Principal Components Analysis Based Iris Recognition and Identification System

E. Mattar

***Abstract*— This article focuses on the employment of iris recognition technique and their application in security systems. The implementation of such a system is based on the processing of an iris (scene) using Principle Component Analysis known in the literature as (PCA). This is done by an iris segmentation algorithm of (Libor Masek). Libor Masek algorithm is utilized here to segment an iris from some undesired noises and ingredients in an eye image. This rather helps to acquire the most accurate iris scene. Eigen irises are hence obtained using the PCA method. Eigen of irises are then utilized to train an Artificial Neural Network (ANN) recognition system. This is followed by transforming a set of irises into a new space. Transformed irises are accumulated in a database, where they are compared with a set of test irises transformed in the same state of the recognition cycle. The proposed system has resulted in accurate results up to (91%) for identifying a pre-stored individuals.**

***Index Terms*— Iris recognition, Principal Component Analysis, Pattern recognition, Eigen vectors.**

I. INTRODUCTION

A. The Biometric Technology

The use of biometric systems has been increasingly encouraged by both government and private entities in order to replace or improve traditional security systems. The iris is commonly recognised as one of the most reliable biometric measures: it has a random morphogenesis and no genetic penetrance. In 1987, Flom and Safir [1] studied the problem and concluded that iris morphology remains stable throughout human life, where they have estimated that, the probability of the existence of two similar irises on distinct persons at 1 in (1072). A biometric system provides automatic recognition of an individual based on some unique feature or characteristic possessed by the individual. Biometric systems have been developed based on fingerprints, facial features, voice, hand geometry, handwriting, the retina [2], and the one presented in this paper, the iris. Biometric systems work by first capturing a sample of the feature, such as recording a digital sound signal for voice recognition, or taking a digital colour image for face recognition. The sample is then transformed using some sort of mathematical function in to a biometric template.

The biometric template will provide a normalized, efficient and highly discriminating representation of the feature, which can then be objectively compared with other templates in order to determine identity. Most biometric systems do permit two modes of operation. An enrolment mode for adding templates to a database, and an identification mode, where a template is created for an individual and then a match is searched for in the database of pre-enrolled templates [4]. Biometric systems work by first capturing samples of the feature, such as image for face recognition, digital voice for voice recognition etc ... Such samples are then transformed using some sort of mathematical functions to produce some characteristic property for identification. A good biometric system is characterized by the use of a feature that is; highly unique – so that the chance of any two people having the same characteristic will be minimal, stable so that the feature does not change over time, and be easily captured – in order to provide convenience to the user, and prevent misrepresentation of the feature.

B. The Human Eye

An iris is a thin circular diaphragm, which lies between the cornea and the lens of the human eye. A front-on view of the iris is shown in Fig. 1.1. The iris is perforated close to its center by a circular aperture known as the pupil. The function of the iris is to control the amount of light entering through the pupil, and this is done by the sphincter and the dilator muscles, which adjust the size of the pupil. The average diameter of the iris is 12 mm, and the pupil size can vary from (10%) to (80%) of the iris diameter [4]. A front-on view of the iris is shown in Fig. (1). The iris is perforated close to its centre by a circular aperture known as the pupil. The function of the iris is to control the amount of light entering through the pupil, and this is done by the sphincter and the dilator muscles, which adjust the size of the pupil. The common diameter of the iris is 12 mm, and the pupil size can vary from (10% to 80%) of the iris diameter [4].

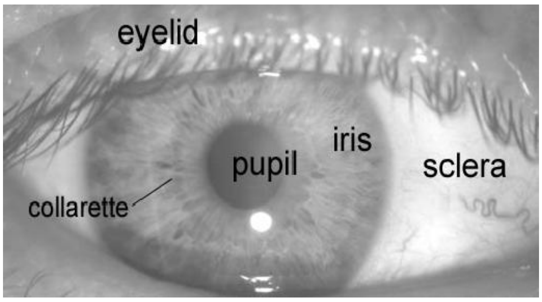


Fig. (1) : A front view of the human eye. Wolff, [4].

Formation of iris begins during the third month of embryonic life [4]. The unique model on the surface of the iris is

Manuscript received May, 2013.

E. Mattar, Department of Electrical and Electronics Engineering, College of Engineering, University of Bahrain, P. O. Box 13184, Kingdom of Bahrain

formed during the first year of life, and pigmentation of the stroma takes place for the first few years. Formation of the unique patterns of the iris is random and not related to any genetic factors [4]. The only characteristic that is dependent on genetics is the pigmentation of the iris, which determines its color.

