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A Study on the Face Recognition Using PCA Algorithm

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Abstract

In this paper, a face recognition algorithm system using Principal Component Analysis (PCA) is proposed. The algorithm recognized a person by comparing characteristics (features) of the face tc those of known individuals of Intelligent Control Laboratory (ICONL) face database. Simulations are carried out to investigate the algorithm recognition performance, which classified the face as a face or non-face and then classified it as known or unknown one. Particularly, a Principal Components of Linear Discriminant Analysis (PCA + LDA) face recognition algorithm is also proposed in order to confirm the recognition performances and the adaptability of a proposed PCA for a certain specific system.

Key Words : Face recognition, Principal Component Analysis (PCA) Algorithm, Intelligent Control Laboratory (ICONL) database, Linear Discriminant Analysis (LDA) Algorithm

1. 서 론

Computational models of face recognition are being implemented over the last 20 years. They are not only contributing to theoretical insights but also to practical applications in industrial fields. Some of the practical application's inputs are the still face images while others are real time dynamic face images. In this paper, still face images are used for preprocessing and simulation.

Our interested are based on so-called eigenfaces, conceptually a simple idea going back to Sirovich and Kirby [1]. The idea behind eigenfaces is to find an orthonormal basis for the subspace or 'face space' containing all the facial features. Such features may or may not be directly related to our intuitive portion of face features such as the eyes, nose, lips, hair, and etc. But, the attractive viewpoint of this concept lies in the fact that the 'face space' has the low dimensions and can make substantially their dimensions reduce without any loss of the image resolution. We can develope various efficient systems based on this key idea, the most notably by the Media Laboratory at MIT; see [2, 3, 4]. The proposed face recognition approach in this paper is based on this key word, the Principal Component Analysis (PCA) algorithm.

One of the problems that any face recognition system must be confronted is the fact that different images of the same face can vary enormously with respect to size, position, orientation, lighting conditions, and facial expression. Thus, it may be hard to compare different images of the same face under different conditions. Face recognition systems in general tend to include a preprocessing stage where the image is normalized with respect to the above-mentioned variations.

The preprocessing state in this paper involves the designation and normalization of Intelligent Control Laboratory (ICONL) database. The preprocessed database is used to examine the adaptability of face recognition algorithm of the paper. The adaptability and the robustness of the algorithm are simulated by classifying the face images as a face or non-face and then as a known or unknown individual to the initialized training set. This paper describes the proposed algorithm in detail in Section 2 and 3, and presents the simulation results in Section 4, which also includes the simulation results of the Principal Components of Discriminant Analysis face recognition algorithm. Finally, the conclusion is summarized in Section 5.

2. Eigenfaces

Eigenface method is attempted by Sirovich and Kirby[1], Turk and Pentland[5] and A.J. O'Toole, H.Abdi, K. A. Deffenbachar and D. Valentin[6]. And, it is verified good for the recognition strategy[1, 5] in controlled condition.

In mathematical terms, eigenface method is to find the principal components of the distribution of faces, or the

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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 and can be displayed as a sort of ghostly face as shown in Fig 4. Each eigenface deviates from uniform gray where some facial features differ among the set of face images; and they are a sort of maps of the variations between faces. Each individual face can be represented exactly in terms of a linear combination of the eigenfaces. Each face can be approximated using the 'best' eigenvectors for most eigenfaces - those that have the largest eigenvalues and which therefore account for the most variation within the set of face images. The overall structure of a proposed face recognition algorithm, which consists of the system database initialization step and the face recognition phase step is shown in Fig. 1.

