

## Iris Recognition based on Local sharp Variation Points

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**Abstract**— A wide variety of systems require reliable personal recognition schemes. With the development of biometric recognition technology it is found that iris is one of the most reliable biometric recognition schemes because of its randomly distributed features and unique characteristics. The method discussed in this paper recognized the key local variation points to represent the characteristics of the iris. Thus to characterize the most important features from two dimensional original iris images, a set of 1-D intensity signals which consist of most sharp variations is constructed. In later stage a dyadic wavelet transform is used to precisely locate the position of local sharp variations points which is recorded as features. Exclusive OR operation is used as matching metric. The system performance is analyzed on 756 iris images of standard CASIA-Iris-Version1 database.

**Keywords**—Local Sharp Variation Points, Dyadic Wavelet, Equal Error rate, Genuine Accept rate.

### I. Introduction

Security of computer and financial systems plays a crucial role, nowadays. These systems require remembering many passwords that may be forgotten or even stolen, which is disastrous for the user. To avoid these problems, biometrical systems based on physiological characteristics of a person are taken into consideration in different applications. Among various approaches, iris-based personal recognition is referred to as the most promising one because of its high accuracy, good stability, and high recognition speed [i]. The iris texture is different between persons and between the left and right eye of the same person. The color of the iris can change as the amount of pigment in the iris increases during childhood. Nevertheless, for most of a human's lifespan, the appearance of the iris is relatively constant [ii]. The iris is a thin circular diaphragm, which lies between the cornea and the lens of the human eye. A front view of human eye is shown in Figure 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.

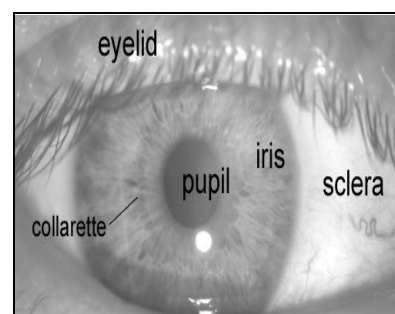


Figure 1: Front View of Human Eye. [ii]

Image processing techniques can be employed to extract the unique iris pattern from a digitised image of the eye, and encode it into a biometric template, which can be stored in a database. This biometric template contains an objective mathematical representation of the unique information stored in the iris, and allows comparisons to be made between templates. When a subject wishes to be identified by iris recognition system, their eye is first photographed, and then a template created for their iris region. This template is then compared with the other templates stored in a database until either a matching template is found and the subject is identified, or no match is found and the subject remains unidentified. In 1994, John Daugman obtained the patent for “Biometric personal identification system based on iris analysis” [iii]. Some other iris recognition systems were also developed by other people, such as Wildes et al. [iv], Lim et al. [v], Boles and Boashash [vi] and Li-ma et al. [vii]. Iris feature is convenience for a person to prove his/her identity based on him/her biometrics at any place and at any time. Iris recognition system includes iris capturing, image pre-processing, iris region localization, iris region normalization, iris feature extraction and template matching. Every part is very important for correct recognition person identity.

### II. Approach of Iris Recognition

Iris images consists of many randomly distributed irregular small blocks, such as freckles, Coronas, stripes, furrows, crypts etc. Such randomly distributed and irregular blocks constitute the most distinguishing characteristics of the human iris. These irregular blocks are considered as kind of transient signals which consist of key local sharp variation points [vii], [ix]. The method disused in this paper locates the position of important local sharp variation points in order to form a feature set. As shown in algorithm figure 2, first iris and pupil boundaries are

marked in the original eye image from which iris region is localized. In order to achieve invariance to translation and scale, the annular iris region is normalized into the rectangular block of fixed size. The irregularity in the block leads to local sharp variation points which are used to form a set of 1-D intensity signal. The position of these variation points is recorded as the feature template by using wavelet analysis. Finally to find the similarity or dissimilarity between the two templates exclusive OR operator is used. The detailed explanation is discussed in the following sections.

