IOSR Journal of Electronicsl and Communication Engineering (IOSR-JECE)
ISSN: 2278-2834-, ISBN: 2278-8735, PP: 12-18
www.iosrjournals.org

Iris Recognition: An emerging biometric technology

Kshamaraj Gulmire[1], Sanjay Ganorkar[2]
[1](Electronics &Telecommunication , Pune University,India)
[2](Electronics &Telecommunication , Pune University,India)

ABSTRACT: Iris recognition is a well-known biometric technique. The iris recognition is a kind of the biometrics technologies based on the physiological characteristics of human body, compared with the feature recognition based on the fingerprint, palm-print, face and sound etc, the iris has some advantages such as uniqueness, stability, high recognition rate, and non-infringing etc. Iris recognition, which is divided into four steps: segmentation, normalization, feature extraction and matching. We had taken iris images from database CASIA V4.We use Daugman's method using integrodifferential operator for segmentation & the feature extraction algorithm based on principle component analysis(PCA) & independent component analysis(ICA) for a compact iris code. We use these methods to generate optimal basis elements which could represent iris signals efficiently. In practice the coefficient of these methods are used as feature vectors. Then iris feature vectors are encoded into the iris code for storing and comparing individual's iris patterns. The iris recognition is using principal component analysis & independent component analysis can produce spatially globalfeatures. Hamming distance method is used for matching purpose for principle component analysis & independent component analysis.

Keywords - Biometric recognition, ICA, iris localization, image segmentation, iris recognition, PCA.

I. INTRODUCTION

Identifying or verifying one's identity using biometrics is attracting considerable attention in these years. Biometrics authentication uses information specific to a person, such as a fingerprint, face, palm or iris pattern. Therefore, it is more convenient and securer than the traditional authentication methods. Among all the biometrics authentication methods, iris recognition appears to be a very attracting method because of its high recognition rate [1].

Biometric recognition refers to the process of matching an input biometric to stored biometric information. In particular, biometric verification refers to matching the live biometric input from an individual to the stored biometric template about that individual. Examples of biometrics include face images, fingerprint images, iris images, retinal scans, etc. Thus, image processing techniques prove useful in the biometric recognition. The field of biometrics utilizes computer models of the physical and behavioral characteristics of human beings with a view to reliable personal identification. The human characteristics of interest include visual images, speech, and indeed anything which might help to uniquely identify the individual [5].

Most current authentication systems are password based making them susceptible to problems such as forgetting the password and passwords being stolen. One way to overcome these problems is to employ biometrics (e.g., fingerprints, face, iris pattern, etc.) for authentication. Another important application is to match an individual's biometrics against a database of biometrics [11]. An example application of biometric identification is the matching of fingerprints found at a crime scene to a set of fingerprints in a database. Authentication problem has narrower scope, but the matching technologies are applicable to both verification and identification problems [10]. We will refer to these problems loosely as biometric recognition.

Many biometric sensors output images and thus image processing plays an important role in biometric authentication. Image preprocessing is important since the quality of a biometric input can vary significantly.

For example, the quality of a face image depends very much on illumination type, illumination level, detector array resolution, noise levels, etc [3]. Preprocessing methods that take into account sensor characteristics must be employed prior to attempting any matching of the biometric images. The use of biometric systems has been increasingly encouraged by both government and private entities in order to replace or increase traditional security systems.

The word iris is generally used to denote the colored portion of the eye. It is a complex structure comprising muscle, connective tissues and blood vessels. The image of a human iris thus constitutes a plausible biometric signature for establishing or confirming personal identity. Further properties of the iris that makes it superior to finger prints for automatic identification systems include, among others, the difficulty of surgically modifying its texture without risk, its inherent protection and isolation from the physical environment, and it's easily monitored physiological response to light. Additional technical advantages over fingerprints for automatic recognition systems include the ease of registering the iris optically without physical contact beside the fact that its intrinsic polar geometry does make the process of feature extraction easier.