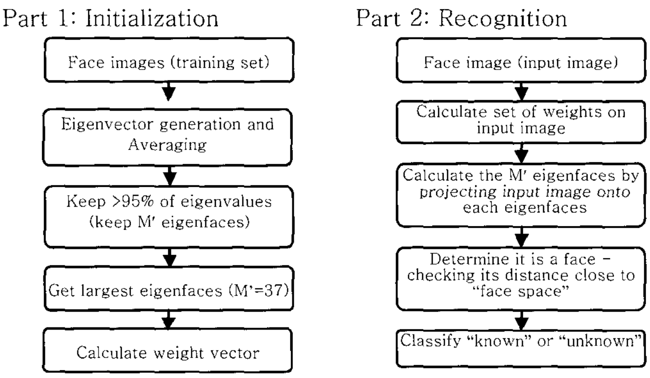

Fig. 1 Overall structure of face recognition algorithm

2.1. Construction of system database initialization

The main idea of construction of system database initialization is to find the most adequate vectors which represent the distribution of training set (60 ICONL face images) within the entire image space. The vectors defined the subspace of training set that calls 'face space'. Hence, the vectors are the eigenvectors of the covariance matrix corresponding to the training set and are face-like in appearance, therefore, they are referred as 'eigenfaces' or 'eigenfeatures'[3].

Practically, the training set is to be $\boldsymbol{\varphi}_T = [\boldsymbol{\varphi}_{T1}, \boldsymbol{\varphi}_{T2}, \boldsymbol{\varphi}_{T3}, \cdots, \boldsymbol{\varphi}_{TM}]$ and the average of the training set is defined by $\boldsymbol{\Psi}_T = 1/M \sum_{n=1}^{M} \boldsymbol{\varphi}_{Tn}$ (M is the number of face images of training set, M = 60), which represented the largest variance distances of entire training set. Each face image of training set differs from the average image by the vector $\boldsymbol{\Phi}_{Ti} = \boldsymbol{\varphi}_{Ti} - \boldsymbol{\Psi}_T$ for $i = 1,2,3,\cdots,M$. The training set is shown in Fig. 2, with its average image shown in Fig. 3. This set of large vector $\boldsymbol{\Phi}_{Ti}$ is the average centered image which is subject to the PCA, to produce the M orthonormal vectors $\mathbf{u}_{Tn}$, and their associated eigenvalues λ_{Tk} that best describes the distribution of the data. They are the significant M eigenvectors and eigenvalues, respectively of the $\mathbf{C}_T$ (covariance matrix) where the matrix $\mathbf{A}_T = [\boldsymbol{\Phi}_{T1}\boldsymbol{\Phi}_{T2}\cdots\boldsymbol{\Phi}_{TM}]$, which is a column - wise concatenation of all the $\boldsymbol{\Phi}_{Ti}$'s. Covariance matrix of $\mathbf{u}_{Tn}$ is calculated by equation (1).

$$\mathbf{C}_T = \frac{1}{M}\sum_{n=1}^{M} \boldsymbol{\Phi}_{Tn}\boldsymbol{\Phi}_{Tn}^{\ T} = \mathbf{A}_T\mathbf{A}_T^{\ T} \tag{1}$$

Determining matrix $\mathbf{C}_T$ is too troublesome and a computationally feasible method is needed to determine the matrix M x M instead of N2 x N2. Therefore, we construct matrix M by M as $\mathbf{C}_T' = \mathbf{A}_T\mathbf{A}_T^{\ T}$, where $\mathbf{C}_{Tm}' = \boldsymbol{\Phi}_{Tm}^{\ T}\boldsymbol{\Phi}_{Tn}$, and the M eigenvectors, $\mathbf{u}'_{Tc}$ of $\mathbf{C}_T'$ is calculated using equation (2).

$$\mathbf{u}'_{Tc} = \mathbf{A}_T\mathbf{v}_{Ti} \tag{2}$$

Then, the normalized weight vectors of $\mathbf{C}_T'$ is formed by:

$$\boldsymbol{\Omega}_T = \max_{1\le i\le n} \left|\mathbf{u}'_{Tc}\,\mathbf{A}_T\right| \tag{3}$$

Fig. 2. Some ICONL face images (112 x 92) - used as the training set in this paper (5 pictures of a subject with different expressions)

