DESIGN OF EFFICIENT FACE RECOGNITION BASED ON PRINCIPLE COMPONENT ANALYSIS USING EIGENFACES METHOD

[1] MR. A. R. SEJANI, [2] PROF. R. C. BUTANI , [3] PROF. Y. J. PARMAR

[1]M.E.[Electronics & Communication] Student,
Department Of Electronics & Communication Engineering,
Marwadi Education Foundation's Group of Institutions, Rajkot, Gujarat, India.
[2] Asst.Professor, Department Of Electronics & Communication Engineering,
Marwadi Education Foundation's Group of Institutions, Rajkot, Gujarat, India.
[3] Asst.Professor, Department Of Electronics & Communication Engineering,
C.U Shah College of engineering & Technology, Wadhwan, Gujarat, India.

ankit.sejani30@gmail.com, ravi_butani@yahoo.com, yagu_ecengineer@yahoo.com

ABSTRACT: *Face recognition systems have been grabbing high attention from commercial market point of view as well as pattern recognition field. It also stands high in researchers' community. Face recognition have been fast growing, challenging and interesting area in real-time applications. A large number of face recognition algorithms have been developed from decades. The present paper refers to different face recognition approaches and primarily focuses on principal component analysis, for the analysis and the implementation is done in free software, Matlab. This face recognition system detects the faces in a picture taken by web-cam or a digital camera, and these face images are then checked with training image dataset based on descriptive features. Descriptive features are used to characterize images. Matlab's Image processing toolbox is used for performing the image analysis.*

Keywords—Eigenfaces,PCA, Face recognition, Image processing, Person Identification, Face Classification, Matlab, Image processing toolbox.

I: INTRODUCTION

Face recognition systems have been grabbing high attention from commercial market point of view as well as pattern recognition field. Face recognition has received substantial attention from researches in biometrics, pattern recognition field and computer vision communities. The face recognition systems can extract the features of face and compare this with the existing database. The faces considered here for comparison are still faces. Machine recognition of faces from still and video images is emerging as an active research area. The present paper is formulated based on still or video images captured either by a digital camera or by a web cam. The face recognition system detects only the faces from the image scene, extracts the descriptive features. It later compares with the database of faces, which is collection of faces in different poses. The present system is trained with the database shown in Figure 2, where the images are taken in different poses, with glasses, with and without beard

II: DETAIL NOTE ON EIGENFACES

Eigenfaces are a set of eigenvectors used in the computer vision problem of human face recognition. Eigenfaces assume ghastly appearance. They refer to an appearance-based approach to face recognition that seeks to capture the variation in a collection of face images and use this information to encode and compare images of individual faces in a holistic manner. Specifically, the eigenfaces are the principal components of a distribution of faces, or equivalently, the eigenvectors of the covariance matrix of the set of face images, where an image with $N \times N$ pixels is considered a point (or vector) in N^2-dimensional space. The idea of using principal components to represent human faces was developed by Sirovich and Kirby (Sirovich and Kirby 1987) and used by Turk and Pentland(Turk and Pentland 1991) for face detection and recognition. The Eigenface approach is considered by many to be the first working facial recognition technology, and it served as the basis for one of the top commercial face recognition technology products. Since its initial development and publication, there have been many extensions to the original method and many new developments in automatic face recognition systems. Eigenfaces is still considered as the baseline comparison method to demonstrate the minimum expected performance of such a system.

Eigenfaces are mostly used to:

a. Extract the relevant facial information, which may or may not be directly related to human intuition of face features such as the eyes, nose, and lips. One way to do so is to capture the statistical variation between face images.