Due to the epigenetic nature of iris patterns, the two eyes of an individual contain completely independent iris patterns, and identical twins possess uncorrelated iris patterns. For further details on the anatomy of the human eye consult the book by Wolff [4]. The iris had been historically recognized to possess characteristics unique to each individual. In the mid-1980s, two ophthalmologists, (Leonard Flom and Aran Safir) have proposed the concept that no two irises are alike.

(Leonard Flom and Aran Safir), researched and documented the potential of using the iris for identifying people and were awarded a patent in 1987. Soon after, the intricate and sophisticated algorithm that brought the concept to reality was developed by (John Daugman, [4]) and patented in 1994. The original work and the continued development have established the Iridian's iris recognition algorithm, [7] as the mathematically unrivalled means for authentication. Compared with other biometric technologies, such as face, speech and finger recognition, iris recognition can easily be considered as the most reliable form of biometric technology [4].

C. Research Objectives and Outline

In this article an iris recognition system based on Principal Component Analysis (PCA) is implemented. PCA is a method used to process a variety of data, where is well known as a method that extract global and fine features, respectively. In this research, it was adapted the ANN PCA related methodology for an Iris Recognition. The development tool was done through Matlab, where an emphasis was given only to the software for performing recognition, and not on the hardware for capturing an eye image. The performance of the encoding technique was executed using the (CASIA) eye images: with a courtesy from the Chinese Academy of Sciences – Institute of Automation, (CASIA) [6]. Hence, following will be the followed steps :

1. An algorithm to segment the iris from the unwanted parts(eyelids, eyelashes)will be used.
2. Eigen Irises will be obtained using PCA.
3. Eigen irises obtained will be used to train the system and to transform the training irises in to a new space.
4. Irises in the new transformed space will be stored in a database, hence will be used in the recognition process.

II. PRINCIPAL COMPONENT ANALYSIS

A. Review Stage

The (PCA) Tool: Principal Component Analysis has been widely used for analyzing computer images. It is employed in biometric industry and systems as a classification tool. PCA does enable someone to measure a difference between two images while allowing expression changes. In the vector space. PCA performs these by computing the eigenvectors and eigenvalues of a covariance matrix of an image data. Keeping merely a few eigenvectors corresponding to the largest "eigenspace" (for details on PCA, refer to [7]). Principle Component Analysis, also known as the Eigen–XY analysis, and is a standard statistical technique for finding directions of maximum variations in data. These directions, called the principle components, where they can be used to reconstruct all of the information within a data set, and can be tested to which level a test image couples with an image of a training set.

Principle components with slighter associated magnitudes can frequently be omitted, as they contribute fewer to the entire reconstruction of each data element. This allows sufficient representation of the original data set with a reduced set of principal components. The principal components are found by computing the eigenvalues and eigen vectors of the (Covariance Matrix) associated with the data. Eigenvectors with largest associated eigenvalues are the principal components that describe the most variation in the data set. Principle Component coefficients of data elements are found by projecting each datum onto the eigenspace of the Covariance Matrix.

B. Preparations of (PCA)

In order to employ PCA for iris processing, firstly it is required to convert an RGB (Red-Green-Blue) scene into a gray scale (black and white) format. It is also possible to use an RGB scene, other than, instead of using a (3-D) matrices, (2-D) matrices are even easier to evaluate. Given a gray scale image, that can be represented as a matrix of intensity values. We can convert it into a vector by placing the column of an image on top of each another. Eye image is a two-dimensional array of size $\in \Re^{(x,y)}$, where (x,y) are width and height of the an image. Each image can thus be represented as a vector of dimension $(x \times y)$:

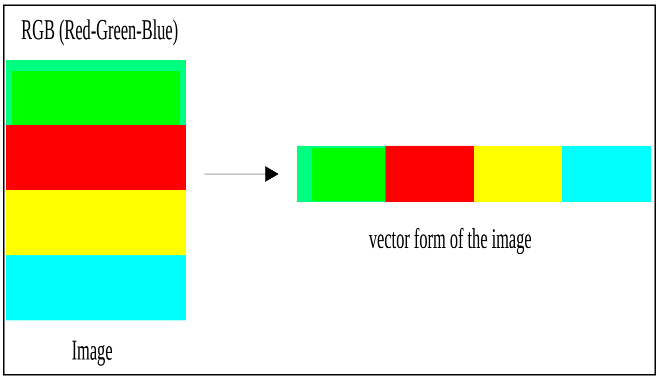


Fig. (2) : Obtaining Vector Form of an Image

C. Training Phase of (PCA)

Letting (X_n) be an image from a collection of (n) images in database.