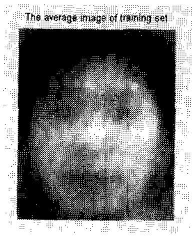

Fig. 3. Average image (Ψ_T) of training set

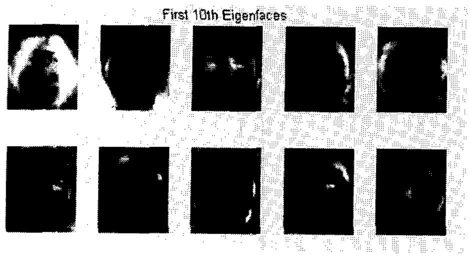

Fig. 4. The first 10th eigenfaces among total 37 eigenfaces

2.2 Recognition classification of ICONL face Images by system database initialization

Once the eigenfaces from the eigenvectors of the training set have be initialized as the system database, the face identification becomes a pattern recognition task. Since the eigenfaces are adequate for describing face images under a very controlled condition and therefore, it is used as the face identification tool in this paper. As mentioned, M eigenfaces is sufficient for the recognition strategy and since the accurate reconstruction of image is not required, therefore a smaller M' eigenfaces is suggested in this paper, M'=37. And then, the 37 eigenfaces are computed into the normalized weight vectors in order to perform the recognition task. In the paper, the recognition task is carried out through two testing sets. Let the testing set from ICONL database to be $\varphi_S = [\varphi_{S1}, \varphi_{S2}, \cdots, \varphi_{SM}]$ and transformed it into its eigenface components or coefficients as $w_S = \mathbf{u}_{TC}{}^T(\varphi_S - \Psi_T)$ for $s = 1,2,3,\cdots,M'$. The average face (Ψ_T) is subtracted and the remainder is projected onto the eigenfaces. The weights (eigenface coefficients) $\Omega_S = [w_1, w_2, w_3, \cdots, w_{M'}]$ of the testing set form a vector that describes the contribution of each eigenface in representing the testing set. Creating the weight vectors are equivalent to projecting the original face image onto the 'face space', the results 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 known as false positive (FP) - incorrectly identified as a match (unwanted result).

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 sets) eigenfaces $\Phi_S = \varphi_S - \Psi_T$ and $\Phi_f = \sum_{s=1}^{s=M'} w_s \mathbf{u}_{Tk}$, its projection onto the face space. The face space metric is defined as:-

$$\varepsilon^2 = \left\| \Phi_S - \Phi_f \right\|^2 \tag{4}$$

The calculated distance is used as a measure of 'faceness' and also as a 'face map'. If a calculated distance of a face image is far from the face space, the face image is not well described by the eigenfaces and therefore it is not considered a face - NF. On the other hand, if a calculated distance lie near the face space, and produced a small and below the chosen face space threshold - must be chosen to represent the minimum acceptable distance from the face space, then the face image is considered as a face.

After the 'faceness' classification, the classified face image as 'face' is then to be determined using face class metric to classified the face image as 'known' or 'unknown' to the training set. The simplest method for determining which face class provides the best description of face images of testing set is to find the face class k that minimizes the Euclidian distance as defined in equation (5) below. The face class metric is defined as:

$$\epsilon^2 = \left\| \Omega_I - \Omega_k \right\|^2 \tag{5}$$

where Ω_k is a vector describing the k-th face class. The face classes Ω_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. The nearest-neighbor face class classification is applied in this paper which is defined as:

$$\epsilon = \underset{1 \le i \le k}{\arg\min} \left\{ \left\| \Omega_I - \Omega_k \right\| \right\} \le \theta_\epsilon \tag{6}$$

The recognition task are summarized as follow:-

1. Calculate the face class vector Ω_k for each subject in the training set by averaging the eigenface pattern vector Ω (Eq. (5)) from the training set face images - 5 face images of one subjects. Then, choose the face class threshold θ_ϵ, which defines the maximum allowable distance from any face class. and a face space threshold β_ε that defines the maximum allowable distance from face space (according to Eq. (4)).
2. Identify the new face image by calculating its pattern vector Ω, determining the minimum distances θ_ϵ to

each known face class (Eq. (5)) and the distance ε to face space (Eq. (4)).

