A Study on the Face Recognition Using PCA

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Abstract

In this paper, a face recognition algorithm system using Principle Component Analysis is proposed. The algorithm recognized a person by comparing characteristics (features) of the face to those of known individuals which is a face database of Intelligence Control Laboratory (ICONL). Experiments were simulated in order to demonstrate the performance of this algorithm due to face recognition which presented for the classification of face and non-face and the classification of known and unknown.

Key Words : Face recognition, Principal Component Analysis (PCA), ICONL database

1. Introduction

Several different techniques have been proposed for computer recognition of human faces but much of the work have ignored the issue of the face stimulus, which is important for face recognition by either treating the face as a uniform pattern or assuming that the positions of features are an adequate presentation. It is not evident, however such representations are sufficient to support robust face recognition.

Information theory approach has been suggested to encode the most relevant features (information) in a group of faces that best distinguish them from one another. Such features may or may not be directly related to our intuitive notion of face features such as the eyes, nose, lips, and etc. The approach transforms face images into a small set of images feature characteristics, called "eigenfaces" or "face space", which are the principle components of the group of faces.

In this paper, the group of faces is an initial training set of 10 faces images of ICONL database. The face recognition problem maybe describe as: Given a face image, we project the face image into subspace spanned by the "face space" and then classify the face by comparing its position in face space with the positions of known individual and display it together with the match if there is.

Each face image of ICONL database is gray scale, vertically oriented frontal view. The face images can be represented exactly in terms of weight vector which calculated by linear combination of each eigenface with the best eigenfaces (the largest eigenvalues); and therefore represent the most variances of the face images.

Our target of this paper is to recognize a face as "unknown" or "known" individual by comparing it with the initial training set, and for that, experiments were simulated. Additionally, experiments of the performance of PCA algorithm due to face recognition which classifying faces as face and non-face were also presented within this paper.

2. Eigenfaces

Eigenfaces method is attempted by Sirovich and Kirby[6], Turk and Pentland[1] and A.J. O'Toole, H.Abdi, K. A. Deffenbachar and D. Valentin[3]. And, it is verified good for the recognition strategy[1] and [2] in controlled condition.

All the faces are located relatively in the same place in face space. Therefore, all the face vectors are located in a very narrow cluster in the face image space, as shown in the Fig 2.1. Hence, the full image space is not an optimal space for face description. Eigenface method aims to build a face space that better describes the faces. The basis vectors of this face space are called the principle components.

In mathematical terms, eigenface method is to find the principle components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images, treats an image as a point (or vector) in a very high dimensional space. The eigenvectors are ordered, each one accounting for a different amount of the variation among the face images. These eigenvectors can be though of as a set of features that together characterize the variation between face images. Each image location contributes more or less to each eigenvector, so that we can display the eigenvector as a sort of ghostly face as shown in Fig 3.3, which is why we call this by eigenface.

Eigenface transformation is non-invertible, in the sense that the basic set is small and can reconstruct only in a limited range of images. The transformation will only be adequate for recognition to the degree that the "face space" spanned by the eigenfaces can account for a sufficient range of faces.

The face recognition algorithm in this paper is summarized into two parts as illustrated in Fig 2.2.

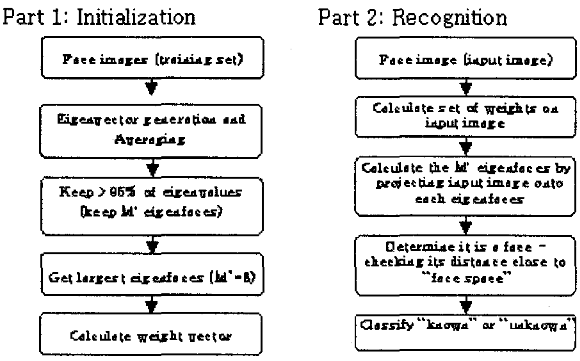

Fig 2.2. PCA face recognition system structure

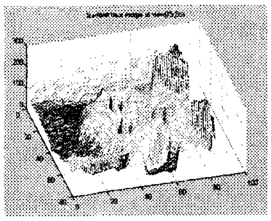
Fig 2.1. Face cluster in "face image space"

3. Making EigenFace

Let the training set of images be $\phi_T = [\phi_{T1}, \phi_{T2}, \ldots, \phi_{TM}]$. The average of the training set is defined by $\Psi_T = \frac{1}{M}\sum_{n=1}^{M}\phi_{Tn}$ (M is the number of images in the training set, M=10 in this paper), which represented the largest variance distances of entire training set. Each face image of training set differs from the average image by the vector $\Phi_{Ti} = \phi_{Ti} - \Psi_T$ and for $i = 1,2,\ldots,M$. The face images of training set is shown in Fig 3.1, with its average image Ψ_T shown in Fig 3.2. This set of large vector Φ_{Ti} is then subject to the PCA, to produce the M orthonormal vectors u_{Tn}, and their associated eigenvalues λ_{Tk} that best describes the distribution of the data. The vector u_{Tn} and scalar λ_{Tk} are the significant M eigenvectors and eigenvalues, respectively of the C_T (covariance matrix). The covariance matrix of is calculated by equation (1).