b. Represent face images efficiently. To reduce the computation and space complexity, each face image can be represented using a small number of dimensions the eigenfaces may be considered as a set of features which characterize the global variation among face images. Then each face image is approximated using a subset of the eigenfaces, those associated with the largest eigenvalues. These features account for the most variance in the training set. In the language of information theory, we want to extract the relevant information in face image, encode it as efficiently as possible, and compare one face with a database of models encoded similarly. A simple approach to extracting the information contained in an image is to somehow capture the variations in a collection of face images, independently encode and compare individual face images. Mathematically, it is simply finding the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images, treating an image as a point or a vector in a very high dimensional space. The eigenvectors are ordered, each one accounting for a different amount of the variations among the face images. These eigenvectors can be imagined as a set of features that together characterize the variation between face images. Each image locations contribute more or less to each eigenvector, so that we can display the eigenvector as a sort if "ghostly" face which we call an eigenface. The face images that are studied are shown in the Figure 1, and there respective eigenfaces are shown in Figure 4, Each of the individual faces can be represented exactly in terms of linear combinations of the eigenfaces. Each face can also be approximated using only the "best" eigenface, which has the largest eigenvalues, and the set of the face images. The best M eigenfaces span an M dimensional space called as the "Face Space" of all the images. The basic idea using the eigenfaces was proposed by Sirovich and Kirby as mentioned earlier, using the principal component analysis and where successful in representing faces using the above mentioned analysis. In their analysis, starting with an ensemble of original face image they calculated a best coordinate system for image compression where each coordinate is actually an image that they termed an eigenpicture. They argued that at least in principle, any collection of face images can be approximately reconstructed by storing a small collection of weights for each face and small set if standard picture (the eigenpicture). The weights that describe a face can be calculated by projecting each image onto the eigenpicture. Also according to the Turk and Pentland, the magnitude of face images can be reconstructed by the weighted sums of the small collection of characteristic feature or eigenpictures and an efficient way to learn and recognize faces could be to build up the characteristic features by experience over feature weights needed to (approximately) reconstruct them with the weights associated with known individuals. Each individual therefore would be characterized by the small set of features or eigenpicture weights needed to describe and reconstruct them, which is an extremely compact representation of the images when compared to themselves.

Approach followed for facial recognition using eigenfaces

The whole recognition process involves two steps,

a. Initialization process

b. Recognition process

The Initialization process involves the following operations:

1.Acquire the initial set of face images called as training set.

2.Calculate the eigenfaces from the training set, keeping only the highest eigenvalues. These M images define the face space. As new faces are experienced, the eigenfaces can be updated or recalculated.

3.Calculate the corresponding distribution in M-dimensional weight space for each known individual, by projecting their face images on to the "face space".

These operations can be performed from time to time whenever there is a free excess operational capacity. This data can be cached which can be used in the further steps eliminating the overhead of re-initializing, decreasing execution time thereby increasing the performance of the entire system.

Having initialized the system, the next process involves the steps,

1. Calculate a set of weights based on the input image and the M eigenfaces by projecting the input image onto each of the eigenfaces

2. Determine if the image is a face at all (known or unknown) by checking to see if the image is sufficiently close to a "free space".

3. If it is a face, then classify the weight pattern as either a known person or as unknown.

4. Update the eigenfaces or weights as either a known or unknown

If the same unknown person face is seen several times then calculate the characteristic weight pattern and incorporate into known faces.

The last step is not usually a requirement of every system and hence the steps are left optional and can be implemented as when the there is a requirement.

III:APPLICATION OF PCA IN FACE RECOGNITION

One of the main applications of the PCA in Computer Vision is in facial recognition.

Generating Eigenfaces

Assume a face image $I(x,y)$ be a two-dimensional M by N array of intensity values, or a vector of dimension $M \times N$. The Training set used for the analysis is of size 110x129, resulting in 14,190 dimensional space. A typical image of size 256 by 256 describes a vector of dimension 65,536, or,

equivalently, a point in 65,536-dimensional space. For simplicity the face images are assumed to be of Size $N \times N$ resulting in a point in N^2 dimensional space. An ensemble of images, then, maps to a collection of points in this huge space.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 subspace. The main idea of the principal component analysis (or Karhunen-Loeve transform) is to find the vectors which best account for the distribution of face images within the entire image space. 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 the original face images. Because these vectors are the eigenvectors of the covariance matrix corresponding to the original face images, and because they are face like in appearance, we refer to them as "eigenfaces".
The Training set images used for the analysis purpose are shown in the Figure 1. And the corresponding eigenfaces for the training sets are shown in the Figure 4.
Let the training set of face images be $\Gamma_1, \Gamma_2 \ldots \Gamma_M$.
The average face of the set is defined by