3. Perform the classification task using the calculated minimum face class distance, face class threshold, face space distance and face space threshold. If the minimum distance of the input face image, $\in_k > \theta_\in$ and the face space distance of the input face image $\varepsilon < \beta_\varepsilon$, then the input face is classified as the associated with the face class vector $\mathbf{\Omega}_k$ - Recognized. If the minimum distance $\in_k < \theta_\in$ but the face space distance $\varepsilon < \beta_\varepsilon$, then the input face image may be classified as 'unknown' - Errors, and optionally if the minimum distance $\in_k < \theta_\in$ and face space distance $\varepsilon < \beta_\varepsilon$, then the face image is classified as 'non-face' which is correspondent to False Positive (FP).

3. ICONL Database Construction

The ICONL face images database was acquired with NetCan Camera SNC-80/320 Samsung that was installed in a computer of Intelligent control laboratory. It took us three days to complete the photography session.

The database contains 140 images of 14 subjects - 2 females and 12 males of students and staff of engineering faculty with the age range of 24 to 55 years old. The photographs were manually taken by clicking on a mouse and were immediately stored inside the computer in RGB format with the resolution 1024 x 768 pixel in bitmap file. All the photographs are vertical oriented frontal view with a range of expressions. The titling of head was allowed in a limited range, approximately thirty degrees. The vertical frontal view is chosen for the frontal view contains inherently more discrimination power then profile view.

3.1 Preprocessing of ICONL database

As few applicable software can automatically extract only the face in the image, the task is performed manually in this paper. The stored RGB images of ICONL database were cropped by accentuating the faces in the middle and resized the image size to 112 x 92 resolution using Adobe Photoshop software to decrease the background effect for the background significantly affects the recognition performance. After that, they were restored as the tagged tiff format image files in the computer.

3.2 Normalization of ICONL database

The normalization of ICONL database was done using Matlab software as follow

i) Image Conversion. After the face images have been readout from the image data base, they all are converted into the 2-D gray-scale face images and quantized to 256 gray levels. As mentioned early in Section 2, the eigenfaces method duel s with 2-D gray-scale images, therefore the normalization of the ICONL database is performed in 2-D gray-scale.

ii) Integer to float conversion. All gray-scale face image is then transformed into float version for the simulations calculations are taking place in double precision floating point.

4. Simulations Design, Procedures and Results

4.1 Designation of ICONL database

Face recognition simulations are characterized by two face images sets:-

i) The training set. It consists 60 images of ICONL database of 12 subjects with 5 images of different expression each and are selected according to numerical ascending of 12 subjects with odd numeric. It is used to form a face space in which the recognition is performed.

ii) The testing set. They are divided into 2, testing set A and B. Testing set A contains 60 images of 12 subjects of 5 images. They are the remained 5 images of the subjects in training set, which are selected according to numerical ascending of 12 subjects with even numeric. It is used to be identified via matching against the training set. When a nearest-neighbor classification (closed universe) assumption as face is employed, each image of the set A has a corresponding match to the training set. Note that the assumption is important in order to evaluate the recognition performance of the testing set A. Testing set B consisted of the leftover 2 subjects with 10 images each. They are the numerical ascending from number 13 to 14. Set B is used to be identified via matching against the training set in which each image correspondent to un-match to the training set when the nearest-neighbor classification (closed universe) assumption as face is employed.

4.2 Simulations of ICONL database using PCA Algorithm

Practically, we need a system that does not make any mistake by the adequate adjustment of thresholding, thus, most of the face images would be misclassified by the system and they are referred to the rejected one that correspondent to 'False Positive' of the testing set A and B in Table 1 and 2. Several thresholds ($\theta_\in$) have been computed over the statistics of the minimum face class distance distribution for the testing set A and B. Basically, there are four basic threshold values, two mean values - m1 and m2, and two variance values - v1 and v 2. The recognition performance for each threshold and for the combination of those thresholds are simulated according to the face classification procedures with the idea to move the thresholds among crossing point of the two distributions (mean and variance). The classification outcomes are summarized in Table 1 and 2, respectively.