Iris recognition is gaining popularity as a robust and reliable biometric technology [4]. The iris's complex texture and its apparent stability hold tremendous promise for applying iris recognition in diverse application scenarios, such as

border control, forensic investigations, as well as cryptosystems. Several existing approaches to iris recognition achieve auspicious performance, reporting recognition rates above 99% and equal error rates of less than 1% on diverse data sets. The majority of proposed iris recognition algorithms build upon the work of Daugman, extracting binary iris-codes while simple metrices (e.g. fractional Hamming distance) are applied in the matching process [6].
Boles and Boashash [2] proposed a novel iris recognition algorithm based on zero crossing detection of the wavelet transform, this method has only obtained the limited results in the small samples, and this algorithm is sensitive to the grey value changes, thus recognition rate is lower. In another method followed by Jie Wang [7] the iris texture extraction is performed by applying wavelet packet transform (WPT) using Haar wavelet. The iris image is decomposed in to sub images by applying WPT and suitable sub images are selected and WPT coefficients are encoded. One more technique to extract the feature is Haar wavelet decomposition. Tze Weng Ng, Thein Lang Tay, Siak Wang Khor [8], has proposed Haar wavelet decomposition method for feature extraction. It acquires an accuracy using complex neural network matching method. Coefficients obtained from the decomposition of are then converted to binary codes to be used on calculation of hamming distance for matching purpose. Zhonghua Lin, Bibo Lu [9], has proposed iris recognition based on the optimized gabor filters. The recognition rate is high, the recognition speed is guaranteed. Iris recognition will need in future for security.

II. CASIA DATABASE

The data samples used in our experiments were taken from the Chinese academy of Sciences (CAS) [13]. Iris recognition has been an active research topic in recent years due to its high accuracy. There is not any public iris database while there are many face and fingerprint databases. Lack of iris data for algorithm testing is a main obstacle to research on iris recognition. To promote the research, National Laboratory of Pattern Recognition (NLPR), Institute of Automation(IA), Chinese Academy of Sciences(CAS) will provide iris database freely for iris recognition researches.
CASIA Iris Image Database (ver 1.0) includes 756 iris images from 108 eyes (hence 108 classes). For each eye, 7 images are captured in two sessions, where three samples are collected in the first session and four in thesecond session. CASIA Iris Image Database (CASIA-Iris) developed by our research group has been released to the international biometrics community and updated from CASIA-IrisV1 to CASIA-IrisV3 since 2002. CASIA- IrisV4 is an extension of CASIA-IrisV3 and contains six subsets. The three subsets from CASIA-IrisV3 areCASIA-Iris-Interval, CASIA-Iris-Lamp, and CASIA-Iris-Twins respectively. The three new subsets are CASIA- Iris-Distance, CASIA-Iris-Thousand, and CASIA-Iris-Syn. CASIA-IrisV4 contains a total of 54,601 iris images from more than 1,800 genuine subjects and 1,000 virtual subjects. All iris images are 8 bit gray-level JPEG files,collected under near infrared illumination or synthesized. The six data sets were collected or synthesized at different times and CASIA-Iris-Interval, CASIA-Iris-Lamp, CASIA-Iris-Distance, CASIA-Iris-Thousand may have a small inter-subset overlap in subjects. More than 3,000 users from 70 countries or regions have downloaded CASIA-Iris and much excellent work on iris recognition has been done based on these iris image databases. Although great progress of iris recognition has been achieved since 1990s, the rapid growth of iris recognition applications has clearly highlighted two challenges, i.e. usability and scalability. Most current iris recognition methods have been typically evaluated on medium sized iris image databases with a few hundreds of subjects. However, more and more large-scale iris recognition systems are deployed in real-world applications. Many new problems are met in classification and indexing of large-scale iris image databases.

III. PRE-PROCESSING

Here consider iris pictures from CASIA database to preprocess & PCA use for feature extraction. And for segmentation Duagman method is used. As shown in Fig.1 is specimen image from database.

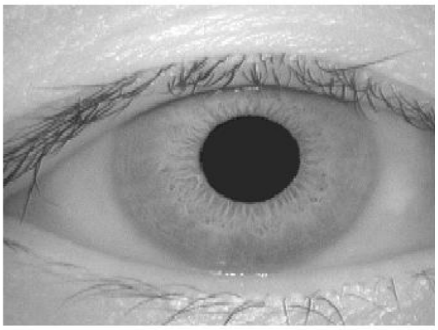

figure 1. Iris Image

For segmentation purpose Daugman method is used, first consider histogram of specimen image for pupil centre, we get pupil localization in Fig. 2.

