Iris recognition based on subspace analysis

Pravin S.Patil

Electronics and Communication
Engineering Department,
SSVPS`s B.S.Deore College of Engineering, Dhule
Maharashtra (INDIA)
pspatil777@gmail.com

ABSTRACT

Biometrics deals with the uniqueness of an individual arising from their physiological or behavioral characteristics for the purpose of personal identification. Among many biometrics techniques, iris recognition is one of the most promising approache. This paper presents traditional subspace analysis method for iris recognition. Initially the eye images have been localized in circular form by using Daugman's grid method and circular Hough transform method. The algorithms for subspace analysis methods namely PCA and LDA are implemented and experimental results are reported. The comparative performance for both the algorithms has been observed in term of recognition rate. The comprehensive experiments completed on UPOL and CASIA V_1 iris databases.

General Terms

Biometrics, Personal Identification, Iris Recognition

Keywords.

Daugman's grid , Hough Transform, PCA, LDA

1. INTRODUCTION

Now a days as security becomes an issue of importance, biometrics [1][4] and iris recognition in particular are attracting great interest.[2] The characteristics of iris are unique for every subject.[3] There are not two irises alike, not even for identical twins. Also, the iris is highly stable over person lifetime.[4] These extraordinary characteristics of iris are distributed its application in border crossing, airports,banks,government,universities,traveling,building and so on. Block diagram of the typical stages of iris recognition system has been shown in Figure 1.

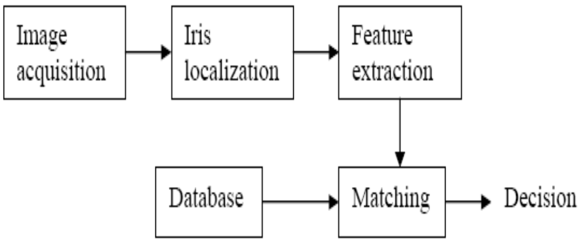


Figure 1. Typical stages of iris recognition system.

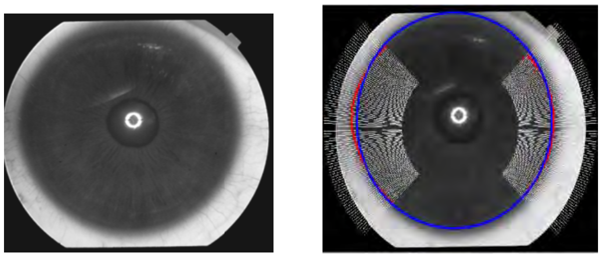
Most of the commercial iris recognition systems implement a famous algorithm using iris codes proposed by Daugman.[5][6] Recently, other researchers Wildes [7], Boles and Boshash [8] and Li Ma and others [9][10][11][12] have contributed new methods. This paper presents subspace analysis method namely PCA and LDA for iris recognition. Reminder of paper has been organized in the following way, circular location of iris are described in section 2.In section 3.the subspace analysis methods have been discussed. Finally experimental results and concluding remarks are mentioned in section 4. and section 5.

2. CIRCULAR IRIS LOCALIZATION

The first stage of iris recognition is to localize the iris and isolate it from digital eye image. The Pupil is exactly at the core of the eye image. Iris portion can be approximated by two circles, one for the iris/sclera boundary and another, which is interior to the first, forms the iris/pupil boundary. The segmentation stage is critical to the success of an iris recognition system, since data that is falsely represented as iris pattern data will corrupt the biometric templates generated, resulting in poor recognition rates. For localization of iris, there are many methods in the literature. We have implemented two methods for iris localization in circular form named as, Daugman's Grid Method and Hough transform Method

2.1 Circular iris localization using Daugman's grid method

Initially the image of the eye is converted to gray scale and its histogram is linearly stretched, as to be able to take benefit of all range given by the 256 levels of the gray scale. Then, following the ideas proposed by Daugman [4], a grid is placed over the image and testing each of the points in the grid, the center of the iris, as well as the outer boundary. (Figure 2).