The thresholds ($\theta_\in$) are arranged in descending order and the first one correspondent to the system with the infinite threshold as explained on the beginning of this section. The 'Recognition in %' column of the table shows the percent that a new image of a person from the database will be recognized correctly - recognition capability.

Table 1. Recognition rate % of PCA for the testing set A

Threshold, $\theta_\in$	Recognized	Errors	FP	Recognition in %
v2 = 211090	58	0	2	96.7
m2 + sqrt(v2) = 3707.1	57	1	2	95.0
m2 = 3247.7	56	2	2	93.3
(m1+sqrt(v1)+m2+sqrt(v2))/2 = 3197.6	55	3	2	91.7
m1 + sqrt(v1) = 2688.1	49	10	1	81.7
(m1 + m2)/2 = 2578.3	48	12	0	80.0
m1 = 1908.9	30	30	0	50.0
m2/2 = 1623.8	24	36	0	40.0
m1/2 = 954.46	6	54	0	10.0
< = 700	0	60	0	0

Note : m1, m2 - mean1 & 2 - v1, v2 - variance 1 and 2, sqrt - square root

Table 2. Recognition rate % of PCA for the testing set B

Threshold, $\theta_\in$	Recognized	Errors	FP	Recognition in %
v2 = 211090	0	0	20	0
m2 + sqrt(v2) = 3707.1	0	3	17	0
m2 = 3247.7	0	11	9	0
(m1+sqrt(v1)+m2+sqrt(v2))/2 = 3197.6	0	11	9	0
m1 + sqrt(v1) = 2688.1	0	18	2	0
(m1 + m2)/2 = 2578.3	0	19	1	0
m1 = 1908.9	0	20	0	0
m2/2 < = 1623.8	0	20	0	0

Note : Recognized - 'known face', Errors - 'unknown face' and FP - 'False Positive'

The overall PCA simulation results of the recognition capability accuracy for the testing set A and B are illustrated in Fig. 5 and 6. The corresponding threshold values are arbitrary set from 0 to 5000. The graphs are plotted as functions of the rejection error rate which is the function of faces rejected as 'unknown', and the function of achieved recognition rate which is the function of faces recognized as 'known'. Both are controlled by the threshold parameter ($\theta_\in$).

