ANALYSIS OF PARTIAL IRIS RECOGNITION USING A 1-D APPROACH

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ABSTRACT

Iris recognition has been shown to be very accurate for human identification. In this paper, we investigate the performance of the use of a partial iris for recognition. A partial iris identification system based on a one-dimensional approach to iris identification is developed. The experiment results shows that a more distinguishable and individually unique signal is found in the inner rings of the iris. The results also show that it is possible to use only a portion of the iris for human identification.

1. INTRODUCTION

The iris is the round, pigmented tissue that lies behind the cornea [1]. The patterns within the iris are very unique to each person, and even the left eye is unique from the right eye [2]. Compared with other biometric features such as face and fingerprint, iris patterns are more stable and reliable [11,12].

Since ophthalmologists Flom and Safir first noted the uniqueness of the iris patterns in 1987 [3], various algorithms have been proposed for iris recognition [1, 4-10], which include the quadrature 2D Gabor wavelet method [1], the Laplacian parameter approach [6], zero-crossings of the one-dimensional (1D) wavelet [7], the independent component analysis (ICA) approach [8], Gabor filtering and wavelet transform [9], and the texture analysis using multi-channel Gabor filtering and wavelet transform [10]. Recently, Du *et al.* designed a local texture analysis algorithm to calculate the local variances of iris images and generate a one-dimensional iris signature [4, 5], which relaxed the requirement of a significant portion of the iris for identification and recognition [5].

Currently, iris recognition systems require a cooperative subject [11]. Partial iris recognition algorithms would be very important in designing systems, where capturing the entire iris may not be feasible.

In this paper, we investigate the accuracy of using a partial iris for identification. In addition, we also investigate which portion of the iris has most distinguishable patterns. A partial iris identification system based on a one-dimensional approach to iris identification system is developed. The experimental results show that it is possible to use only a partial iris image for human identification.

2. ONE DIMENSIONAL APPROACH TO IRIS IDENTIFICATION

In this paper, the one dimensional approach proposed by Du *et al.* [4, 5] is used as a technique for recognition analysis. Here, we briefly introduce the one-dimensional approach.

Fig. 1 shows the one-dimensional iris identification system architecture, which includes the Preprocessing Module, the Mask Generation Module, the Local Texture Pattern (LTP) Module, the Iris Signature Generation Module, the Enrollment Module, the Iris Signature Database and the Iris Identification Module.

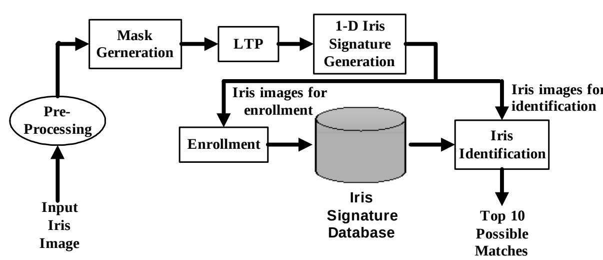

Figure 1. One-dimensional Iris Identification System Architecture [4, 5].

The Preprocessing Module finds the pupillary boundary, the limbic boundary, the eyelids, and the eyelashes in the input raw iris image. In addition, the iris image is transformed to the polar coordinates from rectangular coordinates in this step. At this point in the processing, an image is created which each row represents a concentric circle of iris pixels.

The Mask Generation Module isolates the iris pixels and normalizes the distance between the limbic boundary and the pupillary boundary to a constant $\tilde{L}$ pixels. Here we select $\tilde{L} = 65$. In this way, we achieve resolution invariance.

The LTP Module generates the local iris patterns by using overlapped windows to calculate the local variances.

The Iris Signature Generation Module builds a one-dimensional signature for each iris image by averaging the LTP values of each row. If more than 65% of the pixels in a row are non-iris, the signature value for that row is set to be 0.

The Enrollment Module averages multiple iris signatures generated from the same iris to create the one-dimensional iris signature template for later identification.

The Iris Signature Database collects the one-dimensional iris signatures and stores them in the database for further identification.

The Iris Identification Module matches the iris signature generated from a newly input iris image with the enrolled iris signatures inside the database. The matching score is based on the *Du* measurement [5]. The output of this module is the 10 closest matches from the database.

The merit of this one-dimensional LTP method is that it relaxes the requirement of using a major part of the iris, which can enable partial iris recognition. In addition, this approach generates a list of possible matches instead of only the best match. In this way, the users could potentially identify the iris image by another level of analysis.

3. PARTIAL IRIS IDENTIFICATION ANALYSIS

In our partial iris identification analysis, we used part of the iris image to generate the one-dimensional signatures. Fig. 2 shows the system architecture for generating the partial iris and the partial iris signature for iris identification, which includes the Partial Iris Generation Module, the Preprocessing and Mask Generation Module, the LTP Module, the 1-D Partial Iris Signature Generation Module, the Iris Signature Database Module, and the Iris Identification Module.