(a) (b)

Figure 2. Boundary detection using Daugman's grid method (a) an iris image from UPOL database, (b) detected outer boundary.

The detection is performed maximizing *D*, where

$$D = \sum_m \sum_{k=1}^{5} (I_{n,m} - I_{n-k,m}) \qquad (1)$$

being,

$$I_{i,j} = I(x_0 + i\Delta_r \ cos(j\Delta_\theta),\ y_0 + i\Delta_r \ sin(j\Delta_\theta)) \qquad (2)$$

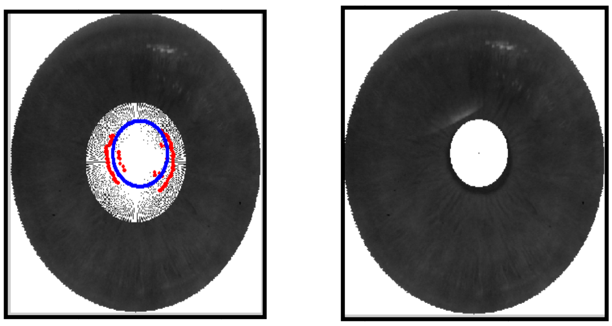
where,

(x_0, y_0) is a point in the grid which is taken as center,

Δ_r and Δ_θ are the increments of radius and angle,

I (*x*, *y*) is the gray level of the image at pixel (*x*, *y*) and *D* is the maximum variation in gray level.

In this way the outer bound between the sclera and the limbus is detected, which is the outer bounds of the iris. Then the biggest square inside this circle of the iris is considered, and the same process is performed in order to find the inner boundary. The points inside this last border are also suppressed, obtaining the image as shown in Figure 3.(a). In the last step of the pre-processing block, the image of the isolated iris is scaled to achieve a constant diameter regardless of the size in the original image. This can be easily observed from the Figure 3.(b).



(a) (b)

Figure 3. Boundary detection using Daugman's grid method (a) detected inner boundary, (b) isolated iris image.

2.2 Circular iris localization using Hough transform

The circular Hough transform have been employed to deduce the radius and centre coordinates of the pupil and iris regions.[11][13] Initially, an edge map is generated by calculating the first derivatives of intensity values in an eye image and then thresholding the result. From the edge map, votes are cast in Hough space for the parameters of circles passing through each edge point. These parameters are the centre coordinates x_c and y_c, and the radius r, which are able to define any circle according to the equation given by,

$$x_c^{\ 2} + y_c^{\ 2} - r^2 = 0 \qquad (3)$$

A maximum point in the Hough space will correspond to the radius and centre coordinates of the circle best defined by the edge points as,

$$(-(x-h_j)\sin\theta_j+(y-k_j)\cos\theta_j)^2 = a_j((x-h_j)\cos\theta_j+(y-k_j)\sin\theta_j) \qquad (4)$$

where, a_j controls the curvature,

(h_j, k_j) is the peak of the parabola, and

θ_j is the angle of rotation relative to the x axis.

In performing the preceding edge detection step, we bias the derivatives in the horizontal direction for detecting the eyelids; and in the vertical direction for detecting the outer circular boundary of the iris of the eye images from CASIA V_1 iris database. For finding Hough transform, we provide range of iris and pupil radius as range of circle radius from CAISA V_1 iris database specification and create edge map of eye for iris co-ordinates detection and we create edge map of extracted iris region for pupil radius and co-ordinates from Hough transform. Brightest point in Hough transformed image is the desired center for Iris.