$$\Psi = \frac{1}{M} \sum \Gamma k$$

Each face differs from the average by the vector

$$\Phi = \Gamma i - \Psi$$

An example training set is shown in Figure 1, with the average face Ψ shown in Figure 2. This set of very large vectors is then subject to principal component analysis, which seeks a set of M orthonormal vectors u_k, which best describes the distribution of the data,The kth vector is u_k chosen such that,

$$\Lambda_k = \frac{1}{M} (u_k^T \Phi_n)^2$$

The vectors u_k and Λ_k scalars are eigenvectors and eigenvalues, respectively, of the Covariance matrix

$$C = \frac{1}{M} \sum_{n=1}^{M} \Phi \Phi^T$$

$$= A A^T$$

Where matrix A= $[\Phi_1 \; \Phi_2 \; \Phi_3 \; \Phi_4 \ldots \ldots \ldots \Phi_M]$
The matrix C, however, is $N^2 \times N^2$ by N, and determining the N eigenvectors and eigenvalues is an intractable task for typical image sizes.
A Computationally feasible method is to be funded to calculate these eigenvectors. If the number of data points in the image space is $M(M<N^2)$, there will be only M-1 meaningful eigenvectors, rather than N^2.

The eigenvectors can be determined by solving much smaller matrix of the order $M^2 \times M^2$ which reduces the computations from the order of N^2 to M, pixels. Therefore we construct the matrix L

$$L = A.\, A^T$$

Where

$$L_{mn} = \Phi^T{}_m \Phi_n$$

Fig.1 The Training Images that have been used for analysis

Fig.2 average Image for the training set

and find the M eigenvector u_l of L . These vectors determine linear combination of the M training set face images to form the eigenfaces v_l

$$v_l = \sum u_{lk} \; \Phi_k$$

Where l = 1,2……….M

IV: FACE RECOGNITION

Once the eigenfaces are created, identification ecomes a pattern recognition task. The eigenfaces span an N^2-dimensional subspace of the original A image space. The M' significant eigenvectors of the L matrix are chosen as those with the largest associated eigenvalues. In the test cases, based on M = 6 face images, M' = 4 eigenfaces were used. The number of eigenfaces to be used is chosen heuristically based on the eigenvalues. A new face image (I) is transformed into its eigenface components (projected into "face space") by a simple operation,

$$\Omega_k = V_k^T\left(\Gamma k - \Psi\right)$$

Where k = 1,2……M'

This describes a set of point-by-point image multiplications and summations. Figure 4 shows three images and their projections into the seven-dimensional face space, the weights form a vector

$$\Omega^T = [\Omega_1, \Omega_2 \Omega_3\, \Omega_4 \ldots\ldots \Omega_{M'}]$$

that describes the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images. The vector is used to find which of a number of predefined face classes, if any, best describes the face. The simplest method for determining which face class provides the best description of an input face image is to find the face class *k* that minimizes the Euclidean distance

$$\varepsilon_k = \| \Omega - \Omega_k \|$$

Where Ω_k is a vector describing the k[th] face class.

A face is classified as belonging to class *k* when the minimum ε_k is below some chosen threshold $\theta\varepsilon$ Otherwise the face is classified as "unknown". The distance threshold, $\theta\varepsilon$, is half the largest distance between any two face images, Mathematically can be expressed as,

$$\theta\varepsilon = \frac{1}{2} max_{jk} \{\| \Omega - \Omega_k \|\}$$

Where j, k = 1,2……M

Recognition process can formulated as:

If

$\varepsilon \geq \theta\varepsilon$ then input image is not a face

$\varepsilon < \theta\varepsilon$,$\varepsilon k \geq \theta\varepsilon$ then input image contains an unknown face

$\varepsilon < \theta\varepsilon$, $\varepsilon k' = min\ \{\varepsilon k\} < \theta\, \varepsilon$ then image contains face of individual *k'*

- In the first case, an individual is recognized and identified.
- In the second case, an unknown individual is present.
- In the first case, the image is not a face image. Case one typically shows up as a false positive in most recognition systems

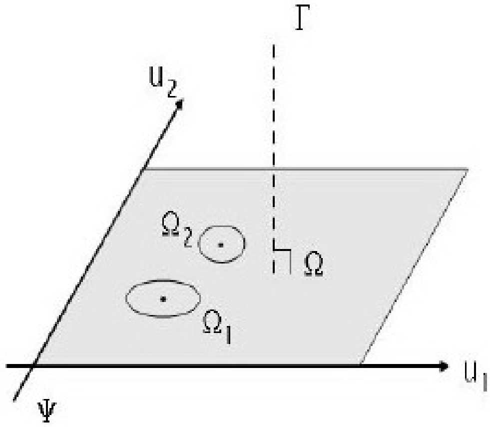

Fig. 3 Visualization of a 2D face space, with the axes representing two Eigenfaces.

