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RECOGNITION OF HUMAN IRIS PATTERNS FOR BIOMETRIC IDENTIFICATION

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ABSTRACT

In this paper, efficient biometric security technique for iris recognition system with high performance and high confidence is proposed. The proposed system is based on an empirical analysis of the iris image and it is split into several steps using local image properties. The system steps are, the preprocessing stage; determine the location of the iris boundaries; converting the iris boundary to the stretched polar coordinate system; extracting the iris code based on texture analysis using wavelet transforms; and classification of the iris code. The proposed system uses the haar wavelet transforms for texture analysis, and it depends heavily on knowledge of the general structure of a human iris. Experimental results showed that the proposed technique has a quite effective performance and encouraging results, with error rate 0.6% in case of CASIA database and 16.6% in Ubiris database. The proposed technique could potentially improve iris identification efficiency, the system only needs to store 25 x 25 images feature vector which increases the matching process speed and decreases the system complexity compared with other techniques. The subject image is not compared to every image in the database, thereby decreasing the search time and simplifying the computational complexity.

KEYWORDS: Biometric, iris recognition, pupil, iris, image segmentation.

1. INTRODUCTION

Biometric is best defined as the science of using unique physiological or behavioral characteristics to verify the identity of an individual. Biometric characteristics are unique to individuals and cannot be lost or stolen like password, making them only convenient but also more effective in the prevention of theft. They

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include finger print, iris scanning, hand geometry, voice pattern, facial recognition and other techniques.

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 colored image for face recognition. The sample is then transformed using some sort of mathematical function into a biometric template. The biometric template will provide a normalized, efficient, highly discriminating representation of the feature which can then be compared with other templates in order to determine identity.

The iris as an externally visible yet protected organ whose unique epigenetic pattern remain stable through out adult life. These characteristics make it very attractive for use as a biometric for identifying individuals. Compared with other biometric technologies such as face, speech, and finger. Iris recognition can easily be considered as the most reliable form of biometric technology, because the ophthalmologists noted from clinical experience that every iris had a highly detailed and unique texture, which remained unchanged in clinical photographs spanning decades, even the medical surgery can't change it.

The basic procedure for iris recognition is the same for most biometric systems, see Fig.1. The main stage of iris recognition is to isolate the actual iris region in a digital eye image. A technique is required to isolate and exclude these artifacts as well as locating the circular iris region.

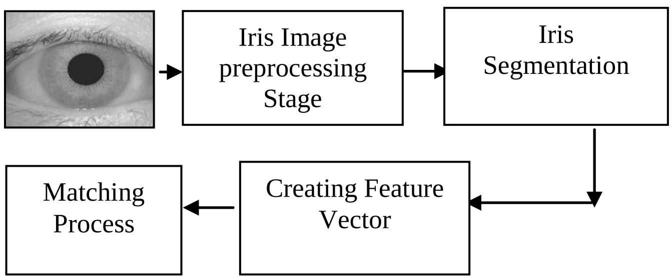


Fig.1. Block diagram of iris recognition systems.

The success of segmentation depends on the imaging quality of eye images. The proposed technique uses four iris image databases. The CASIA [1] image database from the National Laboratory of Pattern Recognition "NLPR", Institute of

Automation “IA”, Chinese Academy of Science “CAS”, which includes 756 iris images from 108 different persons. These images acquired during different sessions and the time interval between two collections is one month which is a real world application case. An image in CASIA iris database does not contain specular reflections due to the use of near infra-red light for illumination. UBIRIS [2] database is composed of 1877 images collected from 241 persons during September, 2004 in two distinct sessions. It constitutes the world´s largest public and free available iris database at present date. UPOL [3], MMU [4], LEI [5] databases, however, the images in the LEI database, Ubiris database, Upol iris image database , and MMU iris image database, contain these specular reflections, which are caused by imaging under natural light.

Also persons with darkly pigmented irises will present very low contrast between the pupil and iris region if imaged under natural light, making segmentation more difficult. 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.