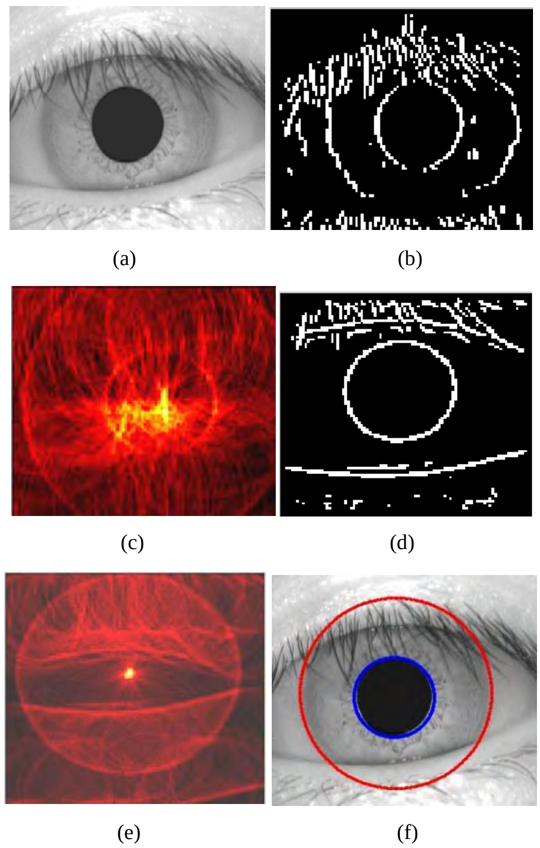


Figure 3.(a) Original eye image (CASIA: 14_1_1.bmp) from CASIA database,(b) Vertical edge map of eye, (c) Hough transform, (d) Horizontal edge map, (e) Hough transform image showing center of the iris, (f) Localized iris image.

The eyelids / eyelashes are occluding part of the iris, so only the portion of the image below the upper eyelids and above the lower eyelids are included.[13]This is achieved by changing the gray level above the upper eyelids and below the lower eyelids to ‘0’ (black). Thus the resultant image obtained has been presented in Figure 4.

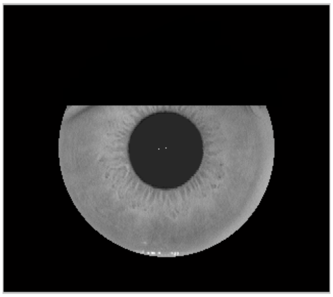


Figure 4.Resultant iris after removal of the eyelids / eyelashes.

3.IRIS RECOGNITION USING SUBSPACE ANALYSIS

Subspace analysis is one of the popular multivariate data analysis methods, which has been widely used in pattern recognition. PCA and LDA are well-known approaches to face recognition that use feature subspaces.[14][15] These methods find a mapping between the original feature spaces to a lower dimensional feature space. For both these methods of iris recognition an assumption was made about the same level of relevance of each iris to the corresponding category.

3.1 Principal Component Analysis (PCA)

Principle Component Analysis (PCA) is also called as the "Hotteling Transform." The main use of PCA is to reduce the dimensionality of the data set while retaining as much information as is possible. It computed a compact and optimal description of the iris data set. PCA is a statistical procedure which rotates the data such that maximum variability is projected onto the axes Figure 5. Essentially, a set of correlated variables are transformed into a set of uncorrelated variables which are ordered by reducing variability. The uncorrelated variables are linear combinations of the original variables, and the last of these variables can be removed with minimum loss of real data. Thus one can define PCA as, "Find an orthogonal co-ordinate system so that the correlation between different axes is minimized."[16][17]

An image may be viewed as a vector of pixels where the value of each entry in the vector is the grayscale value of the corresponding pixel. For example, an 8×8 image may be unwrapped and treated as a vector of length 64. The image is said to sit in N-dimensional space, where N is the number of pixels (and the length of the vector). This vector representation of the image is considered to be the original space of the image. The original space of an image is just one of infinitely many spaces in which the image can be examined. Two specific subspaces are the subspaces created by the eigenvectors of the covariance matrix of the training data and the basis vectors calculated by Fisher discriminant. The majority of subspaces, including Eigen space, do not optimize discrimination characteristics. Eigen space optimizes variance among the images.

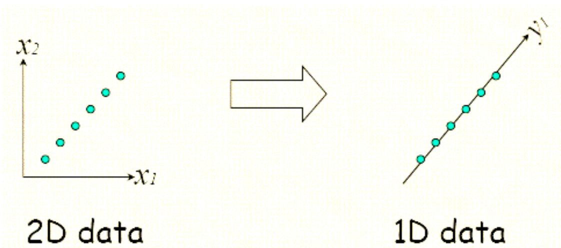


Figure 5. Definition of PCA.