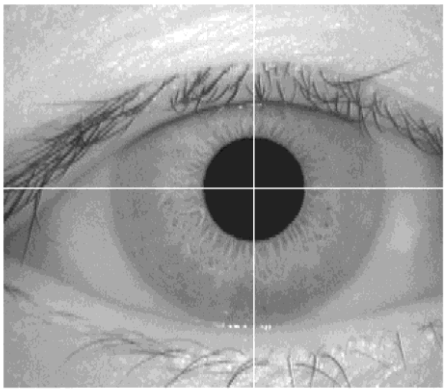

figure 2. Pupil Localization

The result of segmentation of iris image by Daugman's method using integrodifferential operator is shown in Fig.3.

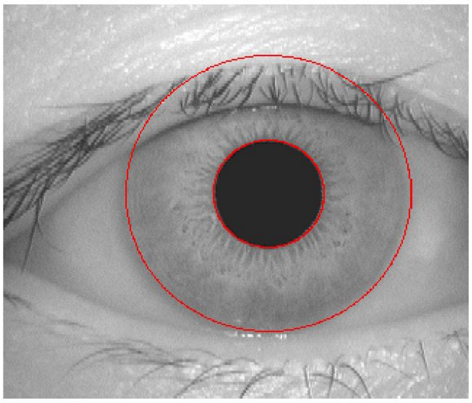

figure 3. Segmented Image

IV. PRINCIPLE COMPONENT ANALAYASIS

We proceed with the Principal Component Analysis (PCA) of the iris. The PCA is a statistical method under the broad title of factor analysis. Because PCA is a classical technique which can be applied in the linear domain, they are suitable in applications having linear models such signal processing, image processing, communications etc.

It detects Irises based on the principal Component technique analysis. The Principal Component Analysis (PCA) is one of the most successful techniques that have been used in image recognition and compression. There has been a lot of work carried out on face recognition using the PCA. This paper tries to use the same concepts in trying to detect Irises. Identification starts with localizing the portion of the eye that corresponds to the iris. After localization, the iris is centre aligned with the image frame and unwanted portions of the iris occluded by the eyelids is removed.

PCA is a useful statistical technique that has found application in field such as face recognition and image compression, and is a common technique for finding patterns in data of high dimension. It involves a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called principal component. The first principal component accounts for as much for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. Depending on the field of application, it is also named the discrete Karhunen- Loeve transform (KLT), the Hotelling transform or proper orthogonal decomposition (POD).

PCA was invented in 1901 by Karl Pearson. Now it is mostly used as a tool in exploratory data analysis and for making predictive models. PCA involves the calculation of the eigen value decomposition of a data covariance matrix or singular value decomposition of a data matrix, usually after mean centering the data for each attribute. The results of a PCA are usually discussed in terms of component scores and loadings.

PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way which best explains the variance in the data. If a multivariate dataset is visualized as a set of coordinates in a high-dimensional data space (1 axis per variable), PCA supplies the user with a lower-dimensional picture, a "shadow" of this object when viewed from its (in some sense) most informative viewpoint.PCA is closely related to factor analysis; indeed, some statistical packages deliberately conflate the two techniques. True factor analysis makes different assumptions about the underlying structure and solves eigenvectors of a slightly different matrix. Details PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. PCA is theoretically the optimum transform for given data in least square terms. For a data matrix, XT, with zero empirical mean (the empirical mean of the distribution has been subtracted from the data set), where each row represents a different repetition of the experiment, and each column gives the results from a particular probe.

Given a set of points in Euclidean space, the first principal component (the eigenvector with the largest eigen value) corresponds to a line that passes through the mean and minimizes sum squared error with those points. The second principal component corresponds to the same concept after all correlation with the first principal component has been subtracted out from the points. Each eigen value indicates the portion of the variance that is correlated with each eigenvector. Thus, the sum of all the eigen values is equal to the sum squared distance of the points with their mean divided by the number of dimensions. PCA essentially rotates the set of points around their mean in order to align with the first few principal components. This moves as much of the variance as possible (using a linear transformation) into the first few dimensions. The values in the remaining dimensions, therefore, tend to be highly correlated and may be dropped with minimal loss of information. PCA is often used in this manner for dimensionality reduction. PCA has the distinction of being the optimal linear transformation for keeping the subspace that has largest variance. This advantage, however, comes at the price of greater computational requirement if compared, for example, to the discrete cosine transform. Nonlinear dimensionality reduction techniques tend to be more computationally demanding than PCA. We take this method to extract the iris features, and use these steps. Consider data from segmented image, calculate mean. For PCA to work properly, we have to subtract the mean from each of the data dimensions. The mean subtracted is the average across each dimension. Now calculate covariance matrix. This matrix is square matrix, so calculate eigenvectors and eigenvalues of the covariance matrix. These are rather important, as they tell us useful information about our data. Then choosing components and forming a feature vector.