$(P_1, P_{2,} \cdots P_n)$, in Fig. (2), are put as X_n :

$$X_n = \begin{pmatrix} P_1 & P_2 & P_3 & \cdots & P_n \\ \cdots & \cdots & & & \\ & & & & \\ & & & \cdots & \\ \cdots & & & & \cdots \end{pmatrix}$$

(1)

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Average image is defined as ψ :

$$\psi = \left(\left(\frac{1}{M}\right)\sum_{i=1}^{n} X_i\right) \quad (2)$$

After computing the average column vector matrices, it is required to build a differences matrix. Each image (X_n) differ from the average image ψ by the vector :

$$\Phi_i = (X_i - \psi)$$

$$for\ (i = 1,2,3,\cdots,n)$$

$$\Phi = \begin{pmatrix} \Phi_1 & \Phi_2 & \Phi_3 & \cdots & \Phi_n \\ \vdots & \vdots & \vdots & \vdots & \\ & & & & \\ & & & \vdots & \\ & & & & \cdots \end{pmatrix} \quad (3)$$

The covariance matrix of the dataset is thus defined by Equ. (4) as:

$$C = \left(\left(\frac{1}{M}\right)\sum_{n=1}^{M}\left[\Phi_n \Phi_n^T\right]\right) \quad (4)$$
$$C = \Lambda\Lambda^T$$

After computing the covariance matrix C, we hence build the eigenvectors. If we consider eigen vectors u_1 of $(\Lambda\Lambda^T)$. Eigenvectors (u_1) are actually images and are called eigenfaces, among those eigenfaces are the ones with the higher eigen values, and are the most useful in the recognition process. Therefore, those eigenfaces $(M^T \langle M)$ are used for constructing the eye space for image projections, which are used in iris identifying classifying or recognizing.

D. Testing Phase of (*PCA*)

After a training phase, and getting the eigenfaces, we hence move to testing phase to prove our (**PCA)** theory. In order to check weather a picture is one of the samples of our database or not we should transform that picture into eigenfaces as follows:

$$\omega_k = \left(u_1^T (X_n - \psi)\right) \quad (5)$$

ω_k is the k^{th} coordinate of the Φ in new "eye space". Equ. (5) in fact describes the point by point image multiplications and summations resulting in scalar value with dimensions $\Re \in^{(1\times 1)}$ previously defined as weights that define each face. Those weights form a vector:

$$\Omega^T = \begin{pmatrix}\omega_1 & \omega_2 & \cdots & \omega_M\end{pmatrix} \quad (6)$$

Gives the projection vector. Vector describes Ω contribution of each eigenface in representing the input test images. This vector is used in finding the class this input image belongs to, if there are more than one images describing a person, otherwise it is used to find to which input image is it much similar, this will be done by using eucludiean distance between the test image and projection image classes. If we compute the distance by using the ω for the training and test phase, it will give us the distance of the test picture according to the training phase.

$$\varepsilon_k = \left\|(\Omega - \Omega_k)\right\|^2 \quad (7)$$

In Equ. (7), Ω_k describes the k^{th} eye class, which is average of the eigenface representation of the eye images of each individual. An eye will be classified to some class if the minimum (ε_k) is below some threshold, otherwise it will be classified as an unknown picture.

E. Fuzzy C-Means Clustering: (*FCM*)

Fuzzy C-means (**FCM**) is a data clustering technique, through which each data point belongs to a cluster with some degree, that is specified by a membership grade. This technique was originally introduced by Bezdek in 1981 as an improvement on earlier clustering methods. It provides an approach that shows how to group data points that populate some multidimensional space into a specific number of different clusters.

The MatLab Fuzzy Logic Toolbox, command line function (**FCM**) starts with an preliminary guess for the cluster centers, which are intended to mark the mean location of each cluster. The preliminary guess for these cluster centers is most likely incorrect. Furthermore, (**FCM**) assigns every data point a membership grade for every cluster. By iteratively updating the cluster centers and the membership grades for each data point, (**FCM**) iteratively moves the cluster centers to the "right" location contained by a data set.

This iteration is based on minimizing an objective function that represents the distance from any given data point to a cluster center weighted by that data point's membership grade. (**FCM**) is a command line function whose output is a list of cluster centers and several membership grades for each data point.

This can be used to get the information returned by Matlab routine (**FCM**) to facilitate building a fuzzy inference system by creating membership functions to represent the fuzzy qualities of each cluster. For instant, while using some quasi-random two-dimensional data, as shown in Fig. (3), to illustrate how (**FCM**) clustering works.