Fig. 3(a) is an example iris image. The Partial Iris Generation Module will select a portion of the iris based on a particular experiment. In our experiments, we analyzed three different kinds of partial iris images:

- Left-to-Right: The “Left-to-Right” model gradually exposes the iris beginning at the left limbic boundary and concluding at the right limbic boundary. (Fig. 3(b)).
- Outside-to-Inside: The “Outside-to-Inside” model starts at the outer limbic boundary and gradually exposes the iris pattern in concentric rings moving toward the pupil. (Fig. 3(c)).
- Inside-to-Outside: The “Inside-to-Outside” model gradually exposes concentric rings beginning at the pupillary boundary and concluding at the limbic boundary. (Fig. 3(d)).

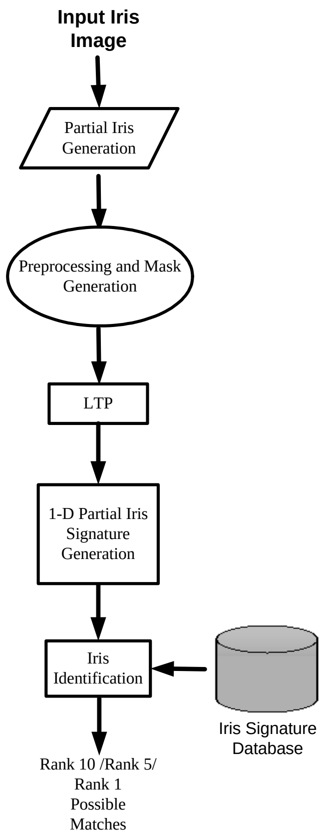

Figure. 2. Partial Iris Identification System

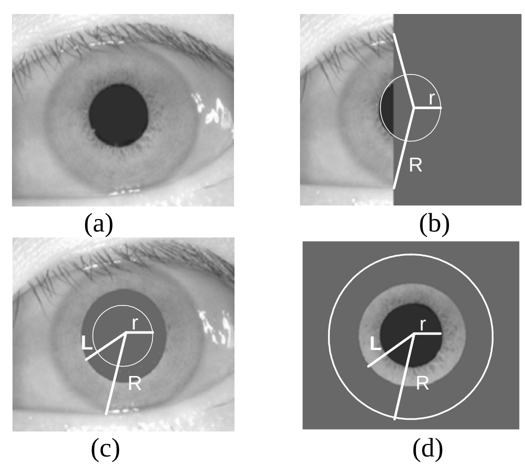

Figure 3. An example of generated partial iris images. (a) The original iris image, (b) Left-to-Right, (c) Outside-to-Inside, (d) Inside-to-Outside. (r, R, and L are pupil, limbic, and partial radius respectively.)

The percentage of the iris used in the identification is calculated differently for these three different approaches.

For Fig. 3(b), the percentage is calculated by: $\text{Partial percentage}=\frac{\text{Area of the Partial Iris}}{\text{Total Area of the Iris}}\times 100\%$; for Fig. 3(c), $\text{Partial percentage}=\frac{\text{R-L}}{\text{R-r}}\times 100\%$; for Fig. 3(d), $\text{Partial percentage}=\frac{\text{L-r}}{\text{R-r}}\times 100\%$ (r, R, and L are defining in Fig. 3).

Depending on the percentage of the iris image used, it may be hard to detect the pupil, the limbic boundary, the eyelids and eyelashes. The Preprocessing and Mask Generation Module will use the information retrieved from the entire iris image to generate the normalized mask for the partial iris image.

The LTP Module generates the local iris patterns by using overlapped windows to calculate the local variances and is similar to that of the 1D Iris Identification System in Fig. 1.

The 1-D Partial Iris Signature Generation Module builds a one-dimensional signature for each partial iris image by averaging the available LTP values of each row.

The Iris Identification Module matches the partial iris signature with the iris signatures inside the database, contained in the Database Module. Here, the iris signatures inside the database are also cut to match the length of the partial iris signature. The matching score is based on the *Du* measurement. The output of this module is the rank 10 closest matches from the database, the rank 5 closest matches, or the rank 1 closest match. (rank 10/rank 5/rank 1 means the matches following in top 10/ top 5/top 1 rank.)

4. EXPERIMENTAL RESULTS

In our experiment, the iris images from the CASIA iris image database [14] were used. It contains 756 iris images from 108 different eyes (each eye has 7 iris images). As stated in [5], 2 sets of iris images are not used because of insufficient iris patterns or unclear iris pattern. Overall, 742 iris images from 106 different eyes are used in the experiment.

In our experiment, the accuracy rate for partial iris recognition is defined as:

$$\text{Accuracy rate}=\frac{\text{Number of Correctly Identified Iris Images}}{\text{Total Number of Iris Images in the Test}}\times 100\% \quad (1)$$

Here "the correctly identified iris images" means the correctly identified iris images in the rank 10/5/1 ranks. The testing results coincide with intuition; as more of the iris pattern is available for analysis, the probability of correct match increases.