Although some of the details may vary, there is a basic algorithm for identifying images by projecting them into a subspace. First one has to select a subspace on which to project the images. Once this subspace is selected, all training images are projected into this subspace. Next each test image is projected into this subspace. Each test image is compared to all the training images by a similarity or distance measure, the training image found to be most similar or closest to the test image is used to identify the test image.

Furthermore, variations within the subspace also affect performance. For example, the selection of vectors to create the subspace and measures to decide which images are a closest match, both affect the performance.

Basically PCA projects images into a subspace such that the first orthogonal dimension of this subspace captures the greatest amount of variance among the images and the last dimension of this subspace captures the least amount of variance among the images. Once images are projected into one of these spaces, a similarity measure is used to decide which images are closest matches. PCA is a standard decorrelation technique and following its application one derives an orthogonal projection basis that directly leads to dimensionality reduction, and possibly to feature selection. PCA generates a set of orthonormal basis vectors, known as principal components (PCs) that maximize the scatter of all the projected samples. If we draw the magnitude plot of Eigen values after sorting the eigen values in decreasing order, then it is observed that the first few leading eigenvectors define the matrix. One can see from Figure 6. that the first 15 eigen values capture most of the energy and that the eigen values whose index is greater than 30 are fairly small and most likely capture noise.

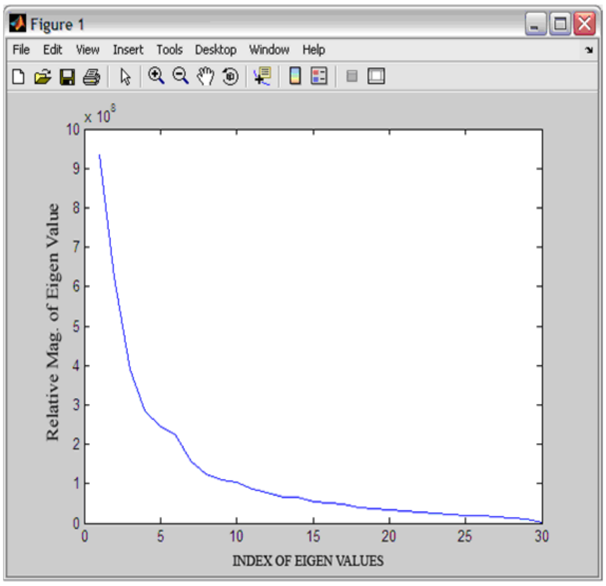


Figure 6.Magnitude plot of Eigen values in descending order.

PCA (or Karhunen-Loeve expansion) identifies variability between human irises. PCA does not attempt to categorize irises using familiar geometrical differences, such as nose length or eyebrow width. Instead, a set of human irises is analyzed using PCA to determine which 'variables' account for the variance of irises. Any grey scale iris image $I(x, y)$, is a two dimensional $N \times N$ array of intensity values (usually 8 bit gray scale). This may be considered a vector of dimension N^2, so that an image of size 256×256 becomes a vector of dimension $65{,}536$ or equivalently, a point in $65{,}536$ dimensional space. An ensemble of images then maps to a collection of points in this huge space. The central idea is to find a small set of irises (the eigenirises) that can approximately represent any point in the iris space as a linear combination. Each of the eigen irises is of dimension $N \times N$, and can be interpreted as an image [18].

The eigen space is a subspace of the image space spanned up by a set of eigenvectors of the covariance matrix of the trained images. These eigenvectors are also called eigen irises because of their iris-like appearance. The covariance matrix is constructed by performing PCA which means rotating the dataset so that its primary axes, the eigenvectors with the highest modes of variation, lie along the axes of the co-ordinate space and move it so that its centre of mass corresponds with the origin (Figure 7.).