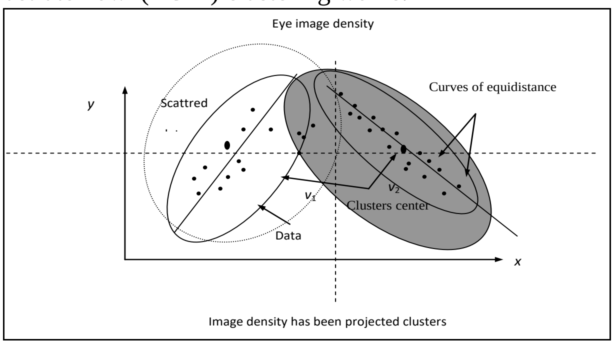


Fig. (3) : A clustering of images. An example of a two-dimensional intense image.

Now the command-line function, FCM , is invoked and asked to find two clusters in this data set.

[center,U,objFcn] = fcm(fcmdata,2);
Iteration count = 1, obj. fcn = 8.941176

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Iteration count = 2, obj. fcn = 7.277177

this is continued to be computed until the objective function is no longer decreasing much at all. The variable center contains the coordinates of the two cluster centers, (U) contains the membership grades for each of the data points, and (*objFcn*) contains a history of the objective function across the iterations. Fig. (4) displays the two separate clusters classified by the (*fcm*) routine. The figure is generated using Cluster centers and are indicated in the figure below by the large characters.

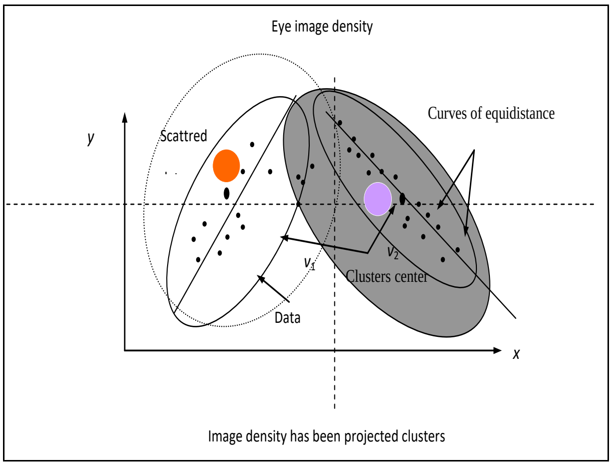


Fig. (4) Data separated into two different clusters after clustering with their centroid

Fuzzy C-means is also used in image segmentati.on, [11], by clustering a set of data based on it's color intensities as shown in Fig. (5).

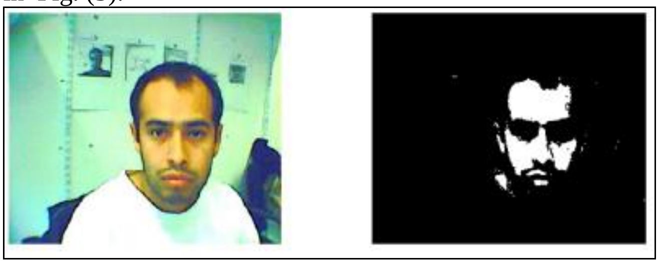


Fig. (5) : (*left*), Real image. (*right*), segmented image, Romdhani S. [11].

III. IMPLEMENTATION

A. Iris Localization, Encoding, and Matching

The following general phases are involved in most of iris recognition systems currently in use :

i. *Localization*: During this step the pupil, sclera and eyelids are segmented.

ii. *Encoding*: This step involves extraction of the most discriminating information present in an iris pattern in order to provide accurate recognition of individuals.

iii. *Matching*: The encoded irises are then stored in the database and are matched with the test encoded iris for the purpose of recognition.

To localize an iris, this was achieved by using the Libor Masek's algorithm of [11], as illustrated in Fig. (6). **PCA** was then used for training the system and extracting the most important features from irises. Hence, to transform an iris image into a new space. The transformed irises are stored in a database, where are compared with other irises for recognition.

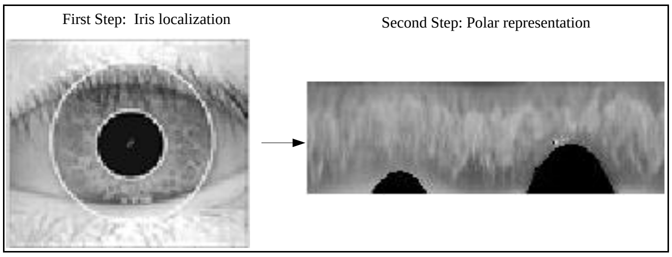


Fig. (6) : Polar representation of the segmented iris along with noise masking.