Fig. 4 shows the iris identification results for the "Left-to-Right" model. On the left side of the curve, the accuracy rate increases gradually and consistently between approximately 45% of iris pattern exposure. The curve is fairly flat until over 55% of iris pattern exposure, where the curve starts increasing again. The curve remaining steady approximately between 45%-55%, corresponds to regions covered by the eyelids and eyelashes. The reflection points of the curves are around 50%, the center of the iris. As the pattern is exposed, and the pupil is revealed, less distinguishable patterns are added to the image due to the relative area the pupil occupies as compared to the iris in the central vertical band of the eye. Once the pupil is fully exposed and more of the iris pattern is again added to the image, the percent chance that the test case matches the original increases, as expected. By slowly increasing the amount of iris area exposed in the "Left-to-Right" models, only a smaller relative area (of iris pattern) is exposed in the central vertical band (45%-55%), limiting its relative effectiveness in aiding in identification.

The performance of partial iris identification from the "Outside-to-Inside" Model is shown in Fig. 5, while the curves for the "Inside-to-Outside" model are shown in Fig. 6. In Fig. 5, the accuracy rate increases, and there is no obvious "knee in the curve". However, in Fig. 6, the accuracy rate increases much more dramatically than the other methods, and as a result, the "knee" for this model is located at approximately 35% of iris pattern exposure.

By setting a threshold for acceptance at a 95% accuracy rate (for rank 10 matching), the "Outside-to-Inside" model requires at least 65% of the iris pattern to be present. Conversely, only 40% on the iris pattern needs to be exposed for the "Inside-to-Outside" model to achieve the same accuracy rate. These experimental results support the conjecture that a more distinguishable and individually unique signal is found in the inner rings of the iris. As one traverses to the limbic boundary of the iris, the pattern becomes less defined, and ultimately less useful in determining identity. For the "Left-to-Right" model, 80% of the iris pattern would be necessary for a 95% accuracy rate for rank 10 matching. In the "Left-to-Right" model, each point of the one-dimensional signature is affected by the portion of the exposed iris, while for the "Inside-to-Outside" and "Outside-to-Inside" models, the points of the generated one-dimensional signature for the partial iris are either very similar to those of the original iris or zeroed out.

From Figs. 4-6, we can also see that using only 40% of the iris can achieve more than 85% accuracy rate for rank 10, 70% accuracy rate for Rank 5, and 45% for Rank 1. It shows that the partial iris recognition is promising for use in human identification using a rank 10/5 technique. However, it would be very challenging to use in human verification (rank 1).

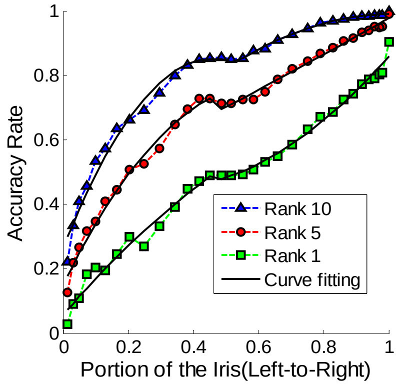

Figure 4. The performance of partial iris identification for "Left-to-Right" Model.

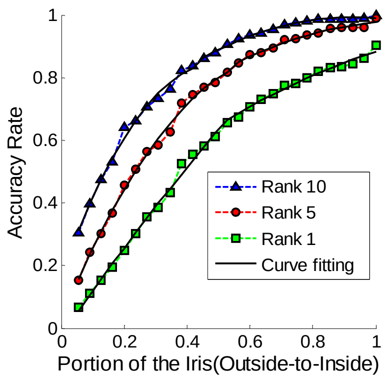

Figure 5. The performance of partial iris identification from the "Outside-to-Inside" Model

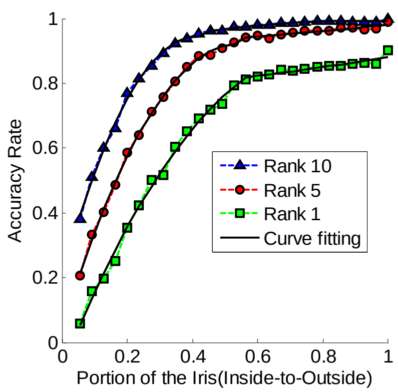

Figure 6. The performance of iris identification from the "Inside-to-Outside" Model

5. CONCLUSIONS

In this paper, the performance of partial iris identification is analyzed using the One-Dimensional LTP Approach. The experiment results show that a more distinguishable and individually unique signal is found in the inner rings of the iris. Also, as expected, the experimental results show that the eyelids and eyelashes detrimentally affect the iris recognition result. By slowly increasing the amount of iris area exposed in the "Left-to-Right" models, only a smaller relative area (of iris pattern) is exposed in the central vertical band, limiting its relative effectiveness in aiding in identification.

Finally, the experimental results show that a partial iris image can be used for human identification.

6. ACKNOWLEDGEMENT

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