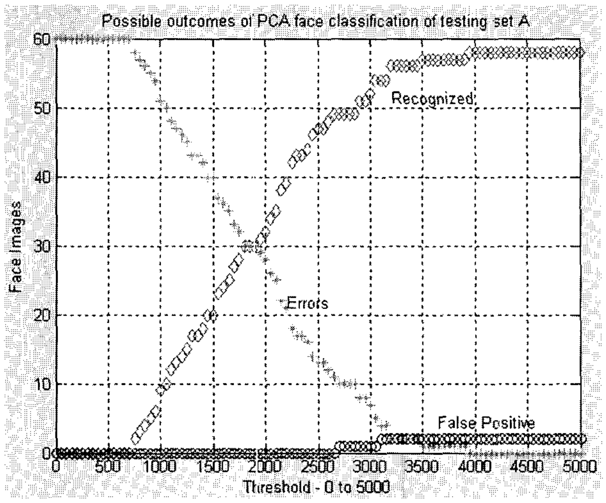

Fig. 5. Graph of recognition accuracy of PCA for the testing set A

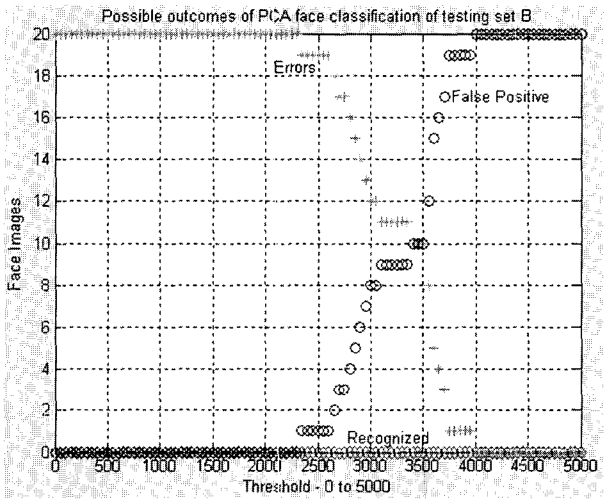

Fig. 6. Graph of recognition accuracy of PCA for the testing set B

4.3 Simulations of ICONL database using PCA + LDA Algorithm

4.3.1 Construction of PCA + LDA [9]

First of all, let the mean for each class of normalized weight vector of the training set (from eq. (3)) be $\overline{\mu_i}$, the overall (global) mean for all classes of normalized weight vector of the training set (eq. (3)) be $\overline{\mu}$, the number of face classes (individual) and the number of faces per face class (number of samples) be $C=12$ and $N_i=5$ in this paper, respectively. Then, the between class scatter matrics B_s of normalized weight vector of the training set and the within scatter class matric W_S

of normalized weight vector of the training set (eq. (3)) were computed as follows:-

$$B_S = \sum_{i=1}^{C} N_i(\bar{\mu}_i - \bar{\mu})(\bar{\mu}_i - \bar{\mu})^T \tag{7}$$

$$W_S = \sum_{i=1}^{C}\sum_{N_i}(N_i - \bar{\mu}_i)(N_i - \bar{\mu}_i)^T \tag{8}$$

With both, eigenvectors and eigenvalues of optimal linear projection of LDA can be calculated as:-

$$B_S \mathbf{u}_i = \lambda_i W_S \mathbf{u}_i \tag{9}$$

where λ_i is the eigenvalues of a face class and $\mathbf{u}_i$ is eigenvectors of face class - keep only 95% of the eigenvalues (maximum) which is correspondent to the PCA algorithm. Here, only 6 eigenvectors were remained to compute the normalized weight eigenvectors as:

$$W_i = \max_{1 \le i \le n} |B_s \mathbf{u}_i| \tag{10}$$

The recognition performance of face classification for the testing set A and B using the Euclidean distance metric were computed with these weight vectors and the results were presented, shall be described in the next section.

4.3.2 Simulation of PCA + LDA

The PCA + LDA algorithm simulation procedures were programmed according to the simulation procedures of PCA algorithm and their outcomes were summarized and presented in the Table 3 and 4.

Fig. 7 and 8 illustrate the overall recognition outcomes of PCA + LDA algorithm for the testing set A and B with threshold values from 0 ~ 2000.

Table 3. Recognition rate % of PCA + LDA for the testing set A

Threshold, θ_ϵ	Recognized	Errors	FP	Recognition in %
v2 = 52057	49	0	11	81.67
m2+sqrt(v2) = 1231.2	48	2	10	80.00
(m1+sqrt(v1)+m2+sqrt(v2))/2 = 1065.7	45	6	9	75.00
m1+sqrt(v1) = 900.1831	43	10	7	71.67
(m1+m2)/2 =821.2276 *	42	11	7	70.00
m2/2 = 501.5422	19	40	1	31.67
m1/2 = 319.6854	3	57	0	5.00
(m2/2)/2 = 250.7711	2	58	0	3.00
(m1/2)/2 = 159.8427	0	60	0	0