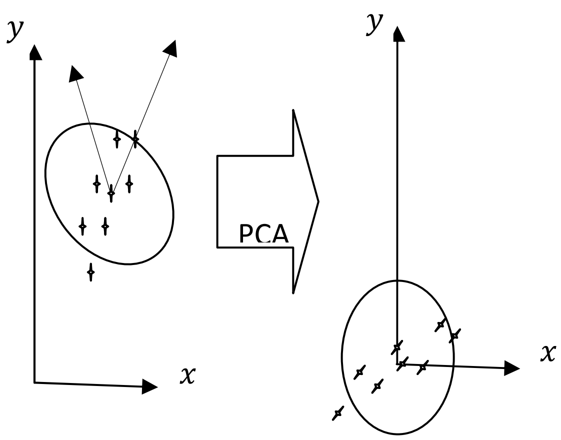
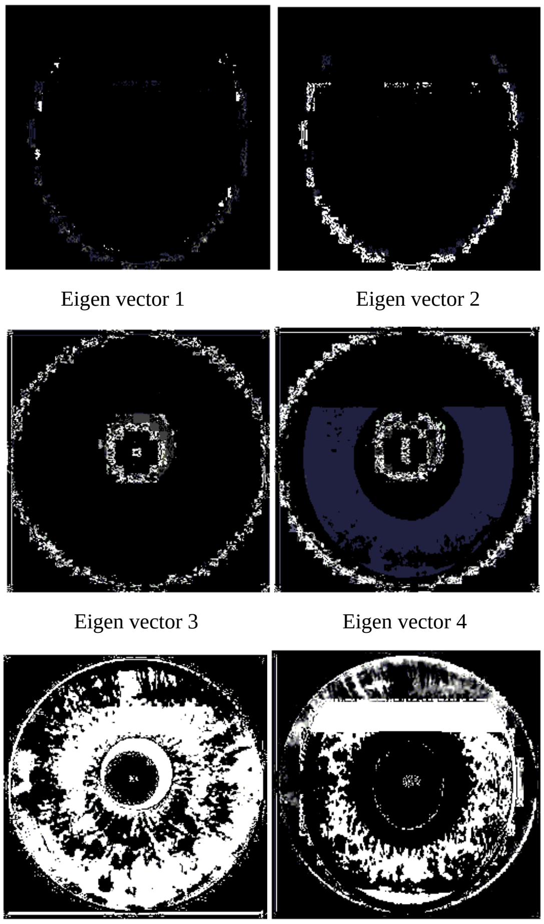


Figure 7. The covariance matrix construction using PCA.

Let an iris image $I(x, y)$ be a two dimensional array of intensity values, or a vector of dimension N. Let the training set of images be $I_1, I_2, ..., I_N$. The average iris image of the set is defined by $m = \frac{1}{N}\sum_{i=1}^{N} I_i$. Each iris differs from the average by the vector $\bar{I}_i = I_i - m$. This set of very large vectors is subject to principal component analysis which seeks a set of K orthonormal vectors $v_k, k = 1, \ldots, K$ and their associated eigen values λ_k which best describe the distribution of data.



Eigen vector 1 Eigen vector 2

Eigen vector 3 Eigen vector 4

Eigen vector 5 Eigen vector 6

Figure 8. Different Eigen vector images.

The covariance matrix C is computed as,

$$C = \frac{1}{N}\sum_{i=1}^{N} \bar{I}_i \bar{I}_i^T = AA^T \qquad (5)$$

where,

the matrix $A = [\bar{I}_1, \bar{I}_2, \ldots, \bar{I}_i]$.

The eigen values λ_k and corresponding eigenvectors v_k are computed for the covariance matrix.

$$C\, v_k = \lambda_k v_k \qquad (6)$$

The space spanned by the e igenvectors v_k, $k = 1, \ldots, K$ corresponding to the largest K eigenvalues of the covariance matrix C, is called the iris space. The eigenvectors of matrix C, which are called eigenirises from a basis set for the iris images. A new iris image G is transformed into its eigeniris components (projected onto the iris space) by,

$$w_k = \langle v_k, (G - \bar{I}_i)\rangle = v_k^T\,(G - \bar{I}_i) \qquad (7)$$

for $k = 1, \ldots, K$.

