast, relatively simple, and has been shown to work well in a constrained environment. It can also be implemented using modules of connectionist or neural networks. It is important to note that many applications of face recognition do not require perfect identification, although most require a low false positive rate. In searching a large data base of faces, for example it may be preferable to find a small set of likely matches to present to the user. For applications such as security systems or human computer interactions, the system will normally be able to "view" the subject for a few seconds or minutes and thus will have a number of chances to recognize the person. In this paper the eigen face technique can be made to perform at very high accuracy, although with a substantial "unknown" rejection rate and thus is potentially well suited to these applications. In this Paper the investigating is done at more detail on the issue of robustness to changes in lighting, head size and head orientation, automatically learning new faces, incorporating a limited no. of characteristic views for each individual and the tradeoffs between the no. of people the system needs to recognize and the number of eigen faces necessary for unambiguous classification.

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