B. Chinese Academy of Sciences Dataset, (CASIA)

All the iris experiments completed in this paper were performed on the (CASIA) dataset provided by the (Chinese Academy of Sciences), [6]. The (CASIA) dataset contains some "non-ideal" iris images of 108 irises with 7 images per one iris. Images in this dataset are strongly occluded, blurred, and defocused. Sample images from CASIA datasets are exposed in Fig. (7).

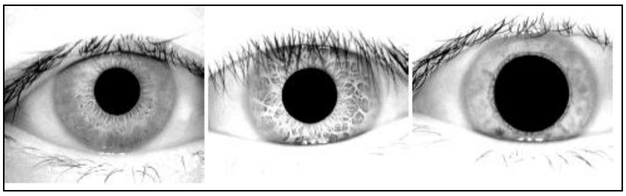


Fig. (7) : Sample images from CASIA dataset, Chinese Academy of Sciences database, [6].
Left: Smaple_1. Center: Sample_2. Right: Sample_3.

C. Iris Segmentation

Fuzzy C-means method was attempted to segment the iris from the eye image. As mentioned earlier, Fuzzy -means partitions the data into clusters based on their similarities. While keeping this in mind, the eye image shown in Fig. (8) was converted to (RGB) and was clustered based on color to four different parts.

It was assumed that the skin will take the first cluster, sclera the second, iris the third and pupil the fourth. Result of each clustered iris can be shown in Fig. (9).

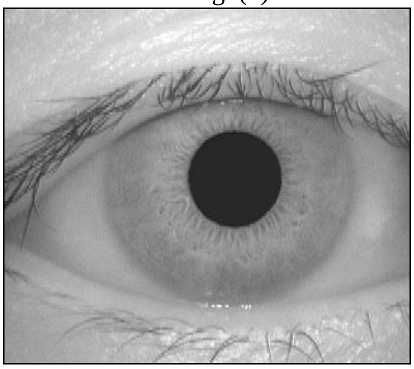


Fig. (8) The original eye. A sample of an eye iris to be clustered. Further processing steps are given in Fig. (9).

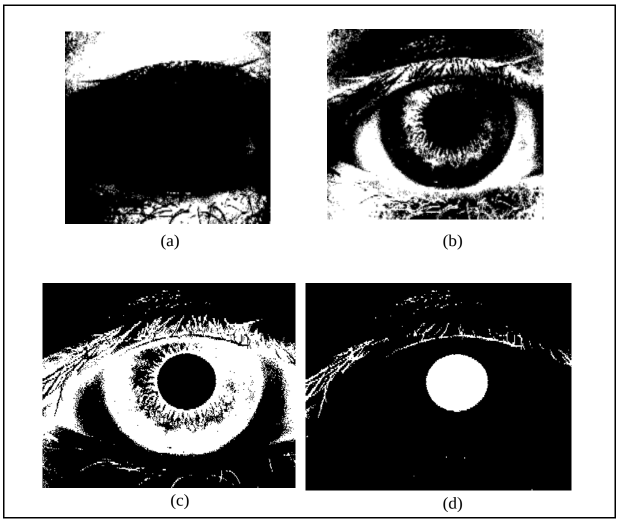


Fig. (9) : Processed iris into different clusters.
(a): Clustered skin. (b): Clustered sclera.
(c): clustered iris. (d): clustered pupil.

D. Eigen Irises Generation

The first objective is to acquire the eigen irises. These will be then be used to train an ANN system. The eigeniris generation implementation is not the one suggested in section (2). In fact, the used eigenirises are the eigenvectors of the matrix $\left(XX^T\right)$. Adopting the notations of section (2), $\left(X\right)$is a matrix containing the input irises - each column representing a column iris vector. The dimension of $\left(X\right)$ is I (number of pixels of each iris) by $\left(I\right)$ (number of faces in the training set). As has been noted, the number of irises in a training set is usually smaller than the number of pixels contained in each iris image. For example, each iris contains (4800) pixels. Hence, the dimension of matrix $\left(XX^T\right)$ is $\left(I \times I\right)$, where $\left(I\right)$ $\left(\Re \in^{(4800\times 4800)}\right)$. This is a waste of both processing time and memory space to compute the eigenvectors by this basic method of SECTION (2). In this sense, a more efficient technique will be presented here. Instead of computing the outer product $\left(XX^T\right)$, the inner product, $\left(X^T X\right)$, is this calculated. Eigenvectors of the outer product are deduced from those of the inner product. Assuming the followings :