The projections w_k form the feature vector $W = [w_1, w_2, ..., w_k]$ which describes the contribution of each of each eigeniris in representing the input image. Different Eigen irises obtained from each vector as shown in Figure 8. Then from all the vector matrices, projection data with low dimensionality is obtained.

We have implemented PCA by seleting the K eigenvectors with the largest eigenvalues as the basis i.e. we have selected the dimensions which can express the gretest variance in iris images. It is found that using this co-ordinate system, an iris can be reasonably reconstructed with as few as 6 co-ordinates and hence selected only six eigen values for our experimental work. It means that a 256×256 pixel iris, which previously took 65,536 bytes to represent in image space will require only 6 bytes. This reduction in dimensionality makes the problem of iris recognition much simpler since we concern ourselves only with the relevent and most discriminatory attributes of the iris.

3.2 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) known as Fisher's Linear Discriminant (FLD) is a popular discriminant criterion that measures the between-class scatter normalized by the within-class scatter.[20]

Let $\omega_1, \omega_2, ..., \omega_L$ denote the number of classes and $\mathrm{N}_1, \mathrm{N}_2, ..., \mathrm{N}_L$, are the number of images within each class. Let $\mathrm{M}_1, \mathrm{M}_2, ..., \mathrm{M}_L$ are the means of the classes and M be and the grand mean. The within-class and between-class

scatter matrices, $\sum \omega$ and $\sum b$ are defined as,

$$\sum \omega = \sum_{i=1}^{L} p(\omega_i) \varepsilon \left\{ \left(\mathrm{Y}^{(p)} - \mathrm{M}_i \right) \left(\mathrm{Y}^{(p)} - \mathrm{M}_i \right)^t \big|_{\omega_i} \right\} \tag{8}$$

$$\sum b = \sum_{i=1}^{L} p(\omega_i) \varepsilon (\mathrm{M}_i - \mathrm{M})(\mathrm{M}_i - \mathrm{M})^t \tag{9}$$

where,

$p(\omega_i)$ is a priori probability,

$\sum \omega, \sum b \in mR$, and

L denotes the number of classes.

FLD derives projection matrix that maximizes the ratio $\left| P^t \sum bP / \right| P^t \sum \omega P \big|$. This ratio is maximized when P consists of the eigenvectors of the covariance matrix A i.e.

$$\sum^{-1} \omega \sum b\psi = \psi \Delta \tag{10}$$ where,

ψ , $\Delta \in R^{m \times m}$ are eigen vector and eigen value matrices of $\sum^{-1} \omega \sum b$ respectively.

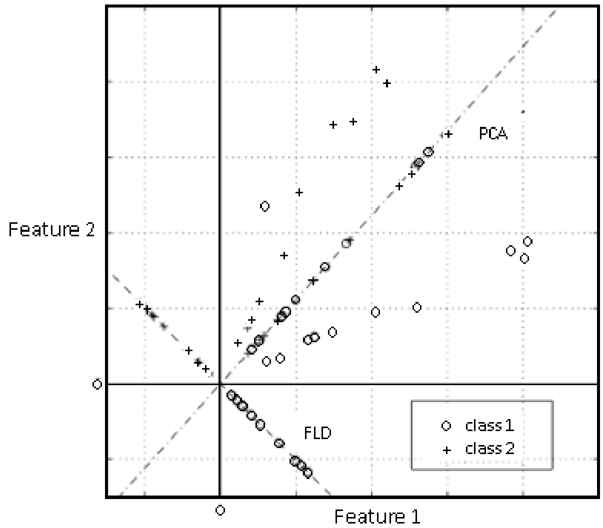


Figure 9. A comparison of PCA and LDA for a two class problem.