Note : m1, m2 - mean1 & 2 - v1, v2 - variance 1 and 2, sqrt - square root

Table 4. Recognition rate % of PCA + LDA for the testing set B

Threshold, θ_ϵ	Recognized	Errors	FP	Recognition in %
v2 = 52057	0	0	20	0
m2+sqrt(v2) = 1231.2	0	2	18	0
(m1+sqrt(v1)+m2+sqrt(v2))/2 = 1065.7	0	5	15	0
m1+sqrt(v1) = 900.1831	0	15	5	0
(m1+m2)/2 = 821.2276 *	0	17	3	0
m2/2 = 501.5422	0	20	0	0
m1/2 = 319.6854	0	20	0	0
(m2/2)/2 = 250.7711	0	20	0	0
(m1/2)/2 = 159.8427	0	20	0	0

Note : Recognized - 'known face', Errors - 'unknown face' and FP - 'False Positive'

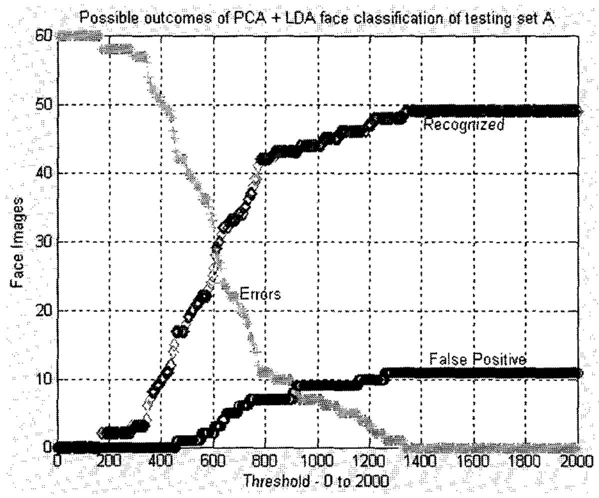

Fig. 7. Graph of recognition accuracy of PCA + LDA for the testing set A

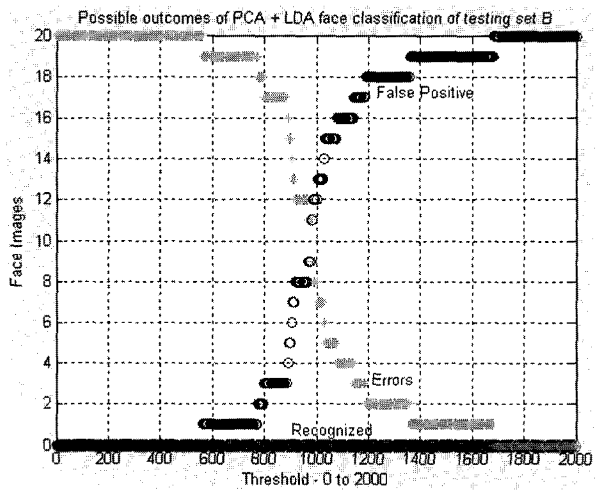

Fig. 8. Graph of recognition accuracy of PCA + LDA for the testing set B

5. Conclusion

The face recognition using PCA algorithm was achieved by the proposed estimator, based on 37 eigenvectors. The simulation results showed the algorithm was satisfactory for recognizing an individual but was somewhat poor in classifying an individual within his or her face class. The achieved recognition rate was 96.7%. Beside this, the proposed algorithm was proved to be worked well under the constrained requirements in this paper, thus, the dimensions of the images spaces were reduced and this made the system only used up a small storage and memory capacity.

Apart from this, a combination algorithm of PCA and LDA was also proposed in this paper in order to carry out a recognition performance comparison rate between two algorithms and to distinguish which algorithm was suitable for certain specific system. The PCA + LDA algorithm face recognition achieved by the proposed estimator, based on 6 eigenvectors. Referring to the simulation results, PCA + LDA algorithm with the threshold value of 821.23 was suggested for a high security system with recognition rate of 70% and if a system that can recognize any face (who ever with one sample image) was preferred, then the PCA algorithm that can recognize a person well with the recognition rate of 96.7% with the threshold value of 3800 was suggested.

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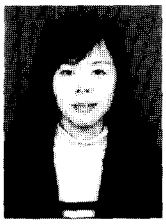

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