i. the matrix $\left(V\right)$ be the outer product, $\left(XX^T\right)$,
ii. the matrix $\left(Q\right)$ be the matrix of the eigenvectors of $\left(V\right)$,
iii. the matrix $\left(P\right)$ be the matrix of the eigenvectors of the outer product, $\left(XX^T\right)$,
iv. and the diagonal matrix be the matrix of the eigenvalues of the inner product and of the outer product, Dorairaj et. al. [11].

This results in $\left(P\right)$ computed as ;

$$P = \left(XQ\right)\sqrt{\Lambda} \qquad (7)$$

Each iris image is converted in to a single column vector as was shown previously in Fig. (2). These column images are used to obtain the eigen irises as illustrated here in Fig. (10).

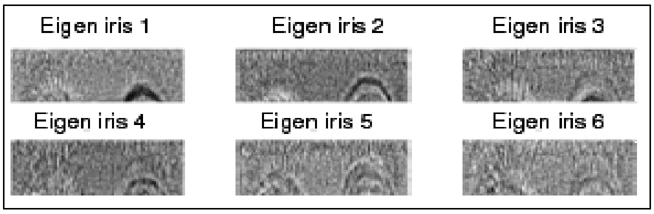


Fig. (10) : The first six eigen irises, Dorairaj et. al. [11].

E. Iris Space

Once the eigenirises have been computed, each iris in the image space can be viewed in the transformed space. The transformation from image space to transformed space is fairly simple. Letting the followings :

i. $\left(E\right)$ be the matrix of the first (eigenirises), where the first column is the first eigeniris and so on.
ii. $\left(e_i\right)$ be a face in the image space, and.
iii. $\left(e_T\right)$ be the same iris in the transformed space.

$$e_T = \left(e_i \times E^T\right)$$

This is a many-to-one transformation, since the dimensionality of the image space is far larger than the dimensionality of transformed space.

F. The Recognition Process

Once the eigenirises have been computed, the transformed space has to be populated with several known irises. Usually these irises are inputted from the used training set. Each known iris is transformed into the new space, where its components are stored a database. At this stage, the identification process can be initiated. An unknown iris is presented to the system. The system project it onto the transformed space and computes its distance from all the stored irises. The iris is identified as being the same individual as the iris which is nearest to it in transformed space. There are several methods of computing the distance between multidimensional vectors. Here, a mean of the distance between the two transformed irises is computed and the shortest mean gives the best match. The overall identification process can be summarized in Fig. (11).

G. The Entire Developed System Overview

The software to perform iris recognition was developed using the MATLAB development environment. A computer system with an Intel Pentium IV processor running at (1.7 GHz) was used. The program is composed of two MATLAB functions - (*get_p_irisdb.m*) and (test.m) the former fetches the eigen vectors and the database of the transformed irises, while the latter function is used for testing as shown Fig. (12).

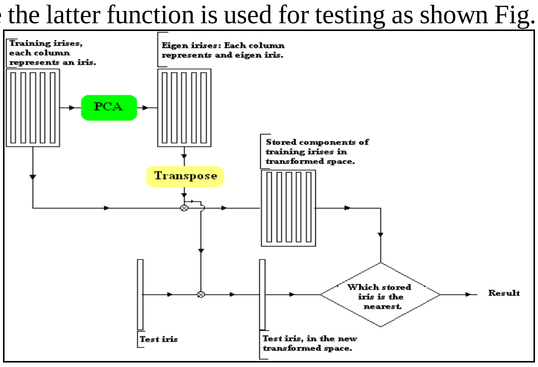
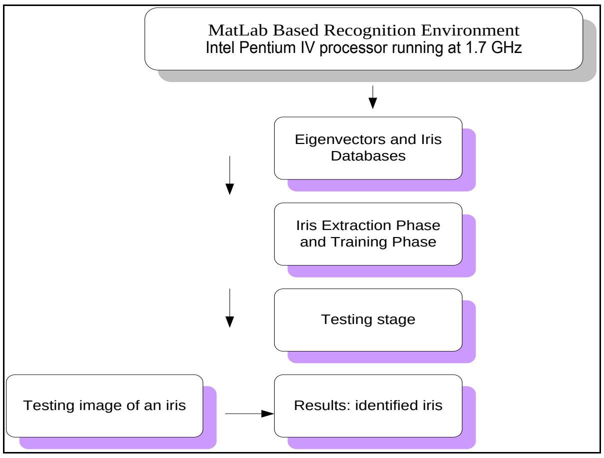
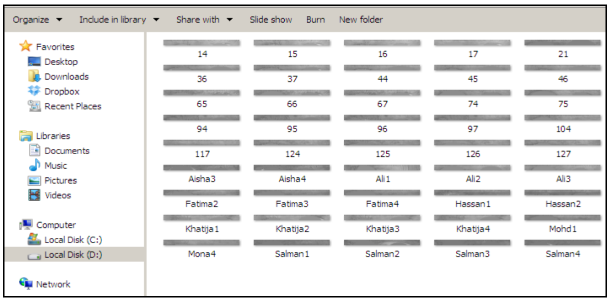


