Iris Feature Extraction Using Optimized Method of Selecting Points with Less Occlusion

Marcus V. C. Rodrigues, Felippe T. Angelo, Felipe M. Masculo, Francisco M. de Assis e Bruno B. Albert

***Abstract*— In Daugman's iris recognition method, the application points determine which pixels of the normalized iris images will be used in the matching stage of the algorithm. In his work, those points are chosen in an equidistant form, referenced here as homogeneous distribution. The homogeneous distribution of these points, often selects pixels that represent eyelids, eyelashes and specular reflections, occlusions that should be extracted from the matching step. A binary mask (occlusion mask), in the matching step, enables disregarding the computation of these bits. However, some template protection schemes have restrictions on the use of such masks, either because of memory/computational cost limitations or because of limitations of the algorithm itself. In this paper, we propose a method that optimizes the distribution of the application points avoiding regions with high rate of occlusions, reducing the impact of not using the occlusion mask in the matching step. The method is based on statistical analysis. The new application points distribution is called optimal distribution. The recognition performance obtained with the optimal distribution of the application points was $EER = 3.1\%$ and $FRR = 6.3\%$ (for $FAR = 0.1\%$) while for the homogeneous distribution without the usage of masks $EER = 4.8\%$ and $FRR = 12.7\%$ (for $FAR = 0.1\%$).**

***Keywords*— Iris recognition, Daugman's method, application points, occlusion mask.**

I. INTRODUCTION

The use of biometrics has been growing over the years due to the necessity of using information inherent to the individual in user identification and authentication systems. The part occupied by others biometrics such as fingerprint, naturally will be occupied by biometrics that allow a template extraction with higher entropy. In this context, iris recognition is a good option for allowing a template extraction ten times higher than the fingerprint biometrics.

Daugman's algorithm [1] is the most used method for the extraction of iris biometric information in commercial systems. Overall, the method can be divided in three main steps: pre-processing, extraction of a binary code and similarity verification. Only some points of the iris are usually selected to represent the characteristics of the iris of an individual, thus reducing the computational requirements of the method. In his method, those points are chosen in an equidistant form, referenced here as homogeneous distribution.

Some works have reported that some points in the iris are better discriminative than others. [2] [3] analyzed the state of the bits in a binary code by intraclass comparisons. The bits that have high variability were classified as fragile bits and they were masked in the similarity verification step. [4] proposed a method that subsample the binary code. The original code had 5,760 bytes and after the subsample, the binary code had 450 bytes.

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The Daugman method of iris recognition, as well as other methods, are usually composed of four steps: Segmentation, Normalization, Feature extraction/encoding and Matching. At the end of the Feature extraction/encoding stage, each selected region of the normalized iris image, will produce a bit-pattern which is independent to that produced by another iris, while two iris codes produced from the same iris will be highly correlated. The problem occurs when this selected region of the iris, is occluded by eyelids, eyelashes and specular reflections, leading to an encoding that does not correspond to iris feature. Therefore, a binary occlusion mask is usually used to indicate which points in the iris region are occluded, with the purpose of disregarding such points that do not contain information about the iris in the matching stage of the algorithm. This procedure provides satisfactory performance results for the biometric systems. Nevertheless, some template protection algorithms have restrictions concerning the usage of the occlusion mask [5] [6], either because of memory/computational cost limitations or because of limitations of the algorithm itself. The present work aims to propose a method to select the application points with less occlusion that distinction between different irises can be made without the usage of the occlusion masks.

To our knowledge, this is different from [3] [4] due to they do not considered the bits that were not taken in account in the similarity verification where the mask was used. The present article has the following structure: in section II, an overview of Daugman's iris recognition method is provided, describing all of its steps. The integro-differential operator used for the detection of the iris contours, the Hamming distance equation and the used quantization method are all briefly presented. In section III, the method for optimal selection of the application points is described. In section IV, the iris image database and the feature extraction software that were used are presented. In section V, the results obtained and their analysis are given. A comparison between the results obtained with the proposed method and the uniformly distributed application points are shown. Finally, in section VI, the conclusions are presented.

II. DAUGMAN'S METHOD

In 1994, John Daugman proposed an algorithm [1] capable of retrieving biometric information from iris images. In this method, an iris image is processed for the extraction of a binary sequence called the iris code, which translates the information contained in the iris pattern. The iris code can be used in systems for identification of persons or in verification/authentication systems. The discriminative measure used by Daugman to compare two iris codes is the normalized Hamming distance, Hd_N.