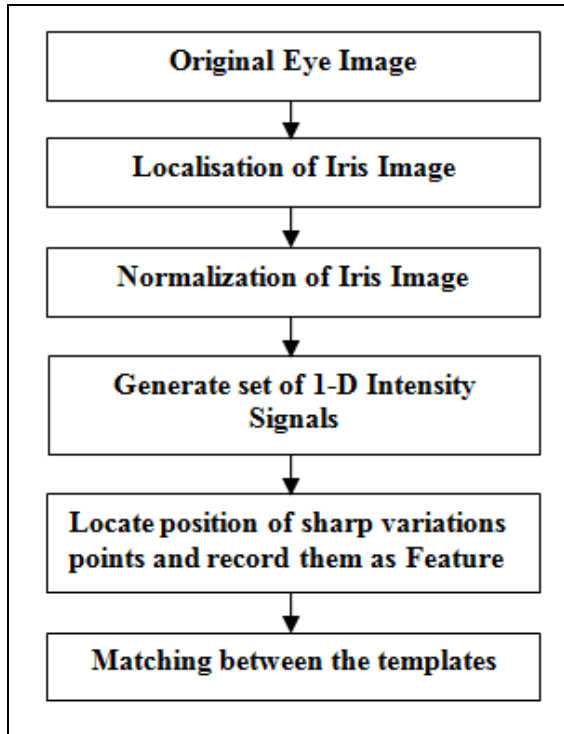


Figure 2: A Algorithm of Implemented Method

**Iris localization:**

The first step in an iris recognition is to locate iris and pupil in an image of eye as shown in figure 3(b). In general, the pupil and the iris are not concentric also pupil radius is not in a fixed ratio to the iris radius [ii]. Hence, parameters such as x-y co-ordinates and radius corresponding to both the iris and the pupil are needed to know. This stage is termed as “Iris localization or iris segmentation”. The implemented system uses an automatic segmentation algorithm based on the circular Hough transform [viii] in which 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  $x_c, y_c$  and the radius r, which are able to define any circle according to the following equation,

$$x_c^2 + y_c^2 - r^2 = 0$$

**Iris Normalization:**

The dimensional inconsistencies between eye images occur due to the stretching of the iris caused by pupil dilation from varying levels of illumination, varying imaging distance, rotation of the camera, head tilt, and rotation of the eye within the eye socket. Such elastic deformation in iris texture will affect the matching results. Thus to achieve more accurate recognition result the normalization process is used which produce iris regions, which have the same constant dimensions. The normalized iris image is shown in figure 3(c). For this purpose Daugman’s Rubber Sheet model is used [iii], [viii]. This homogenous rubber sheet model remaps each point within the iris region to a pair of polar coordinates (r, θ) where r is on the interval [0, 1] and θ is angle [0,2π]. The remapping of the iris region from (x, y) Cartesian coordinates to the normalised non-concentric polar representation is modelled by the following equations,

$$I(x(r, \theta), y(r, \theta)) \rightarrow I(r, \theta)$$

$$x(r, \theta) = (1 - r)x_p(\theta) + r x_i(\theta)$$

$$y(r, \theta) = (1 - r)y_p(\theta) + r y_i(\theta)$$

where  $I(x,y)$  is the iris region image,  $(x,y)$  are the original Cartesian coordinates,  $(r, \theta)$  are the corresponding normalised polar coordinates,  $(x_p, y_p)$  and  $(x_i, y_i)$  and are the coordinates of the pupil and iris boundaries along the θ direction.