$$C_T = \frac{1}{M}\sum_{n=1}^{M}\Phi_{Tn}\Phi_{Tn}^T = A_T A_T^T \qquad (1)$$

The matrix C_T is N^2 by N^2, and determining the N^2 (6,216 x 6,216) eigenvectors and eigenvalues are an intractable task for typical images size. So, we need a computationally feasible method to find these eigenvectors u_{Tn} of C_T. Consider the eigenvectors v_{Ti} of $A_T A_T^T$ such that

$$A_T A_T^T v_{Ti} = \mu_{Ti} v_{Ti} \qquad (2)$$

Premultiplying both sides by A_T, we have

$$A_T A_T^T (A_T v_{Ti}) = \mu_{Ti}(A_T v_{Ti}) \qquad (3)$$

and comparing with equation (2), we see that the N^2 by N^2 is reduced to M by M. Therefore, we construct M by M matrix $C_T' = A_T^T A_T$, where $C_{T_{mn}}' = \Phi_{Tm}^T \Phi_{Tn}$, and find the M eigenvectors, $\boldsymbol{v}_{TG}$ of C_T' by

$$\boldsymbol{u}_{TC} = A_T \boldsymbol{v}_{Ti} \qquad (4)$$

Then, the weight vectors of training set is formed:

$$\boldsymbol{\Omega}_T = \boldsymbol{u}_{TC} A_T \qquad (5)$$

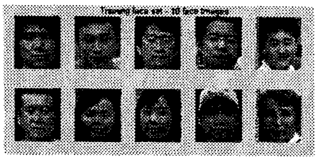

Fig 3.1. Some ICONL Images (74x84) - used as training set this paper (A picture of one person with different expression)

Fig 3.2. Average Image of training set

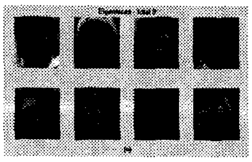

Fig 3.3. Total 8 eigenfaces (image)

4 Recognizing a face image by eigenfaces

An input face image $\boldsymbol{\phi}_I$ is given and transformed into its eigenface components (projected into "face space") by a simple operation, $W_k = \boldsymbol{u}_{Tk}^T(\boldsymbol{\phi}_I - \boldsymbol{\Psi}_T)$ for $k = 1,2,\ldots,M'$. The average face is subtracted and the remainder is projected onto the eigenfaces $\boldsymbol{u}_{Tk}$. This describes M' matrix multiplication and one matrix summation for one weight vector component. Fig 4.1 shows an image and its projection into the (in this case) eight eigenfaces.

Fig 4.1 An original face image and its projection onto the "face space" defined by the eigenfaces of Fig. 3.3.

The weights of input image form a vector $\boldsymbol{\Omega}_I = [\boldsymbol{w}_1, \boldsymbol{w}_2, \ldots, \boldsymbol{w}_{M'}]$ that describes the contribution of each eigenface in representing the input face image. The vector is then used in a standard pattern recognition algorithm to find which of a number of predefined face classes, if any, best describes the face. The 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 Euclidian distance as shown in equation (6) (Turk and Pentland, 1991). The face class metric is defined as:

$$\in^2 = \| \boldsymbol{\Omega}_I - \boldsymbol{\Omega}_k \|^2 \qquad (6)$$

where $\boldsymbol{\Omega}_k$ is a vector describing the kth face class. The face classes $\boldsymbol{\Omega}_I$ are calculated by averaging the result of the eigenface representation over a small number of face images (as few as one) of each individual. A face is classified as belonging to class k when the minimum $\in$ is below some chosen threshold $\theta_{\in}$, which classified face as "known" as illustrated in Fig 4.2. and otherwise as "unknown", as in Fig 4.3.

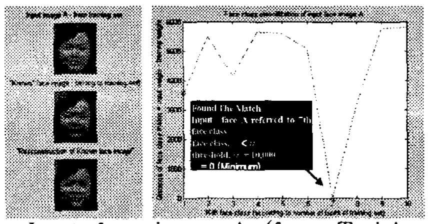

Fig 4.2. Input face image A (from Training set) classified as "known" to training set

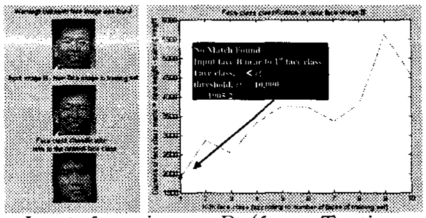

Fig 4.3. Input face image B (from Testing set B) classified as "unknown" to training set