Daugman's method is composed of 6 steps: iris segmentation, normalization, Gabor filtering, selection of the application points, quantization and matching.

1) Iris segmentation: The first step is the localization of the contours of the iris, excluding all other elements that may be present in the eye image: pupil, sclera, eyelids, eyelashes, etc. This step will compose the occlusion mask used in the matching step.

The segmentation is done by the application of the integro-differential operator given by equation 1, in which $G_\sigma(r)$ is a Gaussian smoothing function at scale σ, $I(x,y)$ represent the grayscale value of the pixel at coordinates (x,y) and (x_0,y_0) are the coordinates of the center of the circular contour s with radius r along which the line integral is computed. This procedure results in building the occlusion mask - a binary mask that indicates which pixels belong to the iris. Moreover, the segmentation step provides two contours (pupil and iris) that are used by the normalization step.

$$max_{(r,x_0,y_0)} \left| G_\sigma(r) * \frac{\partial}{\partial r} \oint_{r,x_0,y_0} \frac{I(x,y)}{2\pi r} \, ds \right| \qquad (1)$$

2) Normalization: At this stage, the images obtained in the segmentation step are converted from rectangular to polar coordinates, $I(x,y) \rightarrow I(\rho,\theta)$ and uniformly sampled along both the ρ and θ directions. The normalization step results in rectangular images of fixed size. That is, after the compensation of eventual eye rotations, the features extracted from a particular region of a given iris will always be retrieved in the same spatial location.

Most iris recognition systems use the rectangular to polar conversion, as suggested by Daugman [1], [7] and [8]. There are two reasons for that: 1) The effect of texture variation caused by expansion and contraction of the pupil as a result because of different lighting environment at the time of image acquisition are normalized by the coordinate transformation. 2) When we change the coordinate system to polar, a rotation of the eye caused by the tilt of the head at the time of image acquisition means, in the polar area, only a change in the horizontal direction to the right or left of the normalized image, facilitating the adjustment of rotation required in the matching step.

3) Gabor filtering: Daugman used 2D Gabor filters to extract phase information from the normalized images. The 2D Gabor filter applies quadrature decomposition by using a sine and a cosine modulating a Gaussian function. Four Gabor filters at different frequencies are used. Thus, for each pixel of the normalized iris image, a complex vector is extracted after the filtering operation.

4) Selection of the application points: The application points form a matrix containing the coordinates of all the pixels of the normalized iris images that should be used in the matching stage, reducing, therefore, the processing time of this step. In his work, Daugman proposed the selection of 256 uniformly distributed application points for the creation of the iris code, Figure 1.

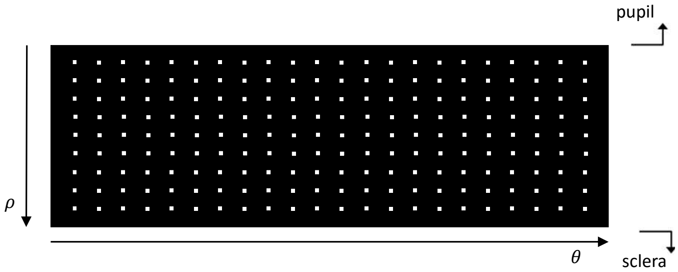

Fig. 1. Uniformly distributed application points, suggested by Daugman.

5) Quantization: In this step, the phase information of the complex vector obtained after Gabor filtering is quantized. With this purpose, the complex plane is divided in 4 quadrants, each represented by 2 bits. In order to reduce the quantization error, to adjacent regions are given codes that differ in only 1 bit ((1,1): 1ºQ, (0,1):2ºQ, (0,0):3ºQ, (1,0):4ºQ).

Therefore, for 256 application points, Daugman's algorithm with four Gabor filters generates an iris code with 2048 bits as well as an occlusion mask with the same length.

6) Matching step: The parameter used by Daugman in order to measure the degree of similarity between two iris codes was the Hamming distance. It was found, as expected, that the Hamming distance for intraclass comparisons (between different iris images originating from the same person) is significantly lower than for interclass comparisons (iris images of different persons), enabling the correct discrimination.