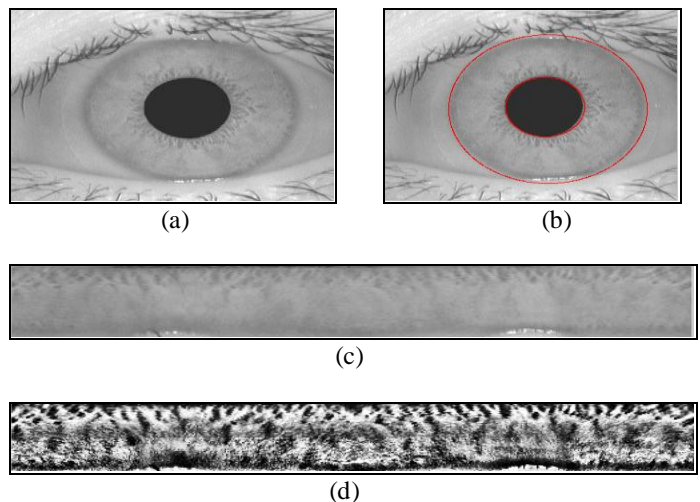


Figure 3: Iris Image Pre-processing: (a) Original Image, (b) Localized Image, (c) Normalized Image, (d) Enhanced Image

**Enhancement:**

The normalized iris image obtained may not have uniform brightness due to position of light sources and also has low contrast. This may affect the subsequent processing in feature extraction and matching. Thus by enhancing the image by

means of histogram equalization each of 32x32 regions produces compensation for the non uniform illumination, as well as improves the contrast of the image. The finer texture characteristics of the iris is obtained, shown in figure 3 (d) which is clearer than normalized iris image.

**Feature Extraction:**

The characteristics of iris can be considered as a sort of transient signals in which local sharp variations are generally used. Thus local sharp variation points of iris are used to extract the features from the enhanced image. The information density in the angular direction corresponding to the horizontal direction in the iris image is much higher than that in other directions. Thus to characterize an iris it may suffice only to capture local sharp variations along the horizontal direction in the iris image. Also it is not necessary to capture local sharp variation points in every line of the iris image for recognition. Hence 2-D normalized image is decomposed into a set of 1-D intensity signals according to the following equation, [vii]

$$S_i = \frac{1}{M} \sum_{j=1}^M I_{(i-1) * M + j} \quad i = 1, 2, \dots, N$$

$$I = \begin{pmatrix} I_1 \\ \vdots \\ I_x \\ \vdots \\ I_k \end{pmatrix} = (I_1^T, \dots, I_x^T, \dots, I_k^T)^T$$

where  $I$  is the normalized image of size 64 x512,  $I_x^T$  denotes gray values of the  $x^{th}$  row in the image  $I$ ,  $M$  is the total number of rows used to form a signal  $S_i$ ,  $N$  is the total number of 1-D intensity signals. In order to precisely locate the position of local sharp variations which generally indicate the appearing or vanishing of an important image structure, the dyadic wavelets has been used.

The dyadic wavelet transform of a signal  $S(x)$  at scale  $2^j$  is given by following equation, [ix], [x]

$$WT_{2^j} S(x) = \frac{1}{2^j} \int S(x) \Psi(\frac{x-X}{2^j}) dX$$

where  $\Psi(x/2^j)$  is the wavelet function at scale  $2^j$ . The local extremum points of the wavelet transform correspond to sharp variation points of the original signal. Therefore, using such a transform, it is possible to locate the iris sharp variation points by local extremum detection. Thus to form a feature for each intensity signal  $S_i$ , the position sequences at two scales are concatenated,

$$f_i = \{d_1, d_2, \dots, d_i, \dots, d_m; d_{m+1}, d_{m+2}, \dots, d_{m+n} : p1, p2\}$$

where  $d_1$  to  $d_m$  components are from the first scale,  $d_{m+1}$  to  $d_{m+n}$  components from the second scale,  $d_i$  denotes the position of a local sharp variation point in the intensity signal, and  $p1$  and  $p2$  respectively, represent the property of the first local sharp variation point at two scales.