2. SURVEY ON PREVIOUS TECHNIQUES

There are large numbers of iris recognition methodologies that present almost optimal results, but only for well segmented images [6]. Some of these iris recognition techniques achieved error rate above 10% in the segmentation phase only. In this section we will describe six iris recognition techniques that are used in our experiments**.**

2.1 Daugman’s Iris Recognition Technique [7, 8]

Proposed in 2003, the author assumes both pupil and iris with circular form and applies an integrodifferential operator defined in Eq. (1) [7].

$$\max_{r,x0,y0} | G_\sigma(r) * \frac{\delta}{\delta r} \oint_{r,x0,y0} \frac{I(x,y)}{2\prod r} ds | \qquad (1)$$

Where I (x, y) is the eye image, r is the radius to search for, G_σ (r) is a Gaussian smoothing function, and s is the contour of the circle given by r, x_0, y_0. The operator searches for the circular path where there is maximum change in pixel values, by varying the radius and centre x and y position of the circular contour. The operator is applied iteratively with the amount of smoothing progressively reduced in order to attain precise localization. Eyelids are localized in a similar manner, with the path of contour integration changed from circular to an arc. Daugman used the log gabor filters to be able to provide optimum conjoint representation of a signal in space and spatial frequency. Gabor filter is constructed by modulating a sine/cosine wave with a Gaussian. And finally Daugman uses the weighted Euclidean distance "WED" in matching phase to compare two templates, Daugman technique considered to be one of the most effective iris recognition techniques and achieved 100% correct recognition rate [8], but the complexity of Daugman's technique is too high.

2.2 Wilde's Iris Recognition Technique [9]

Proposed in 1997, this methodology performs iris contour fitting in two steps. First, the image intensity information is converted into a binary edge map. Second, the edge points vote for particular contour parameter values [9]. The first step is performed via gradient based edge detection. However, before this, the author proposes a histogram based approach to avoid problems with local minima that the active contour model's gradient might experience. Having this, in order to incorporate directional tuning, the image intensity derivatives are weighted to favor ranges of orientation. For example, on the iris/sclera border process, the derivatives are weighted to be selective for vertical edges. The second step is made through the well known circular Hough transform. This methodology is clearly the most common on iris segmentation approaches, having as principal disadvantage the dependence of threshold values for the edge maps construction. This fact can obviously constitute one weak point as we are concerned with robustness, which includes the ability to deal with heterogeneous image contrast and intensities. In order to encode features, Wildes technique decomposes the iris region by application of Laplacian of Gaussian filters to the iris region image. The filtered image is represented as a Laplacian pyramid which is able to compress the data, so that only significant data remains. Wildes make use of normalized correlation between the acquired and database representation for goodness of match and he achieved 99% of correct recognition rate.

2.3 Liam and Chekima's Iris Recognition Technique [10]

Proposed in 2002 [10], and is based on the fact that the pupil is typically darker than the iris and the iris darker than the sclera. Based on this assumption, these authors propose the use of a thresholding technique that converts the initial captured grayscale image to binary. The threshold must be exactly calculated in order to join the pupil and the iris together in a dark region. Assuming that both components have circular form "iris and pupil", the next step consists on creating a ring mask that will run through the whole image searching for the iris/sclera border. The mask radius r and centre coordinates "x, y" will be defined by maximizing equation.

$$S = \sum_{\theta=0}^{2\pi} (x + r\cos(\theta), y + r\sin(\theta)) \quad (2)$$

The next step consists in eliminating all image information outside the iris ring, and upgrading the threshold value in order to capture intensity dissimilarities between the iris and the pupil. Pupil/iris border determination is made according to the same methodology described for the iris/sclera border. As we can see, this method's accuracy is strongly dependent of threshold values that have to be chosen by the user according to captured image characteristics.

2.4 Masek's Iris Recognition Technique [11]

Proposed in 2003 [11] and based on the methodology suggested on wilde's iris recognition technique, the author proposed a method that began with the binary edge image map construction, using the Kovesi edge detector, a variation of the well known Canny edge detector. The next step consists of applying the circular Hough transform in order to determine the iris/sclera border and then the one correspondent to iris/pupil. Masek's used the log gabor filters such as Daugman to be able to provide optimum conjoint representation of a signal in space and spatial frequency. Masek uses the hamming distance in matching phase to compare two templates. This methodology is clearly the most common on iris segmentation approaches, having as principal disadvantage the dependence of threshold values for the edge maps construction. On the other hand Masek's technique have 83.9% correct recognition rate.