This is the final step in PCA, and is also the easiest. Once we have chosen the components (eigenvectors) that we wish to keep in our data and formed a feature vector, we simply take the transpose of the vector and multiply it on the left of the original data set, transposed.

Final Data = Row Feature Vector × Row Data Adjust

Where Row Feature Vector is the matrix with the eigenvectors in the columns transposed so that the eigenvectors are now in the rows, with the most significant eigenvector at the top, and Row Data Adjust is the mean adjusted data transposed. The top value of eigen vector is important which is in row format. The data items are in each column, with each row holding a separate dimension.

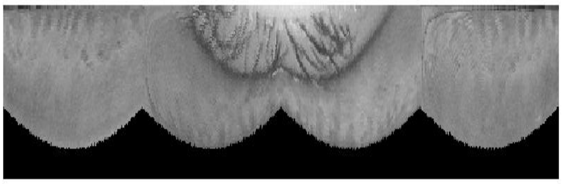

figure 4. Normalized Unwrapped Iris

After feature extraction, will get eigen space model as shown in Fig.4 & for classification Euclidean distance is used.

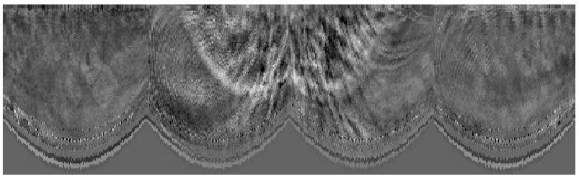

figure 5. Eigen space model

V. INDEPENDENT COMPONENT ANALYSIS

Independent component analysis (ICA) is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals.

ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples. In the model, the data variables are assumed to be linear mixtures of some unknown latent variables, and the mixing system is also unknown. The latent variables are assumed nongaussian and mutually independent, and they are called the independent components of the observed data. These independent components, also called sources or factors, can be found by ICA.
ICA is superficially related to principal component analysis and factor analysis. ICA is a much more powerful technique, however, capable of finding the underlying factors or sources when these classic methods fail completely. The data analyzed by ICA could originate from many different kinds of application fields, including digital images, document databases, economic indicators and psychometric measurements. In many cases, the measurements are given as a set of parallel signals or time series; the term blind source separation is used to characterize this problem. Typical examples are mixtures of simultaneous speech signals that have been picked up by several microphones, brain waves recorded by multiple sensors, interfering radio signals arriving at a mobile phone, or parallel time series obtained from some industrial process.
When the independence assumption is correct, blind ICA separation of a mixed signal gives very good results. It is also used for signals that are not supposed to be generated by a mixing for analysis purposes. A simple application of ICA is the “cocktail party problem”, where the underlying speech signals are separated from a sample data consisting of people talking simultaneously in a room. Usually the problem is simplified by assuming no time delays or echoes. An important note to consider is that if N sources are present, at least N observations (e.g. microphones) are needed to get the original signals. This constitutes the square ($J = D$, where D is the input dimension of the data and J is the dimension of the model). Other cases of underdetermined ($J < D$) and overdetermined ($J > D$) have been investigated.
ICA finds the independent components (aka factors, latent variables or sources) by maximizing the statistical independence of the estimated components. We may choose one of many ways to define independence, and this choice governs the form of the ICA algorithms. The two broadest definitions of independence for ICA are
1)Minimization of mutual information
2)Maximization of non-Gaussianity
The Non-Gaussianity family of ICA algorithms, motivated by the central limit theorem, uses kurtosis and negentropy. The Minimization-of-Mutual information (MMI) family of ICA algorithms uses measures like Kullback-Leibler Divergence and maximum-entropy. Typical algorithms for ICA use centering, whitening (usually with the eigenvalue decomposition), and dimensionality reduction as preprocessing steps in order to simplify and reduce the complexity of the problem for the actual iterative algorithm. Whitening and dimension reduction can be achieved with principal component analysis or singular value decomposition. Whitening ensures that all dimensions are treated equally a priori before the algorithm is run. Algorithms for ICA include infomax, FastICA, and JADE, but there are many others also. In general, ICA cannot identify the actual number of source signals, a uniquely correct ordering of the source signals, nor the proper scaling (including sign) of the source signals. ICA is important to blind signal separation and has many practical applications. It is closely related to (or even a special case of) the search for a factorial code of the data, i.e., a new vector-valued representation of each data vector such that it gets uniquely encoded by the resulting code vector (loss-free coding), but the code components are statistically independent.
Imagine that in a room where two people are speaking simultaneously. There are two microphones, which you hold in different locations. The microphones give you two recorded time signals, which we could denote by $x_1(t)$ and $x_2(t)$, with x_1 and x_2 the amplitudes, and t the time index. Each of these recorded signals is a weighted sum of the speech signals emitted by the two speakers, which we denote by $s_1(t)$ and $s_2(t)$. We could express this as a linear equation,