To form features from different 1-D intensity signals, first local sharp variation point at two scales is used. In order to form a complete feature vector, different 1-D intensity signals are concatenated and expanded feature vector is given by,

$$Ef = \{Ef_{(1,1)}, Ef_{(1,2)}, \dots, Ef_{(i,1)}, Ef_{(i,2)}, \dots, Ef_{(N,1)}, Ef_{(N,2)}\}$$

where  $Ef_{(i,1)}$  and  $Ef_{(i,2)}$  are the binary sequences from the  $i^{th}$  1-D intensity signal at the first and the second scale, respectively.

**Matching:**

To determine whether two iris images are of same or different person, similarity between their corresponding feature vectors is calculated. In this approach a original feature vector is expanded into binary feature vector and then similarity between the expanded feature vector is calculated using ex-or operation. A similarity function is given as below,

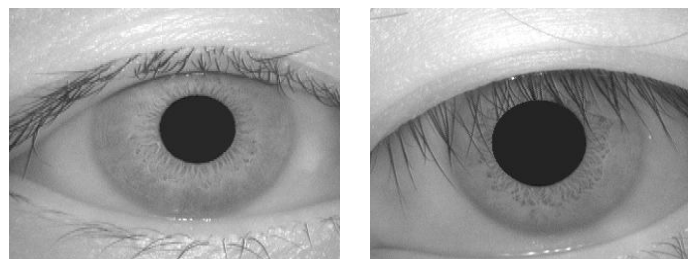
$$D = \frac{1}{N} \sum_{i=1}^N \frac{1}{2L} \sum_{j=1}^2 (Ef_{(i,j)}^1 \oplus Ef_{(i,j)}^2)$$

where  $N$  is the total number of 1-D intensity signals,  $L$  is the length of the binary sequence at one scale,  $Ef^1$  and  $Ef^2$  denote two different binary feature vectors.

**III. Simulation Results and Discussion:**

The experiment is performed on CASIA Version1.0 database using MATLAB 7.0

**Iris Image Database:** Iris images of CASIA Version1.0 (CASIA-IrisV1) [xi] were captured using a specially developed iris camera having 850nm circular NIR illuminators arranged around the sensor to make sure that iris is uniformly and adequately illuminated. CASIA Iris Image Database Version 1.0 includes 756 iris images from 108 eyes. For each eye, 7 images are captured in two sessions where three samples are collected in the first session and four in the second session. All images are stored as BMP format with resolution320\*280 as shown in figure 4 (a) and (b).



(a) 001\_1\_1.bmp

(b) 011\_2\_4.bmp

**Figure 4:** Sample Images of CASIA Version 1.0 database. [xi]

**Performance Evaluation:**

To evaluate the performance of the simulated method the decidability index (DI), receiver operating characteristic (ROC) curve and equal error rate (EER) metrics used.

(1) Decidability index  $d'$  is a distance measured in standard deviations and is a function of the magnitude of difference between the mean of the intra-class distribution  $\mu_s$  and the mean of the inter-class distribution  $\mu_d$ , and also the standard deviation of the intra-class and inter-class distributions  $\sigma_s^2$  and  $\sigma_d^2$  respectively and is given by following equation, [ii]