2.5 GU Hong-Ying's Iris Recognition Technique [12]

Proposed in 2005, the technique based on the standard segmentation approach but a new iris feature extraction approach using both spatial and frequency domain is presented. Steerable pyramid is adapted to get the orientation information on the iris image. The feature sequence extracted on each sub image and used to train support vector machine "SVM" as iris classifier. SVM has drawn great interests recently as one of the best classifier in machine learning, although there is a problem in the use of traditional SVM for iris recognition. It cannot treat False Accept and False Reject differently with different security requirements. Therefore a new kind of SVM called non symmetric SVM is presented to recognition applications. This technique may achieve a very high speed recognition rate but it is very complex according to the design of the SVM. SVM can never be used as a practical classifier "the training cost is too high to be practical" and the decomposition algorithm complexity is order of "N^4" where N is the size of the working set.

2.6 Vijayakumar Bhagavatula's Iris Recognition Techniques [13]

Proposed in 2006, the technique based on the standard segmentation approach, in which the iris inner and the outer boundaries must be located, modeled as non concentric circles. Once the iris region boundaries have been detected, the iris image I "x, y" mapped into polar coordinates I "ρ, θ" using the center of the pupil as region. In this mapping, the radial width of the iris "along the ρ axis" is normalized to one. As a segmentation process normalize for global translation and scale change, while rotation in the original image becomes a cyclic shift in the segmented domain. Also a correlation filter is designed specially for the recognition of one pattern class, given an observed image; he applied the correlation filter by performing cross-correlation between the observed image and the filter. The resulting correlation plane C “x, y” should contain a sharp peak if the observed image is an authentic and no such peak if the observed image is an imposter. The correlation is performed as a frequency domain multiplication, using the computationally efficient fast Fourier transform “FFT”.

3. PROPOSED TECHNIQUE

Intuitively, if we can precisely locate the pupil and the iris in the image and recognize the corresponding shape as well, then we will obtain a high performance algorithm, also if we can take only a part of the iris image “not the whole iris region” we will obtain an algorithm with a low complexity compared with the previous algorithms. This section describes an overview of all fundamental processes in our iris recognition system. These processes are generally referred to as image preprocessing, iris segmentation, feature extraction and matching respectively.

3.1 Image Preprocessing

In the preprocessing stage, we first transform the iris image from RGB mode to Grayscale level and from eight bit to double precision pattern to get a high-resolution image of an iris while at the same time being noninvasive. This is a challenge because the iris is small “about 1cm in diameter” and dark, combined with the fact that human users are sensitive to intense light. There is a need for enough light in order to get a high quality reading with enough detail and contrast. When capturing the iris image one usually obtain a sequence of images in the input sequence but not all the images are clear and sharp, almost all the images that are taken under the natural room light suffer from the specular reflection such as UBIRIS database [3], specular reflection can be shown clear in Fig. 3A.

These specular reflections affect the segmentation process too much and to illuminate these artifacts we use the Wiener filter to prepare the iris image for the segmentation process. The Wiener restoration approach produces more visually clear images as indicated in Fig. 3. The restored image with the greatest amount of fine feature detail corresponds to the image Wiener filtered using an SNR assumption of 200.

The wiener function applies a Wiener filter “a type of linear filter” to an image adaptively, tailoring itself to the local image variance. Where the variance is large, wiener performs little smoothing. Where the variance is small, wiener performs more smoothing. This approach often produces better results than linear filtering.

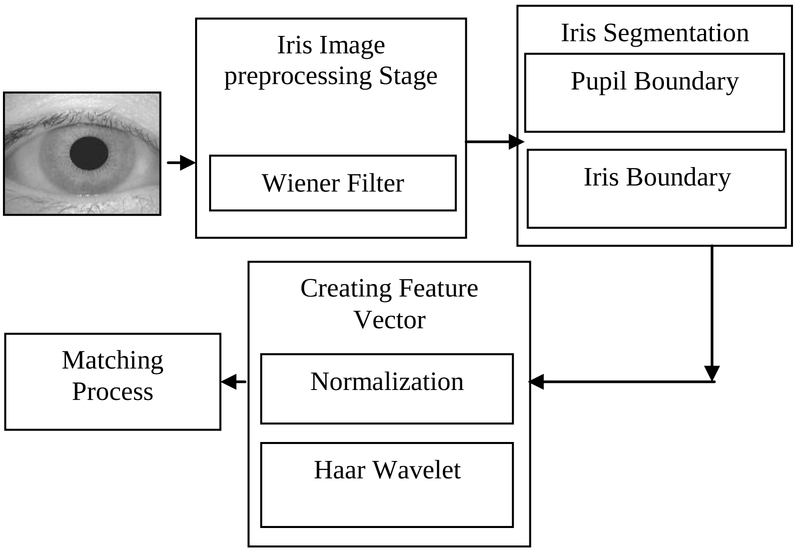
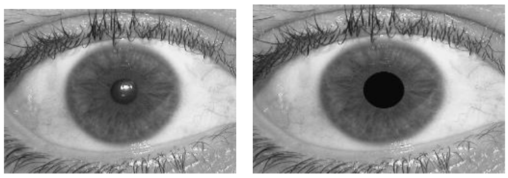


Fig.2. Block diagram of the proposed iris recognition system.