$$x_1(t) = a_{11} s_1 + a_{12} s_2 \qquad (1)$$
$$x_2(t) = a_{21} s_1 + a_{22} s_2 \qquad (2)$$

where, $a_{11},$ $a_{12},$ a_{21} and a_{22} are some parameters that depend on the distances of the microphones from the speakers. It would be very useful if you could now estimate the two original speech signals $s_1(t)$ and $s_2(t)$, using only the recorded signals $x_1(t)$ and $x_2(t)$. This is called the cocktail-party problem. To this problem, the usually method is independent component analysis.
As we know, there is much information in higher order statistics that can't be omitted, to non-Gaussian signal. Therefore we also use ICA to extract features of the iris regions.
As mentioned above, we can think the iris regions like this: X = as(3)
where X are column vectors that have mx1 dimensions;
$a = (a_1, a_2 \ldots \ldots a_n)$ is a m×n matrix that is a basis function;
n is the number of basis functions;
$s = (s_1, s_2 \ldots \ldots s_n)$ are column vectors that have n×1 dimensions.
Each of is a feature coefficient. Therefore a X is equal to linear superposition of
$a = (a_1, a_2 \ldots \ldots a_n)$ and $s = (s_1, s_2 \ldots \ldots s_n)$
To all pictures, the basis functions are the same. The difference is the coefficient vector $s = (s_1, s_2 \ldots \ldots s_n)$
Therefore every picture can be denoted by its feature coefficient vector.
Without loss of generality, we suppose

$a = (a_1, a_2 \ldots \ldots a_n)$ is a invertible matrix. So based function (4), we can get this: $S = wX$ (4)
where, s = is coefficient vector of this picture; $w = (w_1, w_2 \ldots \ldots w_n)$ is the inverse function of a, $w = a^{-1}$, we call it transition matrix. Every coefficient vector s_i can be expressed the forms that w multiply .
The most important supposing of ICA is that is independent, and meet the super-Gaussian distribution. Therefore, the problem of ICA is inducted to how to get the basis function a and its transition matrix w and make the feature coefficient s to meet the super-Gaussian distribution and independent, from the training samples $I = \{x_k, k = 1,2,\ldots\ldots,N\}$ where N is the number of the training samples.

$$I = as \quad (5)$$

There are many statistical methods that measure whether variable meets the super Gaussian distribution. We use FastICA algorithm to make s to meet super-Gaussian distribution. As we know, in all random variables, variables of Gaussian distribution have the maximum entropy. Therefore, in FastICA, we use the measuring function

$$J(y) \quad c\,[E\{G(y)\} - E\{G(\ )\}]^2 \quad (6)$$

where v is a Gaussian random variable that mean is 0, and variance is 1; and G is non quadratic function; we usually take:

$$G_1(u) = \frac{1}{a_1} \log \cos a_1 u \quad (7)$$

$$G_2(u) = -\exp\left(\frac{u^2}{2}\right) \quad (8)$$

When y is meet to Gaussian distribution, J (y) is equal to zero. And J(y) is not equal to zero in other circumstances. Therefore that we only need is the max of J(y). We put the problem mentioned above to change into an optimization problem. We can use the fixed-point iteration method to solve the optimization problem.
To simplify the calculation, we need two following preprocessing:
1) Centering. We take the original training samples to minus the mean, and make the mean of the training samples after centering is zero.
2) Whitening. We have to make the training samples variance is one and independent. Therefore, we can get the aim of dimension reduction, and reduce the computational effort. After feature extraction of figure 1, get figure 7.