A simplified version of face space to illustrate the four results of projecting an image into face space. In this case, there are two eigenfaces (u_1, u_2) and three known individuals (Ω_1, Ω_2, Ω).

Fig.4 Eigenfaces of the corresponding training images shown in Figure (1)

V. IMPLEMENTATION IN MATLAB&RESULT

The above discussed methodologies have been implemented in Matlab.. I have used my friends images for the testing purpose I also have created an Image Database having 30 male test subjects &20 female test subject ,so a total of 50 images.

And the results from the above implementation are

TABLE 1

Table showing the success and error rates of face recognition on Self Created Image Database in various conditions

Condition	Success	Error
Normal	85.00%	15.00%
Light Variations	63.00%	37.00%
Size Variations	56.00%	44.00%

VI:LIMITATION & CONCLUSION

The tests conducted on various subjects in different environments shows that this approach has limitations over the variations in light, size and in the head orientation**,** nevertheless this method showed very good classifications of faces(>85% success rate). A good recognition system should have the ability to adapt over time. Reasoning about images in face space provides a means to learn and subsequently recognize new faces in an unsupervised manner. When an image is sufficiently close to face-space (i.e., it is face-like) but is not classified as one of the familiar faces, it is initially labeled as "unknown" . The computer stores the pattern vector and the corresponding unknown image. If a collection of "unknown" pattern vectors cluster in the pattern space, the presence of a new but unidentified face is postulated. A noisy image or partially occluded face would cause recognition performance to degrade. The eigenface 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 constrained environment.

REFERENCES

[1] M.Turk and A. Pentland, "Eigenfaces for Recognition",Journal of Cognitive Neuroscience, March 2001.
[2] M.A. Turk and A.P. Pentland. “Face recognition using eigenfaces”. In Proc. of Computer Vision and Pattern Recognition, pages 586-591. IEEE, June 1991b.
[3] L.I. Smith. “A tutorial on principal components analysis”
[4] Delac K., Grgic M., Grgic S., “Independent Comparative Study of PCA, ICA, and LDA on the FERET Data Set”, International Journal of Imaging Systems and Technology, Vol. 15, Issue 5, 2008, pp. 252-260
[5] H. Moon, P.J. Phillips, “Computational and Performance aspects of PCA-based Face Recognition Algorithms”, Perception, Vol. 30, 2001, pp. 303-321
[6] Scilab Online Documentation “http://www.scilab.org/product/man/”
[7] Scilab Image Video Processing toolbox “http://sivp.sourceforge.net/”
[8] Aditya kelkar,”Face recognition using Eigenfaces Approach”
[9] Dimitri Pissarenko, “Eigenface-based facial recognition”
[10] Ming-Hsuan Yang, “Recent Advances in Face Recognition”
[11] W. Zhao, R. Chellappa, P.J. Phillips and A. Rosenfeld, “ Face Recognition: A Literature Survey”
[12] Jon Shlens, “A Tutorial on Principal Component Analysis Derivation, Discusson and Singular Value Decomposition”, 25 March 2003, Version 1
[13] R.Chellapa, L.Wilson and S.Sirohey “Human and machine Recognition of Faces: A Survey ”, Proc IEEE, vol.83, pp. 705-740, 2005.
[14] Ming-Hsuan Yang, David J.Kriegman, Narendra Ahuja, “Detecting Faces in Images: A Survey”, Proc IEEE, vol.24, pp. 34-58
[15]L.Sirovich and M. Kirby (1987). "Low-dimensional procedure for the characterization of human faces". Journal of the Optical Society of America A 4: 519–524.
[16] A. Yuille, D. Cohen, and P. Hallinan, “Feature extraction from faces using deformable templates,” Proceedings of IEEE Computer Society Conference on Computer Vision and Templates, pp.104-109,2010.
[17] Image database-my own collection of images