The adaptive filter is more selective than a comparable linear filter, preserving edges and other high-frequency parts of an image. In addition, there are no design tasks; the wiener function handles all preliminary computations and implements the filter for an input image. Wiener, however, does require more computation time than the other linear filters. Wiener works best when the noise is constant-power "white" additive noise, such as Gaussian noise.

$$H(w_s, k_\theta) = \frac{S_g(w_s, k_\theta) - \sigma_n^2}{s_g(w_s, k_\theta)} \tag{3}$$

Where S_g is the 2D discrete Fourier transform “FT” of scaled sinogram g and “w_s, k_θ” denotes the 2D FT coordinates. Notation σ_n^2 is the noise variance. Since the variance of scaled projection data is approximately constant after the scale transformations, it eliminates the difficulty of the estimation of noise power spectrum in the Wiener filtering [14].



(A) (B)

Fig. 3. (A) The original image (image Img_1_1_1.bmp).
(B) The same image after applying the Wiener filter.

3.2 Iris Segmentation

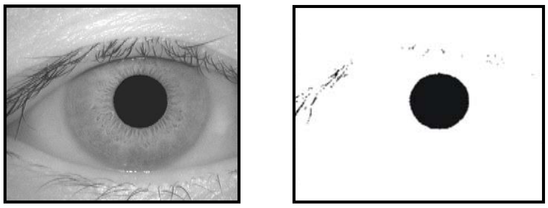
The proposed method performs the segmentation process in two phases. The first phase uses the knowledge that a pupil is a very dark blob of a certain minimum size in the picture, and no other segment of continuous dark pixels are of the same size. The algorithm finds two radial coefficients for the pupil as the pupil is not always perfect circle. The second phase algorithm takes information of the pupil center and tries to find the edges on a one-dimensional imaginary line to the side of the iris. The algorithms will be presented in the next two sections.

3.2.1 Pupillary boundary

Assuming that the eye region is already found in face, and the image is windowed in the eye region “iris, sclera, eyelids”, the pupil is considered a very distinguishable because it has concentration of pixels all of them with very low level intensity “black or almost black”. To find the pupil, we first need to apply a linear threshold in the image,

$$g(x) = \begin{cases} 1: f(x) > 70 \\ 0: f(x) \le 70 \end{cases} \quad (4)$$

Where f is the original image and g is thresholded image Fig.4 and x is the pixel intensity. Pixels with intensity greater than the empirical value of a certain gray level value “from 0 to 256 grayscale” are dark pixels, therefore converted to 1 “black”. Pixels smaller than or equal to this value are converted to 0 “white”. Next, we apply Freeman’s chain code to regions of connected pixels that are assigned value equal 1. Using this knowledge, we can cycle through all regions satisfy this condition.



(A) (B)

Fig. 4. (A) The original image (image 001_1_1.bmp cassia image database).
(B) The threshold image.

Finally, we apply one last time the chain algorithm in order to retrieve the only region in image “hopefully the pupil”. The chain code is a more succinct way of representing a list of points; it may be defined with respect to pixels or boundaries between pixels. The chain code in this case to track the dark pixels in the outer boundaries to get the pupil region. From this region, it is trivial to obtain its central points Fig. 4. Finding the edges of the pupil involves the creation of imaginary orthogonal lines passing through centroid of the region. The boundaries of binarized pupil are defined by the first pixel with intensity zero, from the center to the extremities.

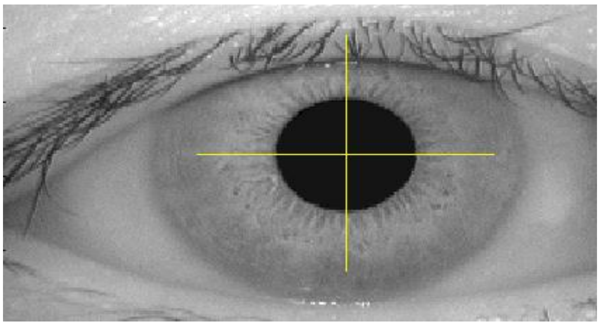


Fig. 5. The pupil center point.