Fig. (11) A flowchart summary of employed iris recognition process.

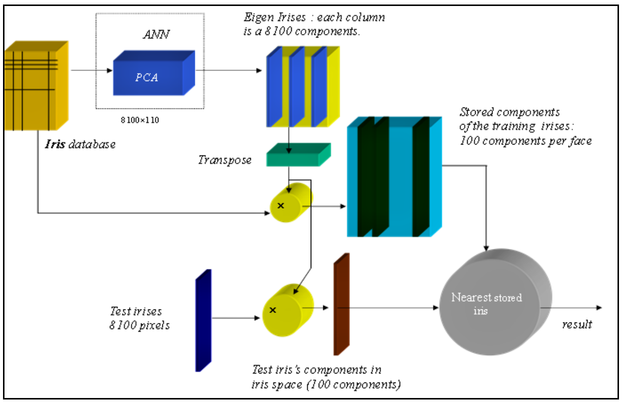
Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication



(*i*)



(*ii*)



(*iii*)

Fig. (12) (*i*) Employed System Overview. (ii) Locally built iris database. (iii) Segment of used Matlab coding environment.

IV. RESULTS VALIDATION

Matlab computing environment was used to test the proposed algorithm. In order to verify the proposed identification methodology, and achieve some testing on the CASIA dataset, four different irises have been used during the training phase. In addition, three different images have been used during the testing phase (as per individual). A success rate of (92.65%) was achieved. In addition, we have to bear in mind that the CASIA dataset contains highly "non-ideal", occluded images as shown in Fig. (13).

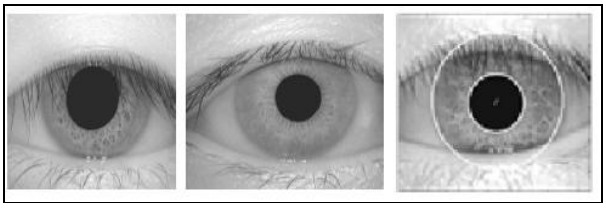


Fig. (13) Testing phase: Eyes are imported from the used freely available CASIA dataset, Chinese Academy of Sciences, [6].

For instant, in Fig. (13) more (30%) of the iris is not accessible by the system due to the eyelid and eyelashes Therefore achieving such a success rate reveals that iris recognition is in fact a very reliable biometric verification system. Test results also show that Principal Component analysis is robust feature extraction technique that can be used in iris recognition systems. Observation was done by reducing the number of training images as shown in Fig. (14).

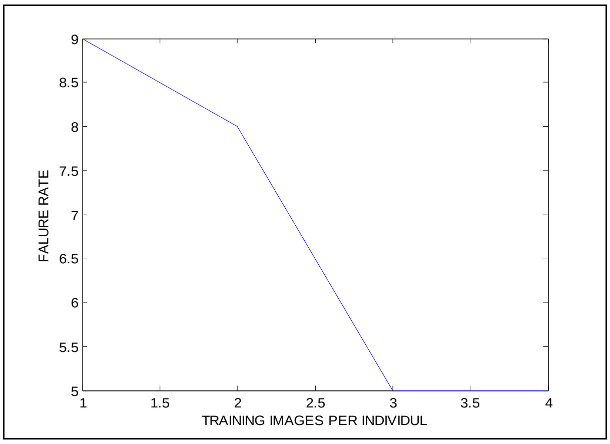


Fig. (14) Failure rate versus training images.

