CROSS-SENSOR IRIS VERIFICATION APPLYING ROBUST SEGMENTATION ALGORITHMS

Abstract—Iris recognition is being widely used in different environments where the identity of a person is necessary. Iris recognition system acquires an eye image; the iris in the image is then segmented and normalized for feature extraction process. The performance of iris recognition systems highly depends on segmentation stage, used to locate the iris region in an eye image. In this paper the comparison of four automatic segmentation methods is presented; those databases were acquired with different iris sensor and analyzed to determine the performance of segmentation algorithms to process images with heterogeneous characteristic in a non-cooperative environment. The ability of the system to work with non-ideal iris images has a significant importance because is a common realistic scenario. The receiver operating characteristic (ROC) curve was used to determine the optimal method that allows better performance in terms of false accept and false reject rates (FAR, FRR). The best performance scores was generated by the Weighted adaptive Hough Transform (WHT) segmentation method with GAR = 91.6-95.6%.

Keywords—Biometric system, Iris Recognition, Segmentation algorithms, Uncontrolled environments.

1. INTRODUCCIÓN

Biometric-based recognition systems have been a topic of active research during the last several years, because they allow accurate person identification and identity verification. Among them, the iris recognition systems have received much attention, because it provides high recognition rates. Nowadays, modern identity management systems are being developed in an attempt to improve iris recognition performance under non ideal situations i.e. unconstrained environments.

These biometric recognition systems are more flexible, the aim has been to achieve automatic acquisition system, where the image acquisition process is transparent to the user. So, it is a challenging problem to maintain a stable iris recognition system which is effective for all type of iris sensors. Indeed, it is well-know that the quality of iris image varies with the type of iris camera used in capture. The optical lens, illumination wavelength and the number of pixels across the sensor are some of the parameters of iris sensor, which determine variations of iris texture patterns. Also, in a real capturing iris images system, the person to recognize usually moves his head in different ways gives rise to non-ideal images (with occlusion, off-angle, motion-blur and defocus) for recognition. Defocus blur and motion blur are the major source of iris image quality degradation [1, 2]. A typical iris recognition system commonly consists of four main modules as shown in Figure 1 [3,4]: Acquisition, the aim is to acquire a high quality image. Preprocessing, involves the segmentation and normalization processes.

The segmentation consists in isolating the iris region from the eye image. The normalization is used to compensate the varying size of the pupil. Feature encoding, uses texture analysis method to extract features from the normalized iris image. The significant features of the iris are extracted as a series of binary codes known as digital biometric template. Matching compares the
user digital biometric template with all the stored templates in the database. The matching metric will give a range of values of the compared templates from the same iris.

Figure 1. Iris recognition system.

Figure 2. Failed iris segmentation results.

In the first stage, the acquisition of poor quality iris images can have a negative impact on segmentation algorithms and may be difficult to normalize and match, increasing the error probability [5]. Poor quality images generate translational and scale errors in segmentation algorithms. Translational errors occur when the center of the segmented circle is deviated $n$ pixels from the center of the true circle. Scale errors occur when the detected and the true circles have different radius values. These two types of errors as shown in figure 2. Most iris recognition systems usually implement the segmentation process in the earliest stages, thus any failure on it compromises the whole recognition process, the segmentation error will further propagate and amplified during the encoding and matching steps.

Figure 2. Failed iris segmentation results.

Source: High confidence visual recognition of persons by a test of statistical independence [3], Iris Recognition: An Emerging Biometric Technology [4].

2. IRIS RECOGNITION SYSTEM

The scheme, shown in Fig. 1, is based on traditional process of iris recognition. However, it was set up to operate with video captured on less constrained environments. Next subsections provide a description of each stage.

2.1 Acquisition stage

This stage is important since iris is small in size and dark in color, especially Asian people and it’s difficult to acquire good quality images for analysis using the standard CCD camera, and ordinary lighting. So, it’s necessary to use a special device to capture images with high quality while remaining non-invasive to the human user, this matter requires careful engineering. Ideally, the captured eye image should be centered in the frame, free of defocus and aberration errors which might be possible to achieve by forcing, for example, to the user to remain perfectly still while the video is taken.

2.2 Preprocessing stage

The preprocessing stage performs the segmentation and normalization tasks whose main propose is to provide a standardized template with the isolated iris region, to enable the encoding and matching stage to perform an accurate iris recognition. Next subsections provide a description of these stages.