In order to avoid the comparison of information not originating from the iris (points covered by the occlusion mask), the terms MX_j and MY_j, which value 1 at the occluded points, are introduced in the Hamming distance equation. In equation 2, it can be seen that the bits occluded according to the mask are disregarded in the Hamming distance calculation.

$$Hd_N = \frac{1}{N - \sum_{k=1}^{N} MX_k + MY_k} \sum_{j=1}^{N} (X_j \oplus Y_j \cdot \overline{MX_j} \cdot \overline{MY_j}) \ . \qquad (2)$$

III. PROPOSED METHOD

Biometric information is not renewable because it is inherent to the person. For that reason, the use of biometric information as security factor requires the existence of schemes to protect such information. They are called template protection schemes. Many template protection schemes impose restrictions to the use of occlusion mask, for example, the crypto-biometric scheme that utilizes passive RFID tags [5] and some template protection systems that use error correction codes [6]. These restrictions might be caused by memory/computational limitations of the physical device that runs the template protection protocol or even the inability of the scheme to use the occlusion mask and to disregard the occluded bits of the iris code.

It was noticed that some regions of the normalized iris image have a higher occlusion rate than others. Given this observation, we propose a method that selects the application points that have the lowest probability of occlusion. For such selection, an a priori learning phase was carried out with the usage of a database, resulting in a statistical summary of the points most influenced by the occlusion mask. A frequency map was plotted; see Figure 2, in which the color at any given coordinates corresponds to the number of times in the database the pixel at that coordinates was occluded. To generate the frequency map, a half of the database was chosen randomly for that goal. The other half was used for generate the histograms presented in the Figure 4 and Figure 5.

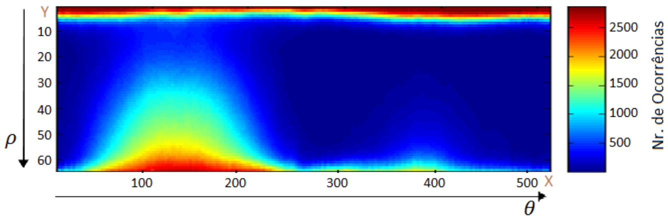

Fig. 2. Frequency map obtained after the statistical study of the regions mostly affected by the mask.

Based on the obtained map, 198 points were chosen to compose the iris code. The choice was conditioned to the points with the lowest occlusion rate, requiring a minimum Euclidean distance of a 5 pixels from each other. In this work, this distribution of the application is called optimal application points. Their distribution can be seen in Figure 3.

The system proposed uses a learning from the database, which is based on the statistical survey the number of occlusions for each of the coordinates of the segmented image.

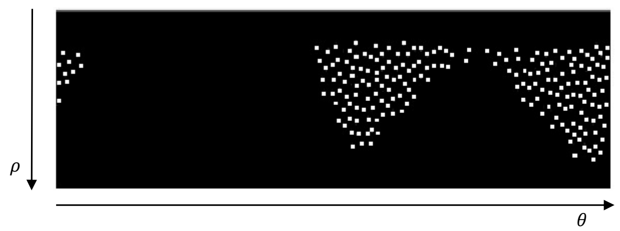

Fig. 3. Optimal application points.

IV. Database and Software Used

For the realization of the experiments we used the eye image database ND-IRIS-0405 [9][10] which is a superset of the images from both ICE2005 and ICE2006.

In this work, we used only the images from ICE2005, which contains 2,953 iris images, captured from 243 different different irises belonging to 132 different subjects.

The system used for the extraction of the iris codes from the images was the OSIRISv4.1[11], software that implements Daugman's algorithm. We used three 2D Gabor filters and 198 application points, obtaining thus iris codes with 1,188 bits.

V. Experimental Results

From the ICE2005 database, 14,240 interclass and 13,836 intraclass comparisons were randomly selected. For each selected pair, an algorithm to compensate eventual eye rotations was previously executed. This algorithm searches the rotation to be applied to the second image of the pair so that it will be aligned to the first image. Therefore, before the extraction of the iris code of the second image, the former image is progressively rotated of θ degrees to the right and to the left. For each one of these rotations, the Hamming distance is calculated. The two iris codes are said to be aligned for the rotation that yields the lowest Hamming distance. The angle θ is stored in the matrix of comparisons.