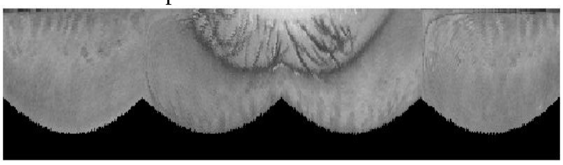

figure 6. Normalized Unwrapped Iris

figure 7. Centered Component

VI. EXPERIMENTAL RESULT

We use images of eyes from 6 persons, and every person has five images of eyes. The top three images are used as test images and the next three images are used for training purpose. We use the Daugman's methods to iris regions segmentation and use Principal Component Analysis for feature extraction. At last, in the identification stage we calculate Euclidean distance between a test image & a training image. The smallest distance among them is expressed, that test image belongs to this class.
The recognition rate is showed in table 1.

Table 1. Experimental Results

Feature Extraction Algorithms	Recognition Rate
Principal Component Analysis	85.3%
Independent Component Analysis	89.5%

VII. CONCLUSION

The Principal Component Analysis & Independent Component Analysis is one of the most successful techniques used in image recognition. A great deal of work has been done in face recognition using the PCA. In literature, eigen faces have been demonstrated to be very useful for face recognition. This is an attempt at using the same technique in identifying irises. The Principal Component Analysis reduces the dimensionality of the training set, leaving only those features that are critical for iris recognition. We used PCA for feature extraction, & get recognition rate 85.3%. The Independent Component Analysis reduces the dimensionality of the training set, leaving only those features that are critical for iris recognition. Iris recognition is a fast developing art. Advantages of iris recognition are very high accuracy, verification time is generally very less & the eye from a dead person would deteriorate too fast to be useful, so no extra precautions have taken with retinal scans to be sure the user is a living human being. Disadvantages of iris recognition are intrusive, a lot of memory for the data to be stored & very expensive. Application of iris recognition are national border controls: the iris as a living passport, secure access to bank accounts at cash machines, forensics, birth certificates, tracing missing or wanted persons. It is a classic biometric application.

VIII. Acknowledgements

The research in this paper was carried out at Sinhgad College of Engineering, Pune. So, special thanks to Guide, Head of Electronics and Telecommunication Department, Principal and Management of Sinhgad College of Engineering.

Journal Papers: REFERENCES

[1]J. G. Daugman, "High Confidence Visual Recognition of Persons by a Test of Statistical Independence", IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 15, pp. 1148-1161, Nov. 1993.
[2]W. Boles, B. Boashash. A human identification technique using images of the iris and wavelet transform. IEEE Transaction on Signal Processing, 1998, 46(4), pp.1185–1188
[3]Lye Wil Liam, Ali Chekima, Liau Chung Fan, "Iris recognition using self-organizing neural network", IEEE 2002.
[4]Daugman G. , "How Iris Recognition Works" , IEEE Transaction on Circuits and System for Video Technology , vol . 14, no. I, pp . 21-30,2004.
[5]U.M. Chaskar, M.S. Suataone, "A Novel Approach for Iris Recognition", IEEE 2010
[6]Lin Zhonghua, Lu Bibo, "Iris Recognition Method Based on the Coefficients of Morlet Wavelet Transform", IEEE 2010 [7] Jie Wang, Xie Mei, "Iris Feature extraction based on wavelet packet analysis", IEEE 2006.
[8]Tze Weng Ng, Thien Lang Tay, Siak Wang Khor, "Iris Recognition using Rapid Haar Wavelet Decomposition", IEEE 2010. [9]Zhonghua Lin, Bibo Lu, "Iris Recognition Method Based on the Optimized Gabor Filters", IEEE 2010.
[10] L.Masek.(2003)."Recognition of human iris patterns for biometricidentification" Online].Available:http://www.csse.uwa.edu.au/~pk/studentprojects/libor/LiborMasekThesis.pdf
[11] R. P. Wildes, "Iris recognition: an emerging biometric technology," Proc IEEE, vol. 85, pp. 1348- 1363, 1997.
[12] Pearson, K. (1901). "On Lines and Planes of Closest Fit to Systems of Points in Space" (PDF). Philosophical Magazine 2 (6): 559-572. http://stat.smmu.edu.cnihistory/pearsonI90 l.pdf.