2.2.1 Segmentation process

The segmentation process consists in isolate the iris region from the eye image. The precision on segmentation task plays an important role in the performance of entire iris recognition system. Since success of the system in upcoming stages is directly dependent on the precision of this stage [6]. The segmentation stage includes three following steps:

- Localization of iris inner boundary (the
boundary between pupil and iris.
- Localization of iris outer boundary (the limbic border between sclera and iris).
- Localization of boundary between eyelids and iris.

2.2.2 Normalization process

The normalization process is used to compensate the varying size of the iris region, in the iris frames, mainly because the stretching of the iris caused by pupil dilatation due to varying illumination levels. This process is done using the linear rubber sheet model proposed by Daugman [3]. This transformation maps each point within the iris region to polar coordinates (r,θ), where r and θ are in the intervals [0,1] and [0,2π] respectively. The mapping of the iris region from Cartesian coordinates, (x,y), to the normalised non-concentric polar representation is given by equation (1).

\[ I(x(r, \theta), y(r, \theta)) \rightarrow I(r, \theta) \]

\[ x(r, \theta) = (1 - r)x_p(\theta) + rx_p(\theta) \]

\[ y(r, \theta) = (1 - r)y_p(\theta) + ry_p(\theta) \]

Where I(x,y) is the region image, (x,y) are the original Cartesian coordinates, (r,θ) are the corresponding normalized polar coordinates, x_p,y_p and x_1,y_1 are the coordinates of the pupil and iris boundaries along the θ direction.

2.3 Feature extraction stage

The extracted features are fed into the encoding stage which is used to obtain the biometric iris signature. This process has two components: First, the normalized iris region is convolved with a 1D Log-Gabor wavelets [7,8], where each signal corresponds to a particular circle extracted from the iris rim, the operator extract the most discriminating information present in an iris region. Second, the filter output is transformed into a binary code using the four quadrant phase encoder, with each filter producing two bits of data for each phasor.

2.4 Matching stage

The operation of this stage consists in the comparison of biometric iris signatures, this produced for each one a numeric dissimilarity value. In this scheme, the Hamming Distance (HD) that incorporates noise masking was employed. The HD measure can be used to make a decision whether the biometric iris signature is produced by the same or different users. The noise mask helps to use only the significant bits in calculating the HD between two biometric iris signatures.

3. IRIS VERIFICATION SCHEME

It is important to highlight that the main goal of this research is to accurately identify people and reduce the user interaction with the system. Therefore, an iris verification system that applies robust methods at level of segmentation stage for cross-sensor iris recognition in unconstrained environment is proposed.

The proposed system comprises the following steps. As image acquisition we used three unconstraint databases. The images set for each subject in the database were tested by four segmentation methods. It allowed to validate the system with one or more images of the iris of a person or persons either for the same type of sensor or multiple sensors simultaneously. Then a normal iris recognition steps were used (normalization, feature extraction and codification, verification and comparison) as it is observed in figure 3.

The principal segmentation stage consists in the results of the best segmentation algorithm. The objective is to compare the performance of verification task for these four segmentation algorithms.

3.1 Databases

To develop robust iris image preprocessing, feature extraction and matching methods across different iris sensors in unconstrained environments is necessary to use database collected with different iris cameras and different capture conditions. This section describes the features of databases used in this work.

3.1.1 Casia-v3-interval

It is an iris database provided by National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences freely for iris recognition researchers. All iris images are 8 bit gray-level JPEG files, collected under near infrared illumination. Almost all subjects are Chinese. Because the database was collected in different times, the CASIA-Iris-Interval has a small overlap in subjects. Iris images of CASIA-Iris-Interval were captured with a self-developed close-up iris camera.

The most compelling feature of this iris camera is that it has designed a circular NIR LED array, with suitable luminous flux for iris imaging. The CASIA-V3-Interval [19], database is composed of high quality NIR illuminated indoor images with 320×280 pixel resolution (2639 images, 395 classes). For the experiments we used the whole database.
3.1.2 CASIA-V4-THOUSAND

The CASIA-V4-THOUSAND [20], contains 20,000 iris images from 1,000 subjects, which were collected using IKEMB-100 camera produced by IrisKing (http://www.irisking.com). IKEMB-100 is a dual-eye iris camera with friendly visual feedback, realizing the effect of “What You See Is What You Get”.

The bounding boxes shown in the frontal LCD help users adjust their pose for high-quality iris image acquisition. The main sources of intra-class variations in CASIA-Iris-Thousand are eyeglasses and specular reflections. It is well-suited for studying the uniqueness of iris features and develops novel iris classification and indexing methods. For the experiments we used a subset composed by 3960 images from the all subjects.