3.2.2 Iris edge detection

The next step towards iris segmentation is finding the contour of the iris. This may seem to be an easy task at first as we already have discovered the pupil location and we have the knowledge that it is concentric to the outer diameter of the iris.

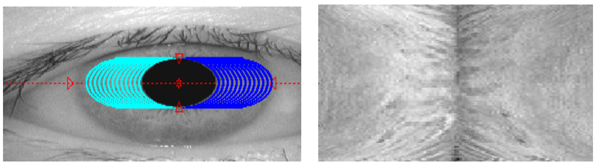
There are some problems in iris detection comes from the anatomy of the eye and the fact that every person is different. Sometimes the eyelid may occlude part of the iris, as it will occur often with the Asians, and no full circularity may be assumed in this case see Fig. 6A. Other times due to variation in gaze direction the iris center will not match the pupil center, and we will have to deal with strips of iris of different width around the pupil see Fig. 6B.

Our method takes in consideration that areas of the iris at the right and left of the pupil which are the ones that most often present visible data extraction. The areas above and bellow the pupil also carry unique information, but it is very common that they are totally or partially occluded by eyelash or eyelid.

Starting from the edges of the pupil, we analyze the signal composed by pixel intensity from the center of the image towards the border and try to detect abrupt increases of intensity level. Although the edge between the iris and the sclera is most of the times smooth, it is known that it always have greater intensity than iris pixels.

(A) (B)

Fig. 6. (A) Iris with the eyelid occludes large parts of the iris region.
(B) Iris with iris center will didn’t match the pupil center.



(A) (B)

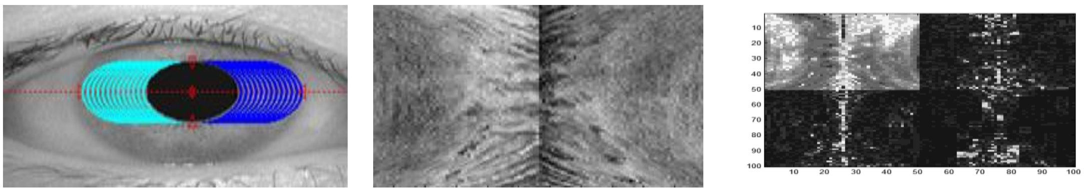
Fig. 7. (A) The iris coordinates for the image 0011_1_1.bmp (Casia database)
(B) The extracted iris region for the same iris image.

We intensify this difference applying a linear contrast filter. It is possible that some pixels inside the iris region are very bright, causing a sudden rise in intensity. That could mislead the algorithm to detect that iris edge at that point. To prevent that from happening, we take the intensity average of small windows and then detect when the sudden rises occur from these intervals.

Once we found the iris boundary, we can extract the iris region, which is the area to the right and left of the pupil, starting at the right fringe of the pupil and then go through the pupil to the left fringe and generate the iris image or the feature vector see Fig. 7B.

3.3 Feature Extractions

Once we get the local iris pattern which is a 100 × 100 image see Fig. 7B so we now have the local iris features but, this iris feature vector is too large to use it in the matching phase so, to generate a 25 ×25 feature vector for this pattern we decide to use the haar wavelet transform. Haar wavelet can be used to decompose the data in the iris region into sub components that appears in different resolution. It divides the iris image into four sub images. These resulted images consist of two high resolution images one image that has been high pass in horizontal and vertical directions and one that has been low pass filtered in both directions see Fig. 8, Fig 9.



(A) (B) (C)

Fig. 8. (A) Image '010_1_2.bmp' from Casia image database.
(B) The segmented iris region 100×100 feature vector.
(C) The same image after applying the first level of haar wavelet transform 50×50 image.