5 Classifying faces by Eigenfaces

We can also use knowledge of "face space" to detect and locate faces in single images. This allows us to recognize the presence of faces apart from the task of identifying them. The faces are referred to testing set in this paper. Let the testing set be $\boldsymbol{\phi}_S = [\boldsymbol{\phi}_{S1}, \boldsymbol{\phi}_{S2}, \cdots, \boldsymbol{\phi}_{SM}]$, transformed it into its eigenface components (projected into "face space") by metric defined in equation (7). From here, the weight vectors of testing set is gathered, defined $\boldsymbol{\Omega}_S = [\boldsymbol{w}_1, \boldsymbol{w}_2, \ldots, \boldsymbol{w}_{M'}]$ as for $k = 1,2,\ldots,M'$.

$$W_S = u_{Tk}^T(\phi_S - \Psi_T) \quad (7)$$

Hence, creating the vectors of weights is equivalent to projecting the original face image onto the low-dimensional face space, we might end up having two different images with the same coordinates, specially of one of the images is not a face at all that projects onto a given pattern vector. In the pattern recognition scheme this will be a false positive (FP), incorrectly identified as a match (unwanted result). This is not a problem for the recognition system. The solution is to estimate the difference between an image and its reconstruction since the distance between the image and its projection onto the face space gives a direct measure of the "faceness", or how well the eigenfaces describe the image. This is simply the distance between the mean-adjusted (setting set) eigenfaces $\Phi_S = \phi_S - \Psi_T$ and $\Phi_f = \sum_{s=1}^{s=M} W_S u_{Tk}$, its projection onto the face space. The face space metric defined as

$$\epsilon^2 = \| \Phi_S - \Phi_f \|^2 \quad (8)$$

The face class and face space metric with specified threshold $\theta_{\in}$ determined whether the testing set did match a face in the training set or not.

6 Procedures and Results

6.1 Database

The ICONL database contains 18 face images of 14 persons compiled from4 subjects with 2 images each and 10 subjects with 1 image each. The subjects are 2 females and 12 males with the age range of 24 to 55 years. The resolution of the images was 74 x 84, 8-bit gray levels and some were shown in Fig 3.1.

6.2 Procedures

In the first experiment, a total of 10 images of ICONL database of 10 subjects with one image each are used as the training set. They were selected according to numerical ascending of 10 subjects with odd numeric and were used as the initial feature extraction system. From the experimented, only 95% of the eigenvectors are been kept, which portrayed 8 eigenfaces out of 10 eigenfaces and they are the initial "face space". Then, the face recognition classification is conducted using these eigenfaces as basic in the second experiments.

Two input images are chosen from ICONL database (face image A from training set and face image B from testing set B) in second experiment for face recognition classification. They are classified belong to one of the 10 subjects or not, referred to Fig 4.2 and 4.3, respectively.

Then, the remained ICONL database is used as the testing sets to classify the face as a face or non-face in "face space". Two testing sets have been set, they are; testing set A contained 4 subjects of one image which was selected numerical ascending of 4 subjects with even numeric. Testing set B was the leftover 4 subjects with 1 image (from subject number 11 to 14). The face classification results of these two testing sets are summarized in Table 6.1 and 6.2. In the tables, we have tried a few different thresholds which were based on the statistics that moved the threshold around the crossing point of the two distributions.

Table 6.1 PCA1 of Testing Set A

Threshold T, $\theta_{\in}$	Recognized1	Errors1	FP1	Recognition in %
variance1 (without T)	2	0	2	50
mean2 + sqrt(variance2)	2	0	2	50
mean2	2	0	2	50
mean1 + sqrt(variance1)	2	0	2	50
(mean1 + mean2)/2	1	2	1	25
mean1	0	3	1	0
mean1/2	0	4	0	0

Table 6.2 PCA2 of Testing Set B

Threshold T, $\theta_{\in}$	Recognized2	Errors2	FP2	Recognition in %
variance2 (without T)	1	0	3	25
mean2 + sqrt(variance2)	1	0	3	25
mean2	1	1	2	25
mean1 + sqrt(variance1)	1	1	2	25
mean1 + sqrt(variance1)	1	3	0	25
(mean1 + mean2)/2	1	3	0	25
mean2/2	0	4	0	0

Note : Recognized - "known faces", Errors - "unknown faces" and "FP" - False Positives

7 Conclusion

This paper presents a face recognition using PCA algorithm. The experimental results show that eigenface method can be applied to face recognition problem with the recognition rate of 50% has been achieved by the proposed estimator, based on a subspace decomposition technique using only the M = 8 eigenfaces. Through the experiments, it proved that the dimension has been reduced and this made a storage and memory capacity smaller. It has a fast convergence with simplicity of algorithm, and has been worked well under the constrained requirements.

8 References

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