3.1.3 MBGC-V2 (VIDEO)

Multiple Biometrics Grand Challenge “MBGC.v2” database [9]. It was collected during the spring of 2008 by The Computer Vision Research Lab at the University of Notre Dame and provided 986 near infrared eye videos. All videos were acquired using an LG2200 EOU iris capture system [10]. The camera uses near-infrared illumination of the eye. The iris video sequences were digitized by a DayStar XLR8 USB video digitizer attached to a Macintosh host system and stored in MPEG-4 format. The size for each frame in the video has 480 rows and 640 columns in 8 bits-grayscale space (intensity values between 0 to 255). The MBGC database presents noise factors, especially those relative to reflections, contrast, luminosity, eyelid and eyelash iris obstruction and focus characteristics. These facts make it the most appropriate for the objectives of real iris systems for uncontrolled environments. We produced our own database of 2000 iris images from the MBGC iris video database v2. 100 videos were randomly selected from this database. Our database contains 15% of noise factors in the iris images.

3.2 Segmentation Evaluation

To evaluate the precision of iris segmentation is not an easy task. Moreover, it is a questionable task, since no ground truth for correct iris segmentation is available. While is almost impossible to design a perfect automatic algorithm for segmentation checks. In this vein, the segmentation scheme is based on a visual comparison of the results obtained by the four segmentation methods. These methods have reported good results in different databases. For this purpose, each database is segmented for each of the segmentation methods and bad segmented images are extracted. Poorly segmented images are those that have a low percentage of iris texture (<60%), because they are occluded by eyelids or eyelashes or contain elements that do not belong to the eye. This occurs due to poor performance of the segmentation algorithm, see figure 4.

3.3 Segmentation Methods

Below will be a brief description of the segmentation algorithms.

3.3.1 Viterbi-based method

We use a Viterbi algorithm based iris segmentation algorithm [11] to find the iris and pupil boundaries. The first step of the segmentation approach consists in a rough localization of the pupil area. First, filling the white holes removes specular reflections due to illuminators. Then, a morphological opening removes dark areas smaller than the disk-shaped structuring element. Then, the pupil area is almost the biggest dark area, and is surrounded by the iris, which is darker than the sclera and the skin. Consequently the sum of intensity values in large windows in the image is computed, and the minimum corresponds to the pupil area. The pupil being roughly located, a morphological reconstruction allows estimating a first center, which is required for exploiting the Viterbi algorithm. The second step consists in accurately extracting the pupil contour and a well
estimated pupil circle for normalization. Relying on the pupil center, the Viterbi algorithm is used to extract the accurate pupil contour. This accurate contour will be used to build the iris mask for recognition purposes.

### 3.3.2 CHT METHOD

Contrast-adjusted Hough Transform (CHT), is based on a Masek [8] implementation of a Hough Transform approach using (database-specific) contrast adjustment to enhance pupillary and limbic boundaries, Canny edge detection to detect boundary curves, and enhancement techniques to remove unlikely edges.

#### 3.3.3 WHT METHOD

Weighted Adaptive Hough and Ellipsopolar Transforms (WHT) [12], is the iris segmentation algorithm implemented in the USIT toolbox. This algorithm applies Gaussian weighting functions to incorporate model-specific prior knowledge. An adaptive Hough transform is applied at multiple resolutions to estimate the approximate position of the iris center. Subsequent polar transform detects the first elliptic limbic or pupillary boundary, and an ellipsopolar transform finds the second boundary based on the outcome of the first. This way, both iris images with clear limbic (typical for visible wavelength) and with clear pupillary boundaries (typical for near infrared) can be processed in a uniform manner.

### 3.3.4 MHT METHOD

Modified Hough Transform (MHT), uses the circular Hough transform initially employed by Wildes et al [13] combined with a Canny edge detector [14,15]. 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 and the radius, for the iris and pupil outer boundaries. These parameters are the centre’s coordinates \((x_p, y_p), (x_i, y_i)\) and radius \(r_p, r_i\), for the iris and pupil outer boundaries respectively.

### 4. EXPERIMENTAL RESULTS

In this section we show the results obtained by the experimental design (figs. 3). The aim of this research was oriented to explore the capacity of the robust methods at level of segmentation stage for cross-sensor iris recognition in unconstrained environments to increase the recognition rates.