$$d' = \frac{|\mu_s - \mu_d|}{\sqrt{\frac{\sigma_s^2 + \sigma_d^2}{2}}}$$

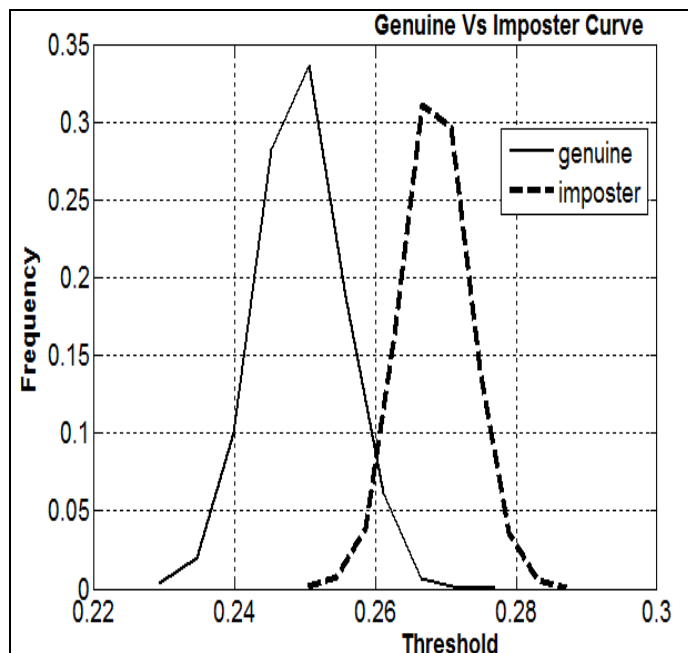
Higher the decidability index, the greater the separation of intra-class and inter-class distributions which allows for more accurate verification. The Occurrences of Genuine (intra-class) and imposter (inter-class) Distribution at different thresholds shown in figure 1 in which each iris image in the database is compared with all the other irises in the database. To have an accurate verification results the distance between intra-class and inter-class distribution should be large which indicates the better discriminability of the extracted features. Figure 5 shows discrimination between genuine and imposter with minimum overlapping area which indicates the false match rate.

(2) A Receiver Operating Characteristic (ROC) shown in figure 6 is a plot of Genuine Acceptance Rate against False Match Rate for all possible system operating points and measures the overall performance of the system. In this implemented system the value of Genuine Acceptance rate is 90% for 0.01% of FMR value. The FMR is the probability of accepting an imposter as an authorized subject and the FNMR is the probability of an authorized subject being incorrectly rejected. An impostor score that exceeds the threshold  $\eta$  results in a false match, while a genuine score that falls below the threshold  $\eta$  results in a false non-match. If  $T^I$  and  $T^G$  are total number of Imposter and Genuine pairs then FMR and FNMR are given by following equations.[viii]

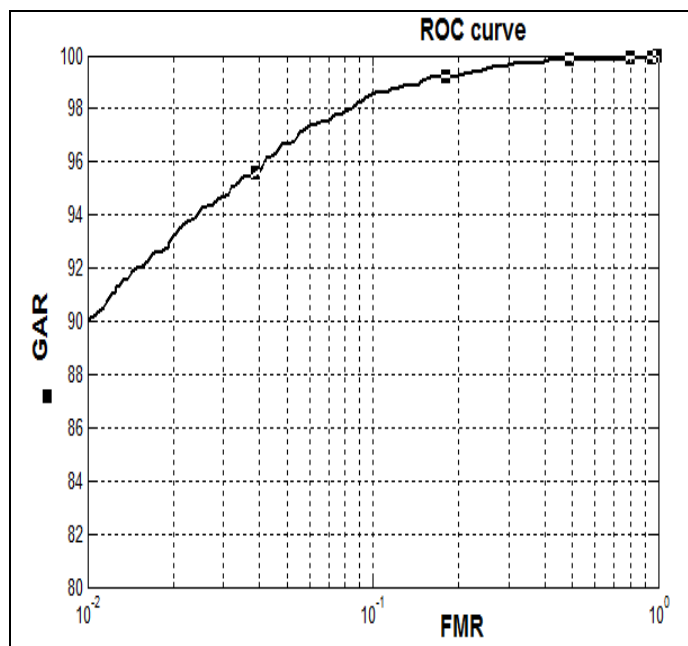
$$FMR(t) = \frac{1}{T^I} \sum_{i=0}^t Imposter(i)$$