The Figure 4 presents the histograms of intraclass and interclass comparisons considering the application points uniformly distributed over the entire normalized iris image, which we call homogeneous distribution of the application points. Two experiments were performed: in the first, in which the occlusion masks were taken into account, the Hamming distances were calculated with equation 2; whereas, in the second, the masks were not considered for the computation of the Hamming distance. In the curves of Figure 4, there is a greater separation between the intraclass and interclass distributions in the first experiment, representing thus an improvement in the performance parameters of the biometric system, as can be seen in Figure 7 and in Table I.

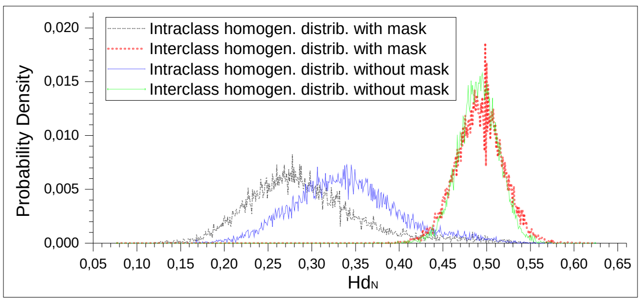

Fig. 4. Histograms of intra/interclass comparisons with homogeneous distribution of application points with/without masks. Hd_N: normalized Hamming distance.

For template protection schemes that do not allow the use of the occlusion mask, we propose in this work a selection method for the application points with low occlusion rate, that we called optimal application points.

Figure 5 presents the histograms of intraclass and interclass comparisons when the occlusion masks are disregarded. It can be seen that using the optimal application points a greater separation between the intraclass and interclass Hamming distance distributions can be achieved, improving the performance parameters FRR (False Rejection Rate) and FAR (False Acceptance Rate), as shown in Figure 6.

In Figure 7, the ROC (Receiver Operating Characteristic) curve is presented, detailing the tradeoff between the FRR

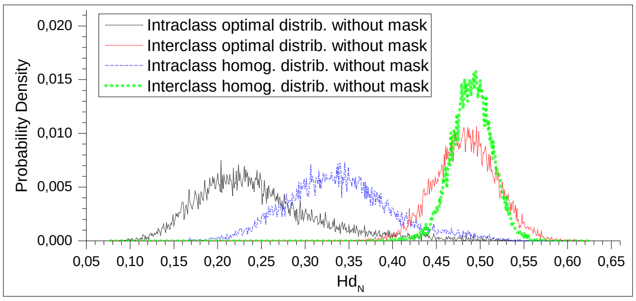

Fig. 5. Histogram of intra/interclass comparisons with optimal/homogeneous distribution of application points without masks. Hd_N: normalized Hamming distance.

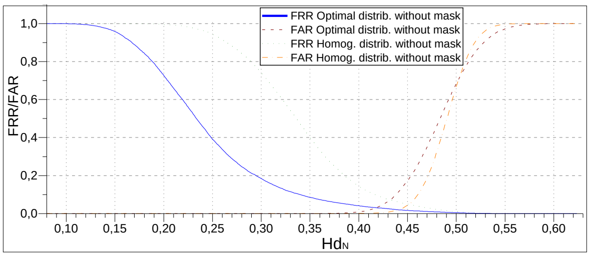

Fig. 6. False Rejection Rate (FRR) and False Acceptance Rate (FAR) for two methods: (a) Optimal distribution of the application points, (b) Homogeneous distribution. Both disregarding occlusion masks. Hd_N: normalized Hamming distance.

and FAR of the four distributions. It can be observed that, by choosing the optimal application points, the use of the occlusion mask is irrelevant to the recognition performance. It can also be observed that the selection of the optimal application points represents a performance improvement over the homogeneous distribution even when the occlusion mask is used (see Table I). It is also shown the equal error rate (EER) line for all experiments whose values are given in Table I.