#### 4.1 Segmentation Results

In this part we discuss the results obtained by segmentation scheme using the presented above segmentation methods on images of the three analyzed iris image databases. Table 1 shows the obtained segmentation results on the analyzed databases. The process of evaluation was manually assessed by visually comparing the segmented iris images. We considered two categories of quality for segmented images: good segmented and bad segmented images. Good segmented images contain more than 60% of the iris texture and less than 40% of eyelids or eyelashes or elements that do not belong to the eye (noise elements). Bad segmented images contain more than 40% of noise elements. As measure of segmentation performance we computed the percentage of good segmented images for each evaluated database by the equation 2:

\[
PGI = \frac{\text{NGSI}}{\text{NTI}} \times 100
\]  

(2)

\[
\text{MS} = \frac{\sum_{i=1}^{4} \text{PGI}_i}{4}
\]  

(3)

Where: NGSI, is the number of good segmented images in the database; NTI is the total number of images in the database. To choose the two best segmentation methods we evaluated the mean value of PGI for each segmentation method in all databases by equation 3.

Table 1. Segmentation results, WHT: Weighted adaptive Hough transform; CHT: Contrast Adjusted Hough transform; MHT: Modified Hough transform.

<table>
<thead>
<tr>
<th></th>
<th>Viterbi</th>
<th>WHT</th>
<th>CHT</th>
<th>MHT</th>
</tr>
</thead>
<tbody>
<tr>
<td>CASIA V3- Interval</td>
<td>2639</td>
<td>2639</td>
<td>2639</td>
<td>2600</td>
</tr>
<tr>
<td>PGI %</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>98,5</td>
</tr>
<tr>
<td>CASIA V4-Thousands</td>
<td>3196</td>
<td>3704</td>
<td>2639</td>
<td>2365</td>
</tr>
<tr>
<td>PGI %</td>
<td>80,7</td>
<td>93,5</td>
<td>66,6</td>
<td>59,7</td>
</tr>
<tr>
<td>MBGC</td>
<td>1736</td>
<td>1663</td>
<td>1747</td>
<td>1764</td>
</tr>
<tr>
<td>PGI %</td>
<td>86,8</td>
<td>83,1</td>
<td>87,3</td>
<td>88,2</td>
</tr>
<tr>
<td>MS %</td>
<td>89,2</td>
<td>92,2</td>
<td>84,6</td>
<td>82,1</td>
</tr>
</tbody>
</table>

Source: Own elaboration from The Center of Biometrics and Security Research [19], [20].

From table 1 it is possible to see that taking into account the mean values obtained for each segmentation method the first two best performances were obtained by Viterbi and Weighted Adaptive Hough transform. These methods obtained stable results on the three evaluated databases.
4.2 Recognition Tests Results

The recognition tests were conducted using the experimental design (fig. 3). The matching probes with the three databases, allowing the generation of the distributions Inter-Class and Intra-Class (Hamming distances for Clients and Impostors), to compare the performance of segmentation algorithms. We used the equal error rate (EER) and the receiver operating characteristics (ROC) curve [16].

In experiments where the results are considered in two classes (Inter-Class and Intra-Class), it is rarely observed a perfect separation between the two groups. Indeed, the distribution of the test results will overlap, as shown in the following figure 5. An important evaluation of any identity verification system consists in determining the point in which the FAR (false accept rate) and FRR (false reject rate) have the same value, which is called EER, because it allows the user to determine the appropriate Th, for a given application.

![Figure 5. Distribution of the test results will overlap; Inter-Class and Intra-Class (Hamming distances for Clients and Impostors).](image)

Table 2. Results in verification task.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Masek</th>
<th>CASIA V3-Interval</th>
<th>CASIA V4-Thousands</th>
<th>MBGC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GAR*</td>
<td>EER</td>
<td>GAR*</td>
<td>EER</td>
</tr>
<tr>
<td>CHT</td>
<td>92.40</td>
<td>7.59</td>
<td>89.18</td>
<td>10.81</td>
</tr>
<tr>
<td>WHT</td>
<td>93.54</td>
<td>6.45</td>
<td>92.65</td>
<td>7.34</td>
</tr>
<tr>
<td>Viterbi</td>
<td>92.59</td>
<td>7.40</td>
<td>89.26</td>
<td>10.73</td>
</tr>
<tr>
<td>MHT</td>
<td>91.51</td>
<td>8.48</td>
<td>91.55</td>
<td>8.44</td>
</tr>
</tbody>
</table>

*GAR is the genuine acceptation rate, (GAR=1-FRR).

The analysis of the distributions Inter-Class and Intra-Class for each segmentation method was compiled on table 2 (see figures 6-8). Table 2 reports the results of the GAR and Equal Error Rate (ERR) for each of automatic segmentation results. Under conditions of CASIA-V3-Interval and CASIA-V4-Thousands databases, the WHT segmentation method obtained the best results with GAR =93.54, 92.65%. These results suggest that WHT segmentation method is more accurate for CASIA databases conditions. For MBGC database the Viterbi segmentation method obtained the best results with GAR =96.26% at FAR ≤ 3.73%. For MBGC database the worse results performance was presented by MHT segmentation method, this algorithm had the highest equal error rate. These results suggest that Viterbi segmentation method is more accurate for MBGC databases conditions since it was taken under infrared lighting conditions similar to CASIA databases.