$$FNMR(t) = \frac{1}{T^G} \sum_{i=t}^{0.5} Genuine(i)$$

$$GAR = 1 - FNMR$$



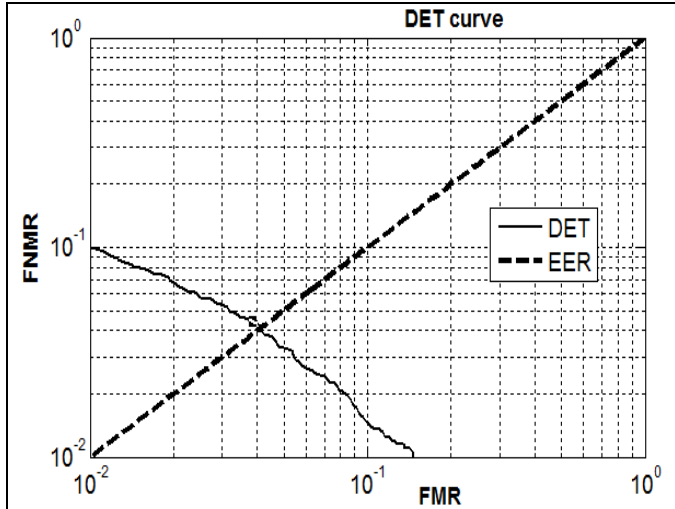
**Figure 5:** Occurrences of Genuine and imposter Distribution at different thresholds



**Figure 6:** Receiver Operating Characteristic curve

(3) Equal Error Rate (EER) shown in figure 7 refers to that point in a Detection Error Trade-off (DET) curve where False Match Rate (FMR) equals the False Non Match Rate (FNMR). The lower the EER value, the better the performance of system. [ii]





**Figure 7:** Detection Error Trade-off curve

#### IV Conclusion:

The presented iris recognition approach has been tested on the CASIA-Iris-Version1 database of greyscale eye images. It consists of a segmentation system that is based on the circular Hough transform, and is able to localize the circular iris and pupil region. The extracted iris region is then normalized into a rectangular block with constant dimensions to account for imaging inconsistencies. The local sharp variation points, are extracted from a set of 1-D intensity signals to form discriminating features using a dyadic wavelet transform. Finally to compute the similarity between a pair of position sequences an exclusive OR operation is used. The performance of the implemented system is evaluated on the parameters such as Decidability Index (DI), False match rate (FMR), False Non-match rate (FNMR), Genuine Accept Rate (GAR) and Equal error rate (EER). The simulation results shows good EER of 0.0404 and GAR of 90%.

#### References:

- [i] J. Daugman. *How iris recognition works. Proceedings of International Conference on Image Processing, Vol. 1, 2002.*
- [ii] Anil k Jain (Michigan State University, USA), Patrick Flynn (University of Notre Dame, USA), Arun A. Ross (West Virginia University, USA) "Handbook of Biometrics". July, 2007.
- [iii] J. Daugman, "Biometric personal identification system based on iris analysis," U.S. Patent 5 291 560, Mar 1, 1994.
- [iv] R. Wildes, "Iris recognition: an emerging biometric technology," *Proceedings of IEEE, vol. 85, pp. 1348-1363, Sept. 1997.*
- [v] S. Lim, K. Lee, O. Byeon and T. Kim, "Efficient iris recognition through improvement of feature vector and classifier", *ETRI Journal, Vol. 23, No. 2, Korea, 2001.*
- [vi] W. Boles and B. Boashash, "A human identification technique using images of the iris and wavelet transform", *IEEE Transactions on Signal Processing, Vol. 46, No. 4, 1998.*
- [vii] Li Ma, Tieniu Tan, Yunhong Wang "Efficient iris Recognition by Characterizing Key Local Variations" *IEEE Transactions on image processing, Vol. 13, No. 6, June, 2004.*
- [viii] Libor Masek, "Recognition of Human Iris Patterns for Biometric Identification Bachelor of Engineering Thesis, The University of Western Australia 2003.
- [ix] S. Mallat and S. Zhong, "Characterization of signals from multiscale edges," *IEEE Transaction on Pattern Analysis. Machine Intell., vol. 14, pp.710-732, July 1992.*
- [x] S. Mallat, *A Wavelet Tour of Signal Processing. New York: Academic, 1999.*
- [xi] <http://biometrics.idealtest.org>, CASIA Iris Image Database version 1.0