LDA known as FLD finds a small number of features that differentiates individual irises but recognizes irises of the same individual. A small number of features are found by maximizing the Fisher Discriminant Criterion [21] which is achieved by maximizing the grouping of individual irises whilst minimizing the grouping of different individual irises. Therefore by grouping irises of the same individual these features can be used to determine the identity of individuals. LDA is defined by the between scatter class S_B and within scatter class S_W. The between scatter class S_B are irises of different individuals while the within scatter class S_W are irises of the same individuals. The between scatter class S_B specifically represents the scatter of features around the mean of each iris class whilst the within scatter class S_W represents the scatter of features around the overall mean for all iris classes. Figure 9. is a comparison of PCA and LDA for a two-class problem in which the samples from each class are randomly perturbed in a direction perpendicular to a linear subspace. In this Figure, both PCA and LDA reduce the dimension by projecting the points from 2-D to 1-D. Note that when comparing the projections in the Figure, PCA smears the class together so that the samples in the projected space are no longer linearly separable. Although PCA achieves larger total scatter, LDA achieves greater between-class scatter and thus the classification is simplified. LDA transformation is strongly dependent on the number of classes, the number of samples, and the original space dimensionality.

Once images are projected into a subspace, determining which images are most like one another is the next task [22]. There are two ways in general to determine how alike images are. One is to measure the distance between the images in N-dimensional space. The second way is to measure how similar two images are. When measuring similarity, one wishes to maximize similarity, so that two like images produce a high similarity value. There are many possible similarity and distance measures like L_1 norm, L_2 norm, covariance, Mahalanobis distance and correlation.

4. RESULTS AND DISCUSSIONS

Both the proposed algorithms for PCA and LDA has been implemented and tested on Pentium-IV processor with 2.6 GHz, 512 MB RAM under MATLAB environment. The recognition rate for the proposed algorithms is carried out in two parts as in-database and out-database. In-database means training images and testing images are the same whereas for out-database training images and testing images are different. The result obtained for in-database are listed in Table 1. and result obtained for out-database are listed in Table 2. The results obtained for in-database of PCA has 86.67% for CASIA V_1 database and that of LDA has 95% for the same database. It means that LDA only maximizes the distance of each subject. As a result, these projected coefficients of different subject could be distributed in the same area and LDA system cannot identify these irises. The results obtained for out-database degrades slightly because the iris images used for recognition have not been presented to the algorithm during training.

Table 1. In-database recognition rate.

Iris database	**Recognition rate**	
	PCA	LDA
CASIA V_1	86.67%	95%
UPOL	84.33%	94%

Table 2. Out-database recognition rate.

Iris database	**Recognition rate**	
	PCA	LDA
CASIA V_1	64.67%	77.5%
UPOL	62.5%	73.67%

5. CONCLUSIONS

PCA and LDA are well-known approaches applied to iris recognition that use feature subspaces. PCA is a standard de-correlation technique and following its application one derives an orthogonal projection basis which directly leads to dimensionality reduction, and possibly to feature selection. Once images are projected into a subspace, classification is performed using similarity measures. The experimental results show improved recognition rates and reduced sensitivity to variations between iris images caused by changes in illumination and viewing directions.

6. REFERENCES

[1] A.Ross and A.K.Jain, 2004 " Multimodal Biometrics: An Overview", Proceeding of European Signal Processing Conference, pp.1221-1224,

[2] U..K..Passport Service May2005. Biometrics Enrollment Trial, Atos Origin,

[3] F.H.Alder 1965,Physiology of the Eye,Mosby.

[4] J. Daugman, , Nov. 1993. "High Confidence Visual Recognition of Person by a Test of statistical independence," IEEE Trans. Pattern analysis and machine intelligence, vol.15, no.11, pp1148-1161.

[5] J.Daugman, 2003. "Demodulation by Complex- Valued Wavelets for Stochastic Pattern Recognition," Int'l J.Wavelets, Multi-resolution and Information Processing, vol. 1, no. 1, pp 1-1

[6] J. Daugman, 2001. "Statistical Richness of Visual Phase Information: Update on Recognizing Persons by IrisPatterns," International Journal for Computer Vision, vol. 45, no. 1, pp 25-38.