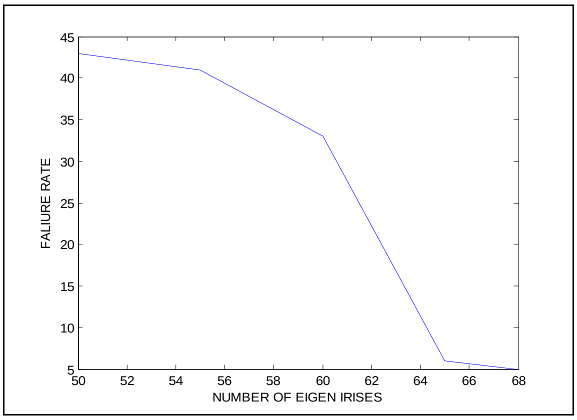


Fig. (15) Failure rate versus the used eigen irises.

A reduction in the number of training images resulted in an increase in the false identification by the adopted system. This is mostly due to the fact that iris images when taken in different positions are slightly out of phase. Therefore multiple iris images of the same individual in the database increases the identification. Daugman [3], however came up with a solution to this problem by making an algorithm that takes the possibility of phase shift in to consideration, by which a single clear iris image per person in the database is adequate to identify the individual independent of the position he/she is in. Another observation was made by decreasing the number of eigen irises used as shown in Fig. (15). The number of eigen vectors required generally depends on the data being used [10]. We have reached the best results when the number of eigen irises where $(M-1)$, where (M) is the total number of database irises used for training. The number of eigen irises required for good result shows us how rich and less compressible is the pattern of the irises [10]. For more irises and further analysis, this can be found in [12].

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

V. CONCLUSIONS

This research article has presented an iris recognition system. The system was tested using grey scale images. The eye images were highly non-ideal and a good portion of the irises were hidden by eyelids and eyelashes. Firstly, an automatic segmentation algorithm is used to (localize) the iris and (segment) it from the unwanted parts of the eye (eyelash, eyelid). Subsequently (PCA) was applied to do an ANN training irises to obtain the Eigen irises, these eigen irises were used to transform an original iris image into a new transformed space which had the dimensions of $\left(\Re \in^{(M\times M)}\right)$, where (M) is the number of iris images used to train the system. These transformed irises were (stored) in an iris database and were used to (compare) the test irises which had been transformed in the same space to perform the recognition process. The research results have achieved a success rate of (92.65%) with a highly non ideal iris images. To this extent, this verifies the high reliability of the iris being used in biometric recognition and highlights the robustness of PCA in image recognition.

REFERENCES

[1] L. Flom, and A. Safir, "Iris Recognition System". *U.S. Patent*, (4641394), (1987).
[2] S. Sanderson, and J. Erbetta, "Authentication For Secure Environments Based on Iris Scanning Technology," *IEE Colloquium on Visual Biometrics*, UK, (2000).
[3] J. Daugman, " How Iris Recognition Works," *Proceedings of 2002 International Conference on Image Processing*, vol. 1, (2002).
[4] E. Wolff, "Anatomy of the Eye and Orbit.", *7th Edition. H. K. Lewis and Co. LTD*, (1976).
[5] R. Wildes. "Iris Recognition: An Emerging Biometric Technology, " *Proceedings of the IEEE Transactions*, vol. 85, no. 9, (1997).
[6] Chinese Academy of Sciences – Institute of Automation. Database of 756 Grey Scale Eye Images. http://www.sinobiometrics.com Version 1.0, (2003).
[7] Iridian Technologies http://www.iridiantech.com.
[8] A. Turk, and A. Pentland, "Face Recognition Using Eigenfaces" , *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 586-590, Hawaii, June (1992).
[9] L. Masek, "Recognition of Human Iris Patterns for Biometric Identification", *Bachelor of Eng. Thesis, the University of Western Australia*, (2003).
[10] S. Romdhani, "Face Recognition Using Principal Component Analysis," *Published M.Sc. Thesis, University of Glasgow*, (1996).
[11] V. Dorairaj, A. Natalia, and G. Fahmy, "Performance Evaluation of Non-Ideal Iris Based Recognition System Implementing Global ICA Encoding, IEEE International Conference on Image Processing, vol. 3, Issue , (11-14), Page(s): III - 285-8, (2005).
[12] M. A Hameed, "Iris Recognition Using Principal Component Analysis", *Technical Project Report, College of Engineering*, University of Bahrain, (2007).

E. Mattar is an associate professor of intelligent control and robotics at University of Bahrain, Bahrain. He has received BSc. in Electrical Engineering (from University of Bahrain in 1986), studied MSc. in Electronics in 1989 (from University of Southampton, UK), and in 1994 he received University of Reading Ph.D. in Cybernetics and Robotics Control. Dr. Mattar has interests in computational intelligence, robotics control, modeling and control.