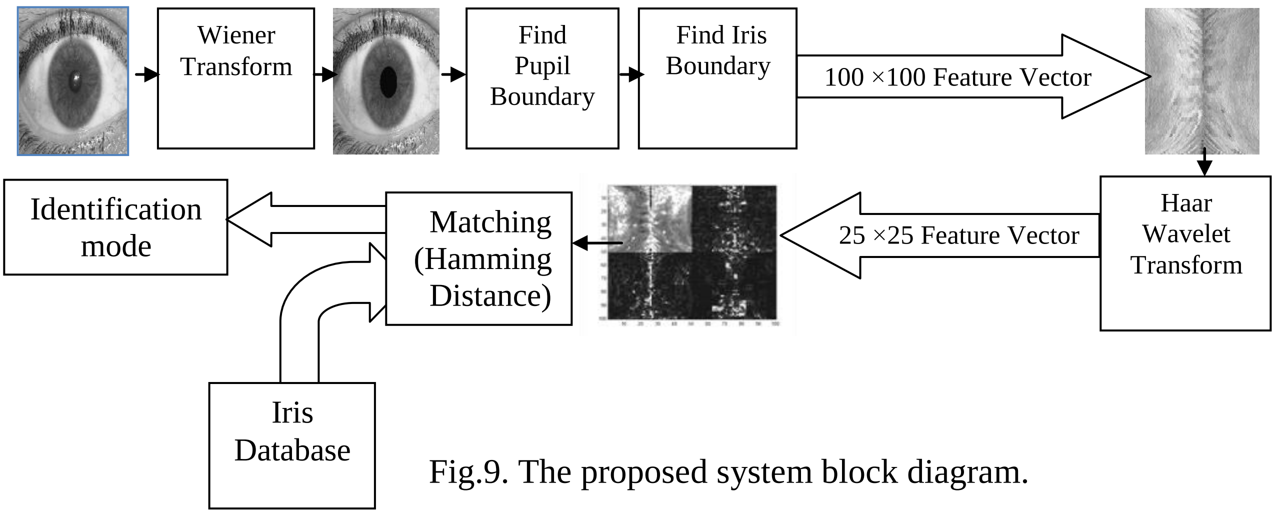


Fig.9. The proposed system block diagram.

In comparison with Daugman's method by using the haar wavelet transform we successfully reduce the feature vector of Daugman who uses a vector of 1024 element. This difference can be explained by the fact that he always map the whole iris region even the parts that occluded by eyelashes while we map only the middle part of the iris obtaining almost half the feature vector.

3.4 Matching

Hamming distance is chosen as a metric for recognition, since bit-wise comparisons were necessary. The Hamming distance algorithm employed also incorporates noise masking, so that only significant bits are used in calculating the Hamming distance between two iris templates. Now when taking the Hamming distance, only those bits in the iris pattern that corresponds to ‘0’ bits in noise masks of both iris patterns will be used in the calculation.

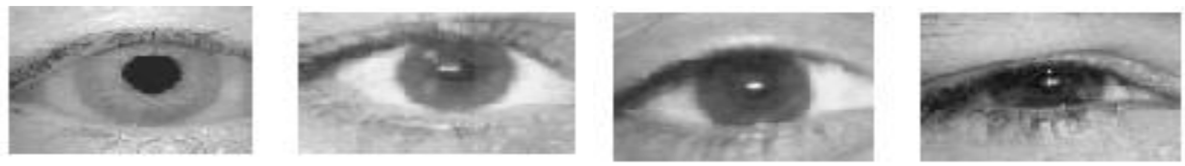
The Hamming distance will be calculated using only the bits generated from the true iris region. Although, in theory, two iris templates generated from the same iris will have a Hamming distance of 0, in practice this will not occur. Normalization is not perfect, and also there will be some noise that goes undetected, so some variation will be present when comparing two intra-class iris templates [6].

This method is suggested by Daugman [7], and corrects for misalignments in the normalized iris pattern caused by rotational differences during imaging. From the calculated Hamming distance values, only the lowest is taken, since this corresponds to the best match between two templates.

4. EXPREMENTAL RESULTS

In this section we compare the results obtained against UBIRIS and CASIA databases.The reason for evaluating these methodologies against only the CASIA and UBIRIS databases is related with the fact that UPOL database just includes images from the internal part of the eye, having the segmentation work almost done. Fig. 10 shows examples of CASIA database image and the different types of noise that are found on UBIRIS “reflections Fig. 10B, focus Fig. 10C and small visible iris part Fig. 10D”.