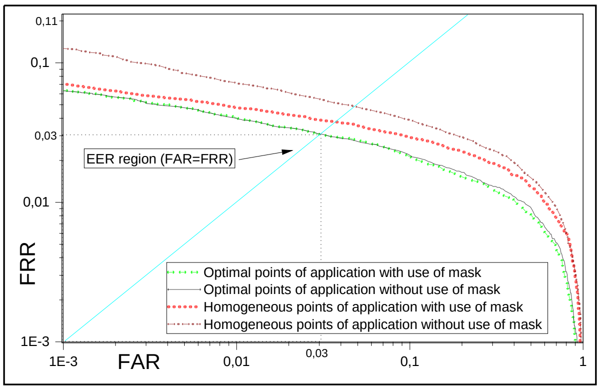

Fig. 7. ROC curve for the four methods: (a) Optimal distribution considering the occlusion mask, (b) Optimal distribution not considering the occlusion mask, (c) Homogeneous distribution considering the occlusion mask, (d) Homogeneous distribution not considering the occlusion mask.

VI. Conclusions

In this work, a new method for the selection of the application points for iris recognition was presented. An occlusion frequency map of all the pixels of the normalized iris image was computed using the database ICE2005. Using this map, we proposed an optimal distribution of the application points. The results show that the iris codes extracted from these optimal points do not need the occlusion masks in the matching stage. The histograms for the intraclass and interclass comparisons were plotted and the performance parameters FRR, FAR and EER for all possible configurations: optimal/homogeneous selection of the application points with/without occlusion masks. Favorable results were obtained when the optimal distribution of the application points proposed in this work was used. For the optimal distribution of application points it was obtained $EER = 3.1\%$ and $FRR = 6.3\%$ (for $FAR = 0.1\%$), whereas for the homogeneous distribution without mask $EER = 4.8\%$ and $FRR = 12.7\%$ (for $FAR = 0.1\%$).

TABLE I
PERFORMANCE TABLE.

	ODCM	ODNM	HDCM	HDNM
EER(FRR=FAR)	3.1%	3.1%	3.8%	4.8%
FRR, for FAR=0.1%	6.31%	6.33%	7.1%	12.7%

Legend:
ODCM-Optimal Distribution Considering the Occlusion Mask
ODNM-Optimal Distrib. Not Considering the Occlusion Mask
HDCM-Homogeneous Distrib. Considering the Occlusion Mask
HDNM-Homogeneous Distrib. Not Considering Occlusion Mask

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References

[1] J. G. Daugman, "High confidence visual recognition of persons by a test of statistical independence," *IEEE Pattern Analysis and Machine Intelligence*, vol. 15, no. 11, pp. 1148–1161, 1993.
[2] R. M. Bolle, S. Pankanti, J. H. Connell, and N. Ratha, "Iris individuality: A partial iris model," *Proc. 17th Int. Conf. Pattern Recognition*, v. 2, pp. 927–930, August 2004.
[3] K. P. Hollingsworth, K. W. Bowyer, and P. J. Flynn, "The best bits in an iris code," *IEEE Trans. Pattern Analysis and Machine Intelligence*, v. 31, n. 6, pp. 964–973, June 2009.
[4] J. Gentile, N. Ratha, and J. Connell, "SLIC: Short-length iris codes," *Proc. IEEE Third Int. Conf. Biometrics: Theory, Applications, and Systems*, pp. 1-5, September 2009.
[5] M. V. C. Rodrigues and F. M. Masculo and F. M. de Assis and B. B. Albert, "Biometrics-based secret key agreement by public discussion with RFID system," *International Conference on Cyberworlds*, October 2014.
[6] S. Kanade, D. Camara, E. Krichen, D. Petrovska-Delacrétaz and B. Dorizzi, "Three factor scheme for biometric-based cryptographic key regeneration using iris," *The 6th Biometrics Symposium (BSYM)*, September 2008.
[7] J. G. Daugman, "Statistical richness of visual phase information: Update on recognizing persons by iris patterns," *International Journal of Computer Vision*, v. 45, No. 1, pp. 25–38, 2001.
[8] J. G. Daugman, "Recognizing persons by their iris patterns," *Advances in Biometric Person Authentication*, p. 5–25, 2004.
[9] K. W. Bowyer and P. J. Flynn, "The nd-iris-0405 iris image dataset," *Notre Dame CVRL Technical Report*, 2009.
[10] M. B. P. Carneiro, "Reconhecimento de íris utilizando algoritmos genéticos e amostragem não uniforme," Ph.D. thesis, Federal University of Uberlândia, Uberlândia, Brasil, 2010.
[11] E. Krichen, A. Mellakh, S. Salicetti, and B. Dorizzi, "Osiris (open source for iris) reference system," *BioSecure Project*, 2008.