[7] R.P. Wildes, Sept. 1997. "Iris Recognition: An Emerging Biometric Technology", Proceeding of IEEE vol.85, pp.1348-1363,

[8] W. Boles and B. Boashash, 1998. "A Human Identification Technique Using Images of the Iris and Wavelet Transform," IEEE Trans. Signal Processing, vol. 46, no. 4, pp 1185-1188,

[9] L. Ma, Y. Wang, and T. Tan, 2002."Iris Recognition Based on Multichannel Gabor Filtering," Proceding of Asian Conference Computer Vision, vol.1, pp 279-283,

[10] L. Ma, T. Tan, Y. Wang, Dec. 2003. "Personal Identification Based on Iris Texture Analysis," IEEE transaction on Pattern Analysis and Machine Intelligence, vol.25, no.12, pp 1519-1533,

[11] L. Ma, Y. Wang, and T. Tan, , 2002. "Iris Recognition Using Circular Symmetric Filters," Proceeding of International Conference on Pattern Recognition, vol.2, pp 414-417.

[12] L. Ma, T. Tan, Y. Wang, June 2004 "Efficient Iris Recognition by Characterizing Key Local Variations," IEEE Transaction on Image Processing, vol.13, no.6, pp 739-750,

[13] W. Kong, D. Zhang, 2001. "Accurate Iris Segmentation Based on Novel Reflection and Eyelashes Detection Model," Proceeding of International Symposium on Intelligent Multimedia, Video and Speech Processing,Hong Kong,

[14] B .K.Gunturk ,A.U.Batur, Y.Altunbasak, M.N.Hayes and R.M.Mersereau May 2003 " Eigenface-Domain Super- resolution for Face Recognition" IEEE Transactions on Image Processing. vol.12,no.5,pp.597-606,

[15] K.N.Plataniotis and A.N.Venetsanopoulos Jan.2003 "Face Recognition using LDA-based Algorithms"IEEE Transctions on Neural Network.vol.14,issue.1,pp.195-200,

[16] Pearson K. "On lines and Planes of Closet Fit to Systems of Points in Space"(PDF) Philosophical Magazine 2(6):559-572; 1901.

[17] http://stat.smmu.edu.cn/history/Pearson1901.pdf

[18] R.Jillela ,A.Ross ,P.J.Flynn, Jan.2011 "Information Fusion in Low-Resolution Iris Videos using Principal Components Transform" Proceeding of IEEE Workshop on Applications of computer vision.,

[19] S.Kumar ,K.Raja,R.Chhootaray and S.Pattnaik 2011. "PCA based Iris Recognition using DWT " International Journal for Computer Technology and Application.vol 2(4),pp.884-893,

[20] Y. Xu, J.Yang, J.Zhang, 2004."A Novel Method for Fisher Discriminant Analysis" Elsevier Journal of Pattern Recognition.vol. 37,pp.371-384,

[21] Y.Xu,G.Lu, Nov.2006 " Analysis on Fisher Discriminant Criterion and Linear Separability of Features Space" International Conference on Computational Intelligence and Security,vol.2,pp.1671-1676,

[22] Q.Guo, J.Liu,H.Zhang,J.Hou,X.Yang Oct.2012 " Enhanced Fisher Discriminant Criterion for Image Recognition" Elsevier Journal of Pattern Recognition.Vol. 45,pp.3717-3724.

[23] "CASIA Iris Image Data base" Institute of Chinese Academy of Sciences2004,http://www.sinobiometric.com

[24] UPOL Iris Image Database, 2000 http://www.inf.upol.cz/iris/.

Pravin Sahebrao Patil holds Bachelor's degree in Electronics &Telecommunication from Marathwada University, Aurangabad (Maharashtra) in 1989, Masters from Motilal Nehru National Institute of Technology at Allahabad in1995 and Ph .d from North Maharashtra University in 2013. His area of interest is communication and Digital image processing. Presently he is working as Professor & Head in Dept.of Electronics & Communication at S.S.V.P.S's Bapusaheb .Shivajirao .Deore College of Engineering,Dhule,Maharashtra.