The proposed technique segmentation method has proven very efficient and reliable when applied to CASIA iris database from all the 756 images the algorithm was not able to find the center and coordinates of the pupil and the iris only for 4 images in other words the algorithm was able to correctly find the center and coordinates of the pupil and the iris for 99.4% of the CASIA iris database. In despite of the algorithm was able to correctly find the center and coordinates of the pupil and the iris for 83.4% of the Ubiris iris database. Also the algorithm was able to match the segmented templates correctly and so we obtain the same percentage as a correct recognition rate.



(A) **(B)** **(C)** **(D)**

Fig.10. (A) CASIA image database , (B) UBIRIS image database (Reflection). (C) UBIRIS image database (Focus), (D) UBIRIS image database (Visible Iris).

Table1 shows the results obtained by each described iris recognition method. All evaluated methods presented distinct accuracy levels on each database. This fact indicates that their accuracy is clearly dependent of the image characteristics, adding one relevant restriction to respective efficiency.

Table 1. Comparison of correct recognition rates “CRRs”.

Technique	CASIA	UBiris	Upol	MMU
Daugman [8]	100%	93.5%	-	-
Wildes [9]	99%	81.1%	-	-
Liam and Chekim [10]	92.7%	56.3%	-	-
Masek [11]	83.9%	-	-	-
GU Hong-Ying [12]	87.89%	-	-	-
Vijayakumar [13]	95.01%	-	-	-
The proposed technique	99.4%	83.4%	85%	99%

Table 2. Comparison of the computation complexity.

Technique	Feature extraction (ms)	Matching (ms)	Feature + Matching (ms)
Daugman[8]	682.5	4.3	686.8
Wild[9]	210.0	401	611
Liam[10]	455.9	8.7	464.6
Mesk[11]	426.8	13.1	439.9
Proposed Technique	2	310	312

From the previous tables it's clear that the proposed technique achieve a very high efficiency compared with the other algorithms in computation complexity. Also we can consider the proposed technique the best one because it achieve the highest correct recognition rate after Daugman technique, but, Daugman technique works only on Casia and Ubiris database and fail with the other two iris databases. Also the proposed technique have the smallest feature vector only 25×25 so that the proposed technique have the smallest computation complexity compared with the other techniques.

Results, having the best and the worst accuracy respectively on UBIRIS and CASIA databases. This fact can be easily explained by the lower contrast between iris and sclera eye parts on CASIA images. Approaches proposed by Wildes [9] and Masek [11] are similar on their methodology, therefore on their results, and have presented a more robustness behavior. However both methods are based on thresholds for constructing binary edges maps. This is an obvious disadvantage comparing to other image characteristics. Apart from being the less accurate, thus obtaining worst results, methodology proposed by Liam and Chekima[10] was the less tolerant to image characteristic changes. This fact can be easily explained by the important role of the threshold operator that is the basis for both inner and outer border iris detection. In particular, probably motivated by the UBIRIS images characteristics, this methodology didn’t at any circumstance reach the 50% accuracy, as opposite to CASIA database where accuracy was beyond 64%.

5. CONCLUSION

A new algorithm for iris recognition has been presented. The proposed algorithm extracts the local information of the iris. Each iris image is filtered with the Haar wavelet transform and then a fixed length feature vector is obtained. Experimental results show that our algorithm can effectively distinguish different persons by identifying their irises. It is also computationally efficient and insensitive to illumination and noise.

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استخدام تصميمات القزحية البشريّة للتّعرّف على الأشخاص

يستخدم البحث كنظامًا للتعرّف على القزحيّة متاحًا للتطويّر لكى يحقّق تكنيك أفضل وأسرع فى التعرف على الأفراد بهدف التعرف على الأفراد باستخدام بصمة القزحية حيث تستخدم قاعدة بيانات للنّظام للعديد من صور العيون ذات الألوان الرّماديّة كوسيلة للمقارنة والتعرف على الأفراد بغض النظر عن اللون الأصلى للقزحية حيث تم تصنيف السمات الفريدة فى القزحية لكى يقارن القالب المستخرج للقرنية بالقوالب المفروزة الأخرى ومطابقتها بها لتحقيق عملية التعرف على الأفراد وقد حقق النظام المقترح فى البحث أعلى فاعلية من النظم السابقة من حيث السرعة كما حقق نسبة نجاح فى التعرف على الأشخاص تصل إلى ٩٩,٤ % بالتطبيق على قاعدة بيانات CASIA ونسبة نجاح فى التعرف على الأشخاص تصل إلى ٨٣,٤ % مع قاعدة البيانات Ubiris.