![Figure 6. The crossover point between the curves FRR and FAR. CASIA-V4-Thousands. WHT segmentation.](image)

![Figure 7. The crossover point between the curves FRR and FAR. MBGC-V2. Viterbi segmentation.](image)
Fig. 8. The crossover point between the curves FRR and FAR. CASIA-V3-Interval. WHT segmentation.

Source: Own elaboration from The Center of Biometrics and Security Research [19].

### 4.2.1 ROC Curve Analysis

The ROC curve was used to obtain the optimal threshold decision. In a ROC curve the false accept rate is plotted in function of the false reject rate for different threshold points. The table 3 (see figures 9-11) contains the obtained results choosing the optima’s decision threshold for discrimination between classes (Intra-Class and Inter-Class) by described improvement using ROC curves; FAR, FRR and GAR.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Mask</th>
<th>FAR</th>
<th>FRR</th>
<th>GAR</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CASIA V3-Interval</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CHT</td>
<td>3.21</td>
<td>8.63</td>
<td>91.36</td>
<td></td>
</tr>
<tr>
<td>WHT</td>
<td>2.39</td>
<td>7.52</td>
<td>92.47</td>
<td></td>
</tr>
<tr>
<td>Viterbi</td>
<td>3.96</td>
<td>8.36</td>
<td>91.63</td>
<td></td>
</tr>
<tr>
<td>MHT</td>
<td>4.29</td>
<td>9.96</td>
<td>90.03</td>
<td></td>
</tr>
<tr>
<td><strong>CASIA V4-Thousands</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CHT</td>
<td>5.03</td>
<td>13.17</td>
<td>86.82</td>
<td></td>
</tr>
<tr>
<td>WHT</td>
<td>4.85</td>
<td>8.39</td>
<td>91.60</td>
<td></td>
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<tr>
<td>Viterbi</td>
<td>6.48</td>
<td>12.57</td>
<td>87.42</td>
<td></td>
</tr>
<tr>
<td>MHT</td>
<td>5.04</td>
<td>9.70</td>
<td>90.29</td>
<td></td>
</tr>
<tr>
<td><strong>MBGC</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CHT</td>
<td>1.21</td>
<td>4.16</td>
<td>95.83</td>
<td></td>
</tr>
<tr>
<td>WHT</td>
<td>1.27</td>
<td>4.36</td>
<td>95.63</td>
<td></td>
</tr>
<tr>
<td>Viterbi</td>
<td>1.83</td>
<td>4.28</td>
<td>95.71</td>
<td></td>
</tr>
<tr>
<td>MHT</td>
<td>3.67</td>
<td>15.42</td>
<td>84.57</td>
<td></td>
</tr>
</tbody>
</table>

These results not only indicate the performance of the compared systems, but also provide information of how much the performance of the system improves with each segmentation method.

![Figure 9. ROC curves together with EER threshold value. CASIA-V4-Thousands. WHT segmentation.](source)

Source: Own elaboration from The Center of Biometrics and Security Research [20].

![Figure 10. ROC curves together with EER threshold value. CASIA-V3-Interval. WHT segmentation.](source)

Source: Own elaboration from The Center of Biometrics and Security Research [20].

![Figure 11. ROC curves together with EER threshold value. MBGC-V2. Viterbi segmentation.](source)

Source: Own elaboration from The Center of Biometrics and Security Research [19], [20].

### 5. CONCLUSIONS

In this paper, we present the results of a comparative analysis of four representative iris segmentation
algorithms for iris images captured under non controlled environments; we used three non-homogeneous databases with varying characteristics. The experimental results show that WHT segmentation method is more accurate databases conditions since it was taken under infrared lighting conditions, the WHT method helps to increases the recognition accuracy and adaptability to work in a less constrained environment, the ability of the system to work with non-ideal iris images has a significant importance because is a common realistic scenario. We used the ROC curves to obtain the optimal decision threshold. From the experimental results, it was concluded that WHT method was superior to the other three methods in terms of accuracy. The results obtained by this WHT method showed the lowest error rates.

Future work is aimed to find a fusion algorithm of segmentation methods that leverage even more texture information present in each eye image. The best segmentation method could be integrated as an optimization to the system developed by Colores et al [17, 18], for an application of iris recognition in uncontrolled environments.

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