Rotation-Invariant Iris Recognition: Boosting 1D Spatial-Domain Signatures to 2D

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Abstract

An iris recognition algorithm based on 1D spatial domain signatures is improved by extending template data from mean vectors to 2D histogram information. EER and shape of the FAR curve is clearly improved as compared to the original algorithm, while rotation invariance and the low computational demand is maintained. The employment of the proposed scheme remains limited to the similarity ranking scenario due to its overall FAR/FRR behaviour.

Introduction

Iris recognition systems are claimed to be among the most secure modalities exhibiting practically 0% FAR and low FRR which makes them interesting candidates for high security application scenarios.
Controlling the computational demand in biometric systems is important, especially in distributed scenarios with weak and low-power sensor devices. Integral transforms (like those already mentioned or others like DFT, DCT, etc.) cause substantial complexity in the feature extraction stage, therefore feature extraction techniques operating in the spatial domain have been designed (e.g. [3]) thus avoiding the additional transform complexity.
An additional issue causing undesired increase in complexity is the requirement to compensate for the possible effects of eye tilt. As a consequence, rotation invariant iris features are highly desired to avoid these additional computations.
Global iris histograms [2] combine both advantages, i.e. rotation invariant features extracted in the spatial domain thus providing low overall computational complexity. However, FAR and FRR are worse compared to state of the art techniques. A recent approach [1] uses rotation invariant 1D signatures with radial locality extracted from the spatial domain. In this work we aim at improving this algorithm.

Rotation Invariant Iris Signatures

Iris texture is first converted into a polar iris image which is a rectangular image containing iris texture represented in a polar coordinate system. As a further preprocessing stage, we compute local texture patterns (LTP) from the iris texture as described in [1]. We define two windows $T(X,Y)$ and $B(x,y)$ with $X > x$ and $Y > y$ (we use 15×7 pixels for T and 9×3 pixels for B). Let mT be the average gray value of the pixels in window T. The LTP value of pixels in window B at position (i,j) is then defined as

$$LTP_{i,j} = |I_{i,j} - mT|$$

where $I_{i,j}$ is the intensity of the pixel at position (i,j) in B. Note that due to the polar nature of the iris texture, there is no need to define a border handling strategy. LTP represents thus the local deviation from the mean in a larger neighbourhood.
In order to cope with non-iris data contained in the iris texture, LTP values are set to non-iris in case 40% of the pixels in B or 60% of the pixels in T are known to be non-iris pixels.

The Original 1D Case and Variants

The original algorithm [1] computes the mean of the LTP values of each row (line) of the polar iris image and concatenates those mean values into a 1D signature which serves as the iris template. Clearly, this vector is rotation invariant since the mean over the rows (lines) is not at all affected by eye tilt. If more then 65% of the LTP values in a row are non-iris, this signature element is ignored in the distance computation. In order to assess the distance between two signatures, the Du measure is suggested [1] although various other measures including l^p-norms would be applicable as well. We also apply the Du measure in all other variants of the algorithm proposed subsequently.
The row-mean of LTP is expected to be higher for rows closer to the pupil for most images and decreasing for increasing distance from the center of the pupil (which is confirmed by experimental results in [1]). The amount of LTP fluctuation might therefore capture different characteristics of different irises better – as a variant of the original algorithm we substitute the mean by variance. In addition to that, we also combine mean and variance by concatenating the mean and variance signatures into a single one.

The 2D Extension

LTP row mean and variance capture first order statistics of the LTP histogram. In order to capture more properties of the iris texture without losing rotation invariance we propose to employ the row-based LTP histograms themselves as features (since histograms are known to be rotation invariant as well and have been used in iris recognition before [2]). This adds a second dimension to the signatures of course (where the first dimension is the number of rows in the polar iris image and the second dimension is the number of bins used to represent the LTP histograms).
In fact, we have a sort of multi-biometrics-situation resulting from these 2D signatures, since each histogram could be used as a feature vector on its own. We suggest two fusion strategies for our 2D signatures:

1. Concatenated histograms: the histograms are simply concatenated into a large feature vector. The Du measure is applied as it is in the original version of the algorithm.
2. Accumulated errors: we compute the Du measure for each row (i.e. each single histogram) and accumulate the distances for all rows.

The iris data close to the pupil are often said to be more distinctive as compared to "outer" data. Therefore we propose to apply a weighting factor > 1 to the most "inner" row, a factor $= 1$ to the "outer"-most row and derive the weights of the remaining rows by linear interpolation.

Experimental Study

For all our experiments we considered images with 8-bit grayscale information per pixel from the CASIA[a] v1.0 iris image database. We applied the experimental calculations on the images of 108 persons in the CASIA database using 7 iris images of each person which have all been cropped to a size of 280×280 pixels.
Our MATLAB implementation applies the LTP algorithm to the extracted iris polar image (360×65 pixels). Following the suggestion in [1], we discard the upper and lower three lines of the LTP polar image due to noise often present in these parts of the data (resulting in a 360×59 pixels LTP patch). The 1D and 2D signatures described in the last section are then extracted from these patches.

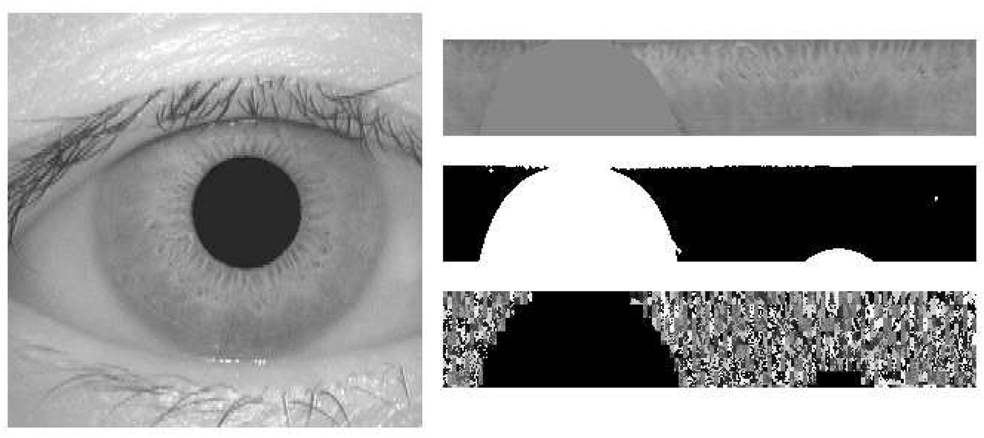

Fig. 1 CASIA iris image and the corresponding iris template, noise mask, and LTP patch.

Figure 1 shows an example of an iris image of one person (CASIA database), together with the extracted polar iris image, the noise mask, and the LTP patch (template, noise mask, and LTP patch have been scaled in y-direction by a factor of 4 for proper display).

[a]`http://www.sinobiometrics.com`

Experimental Results – Du1D

In Figure 2.a, we show the ROC curve of the original version of the Du approach employing 1D signatures based on LTP row mean vectors. The concave shape of the FAR curve for the Du algorithm depicts a steep slope close to zero which means that low FAR values cause unrealistically high FRR. The latter result illustrates the reason why this algorithm is restricted to the similarity ranking scenario in the original work [1].

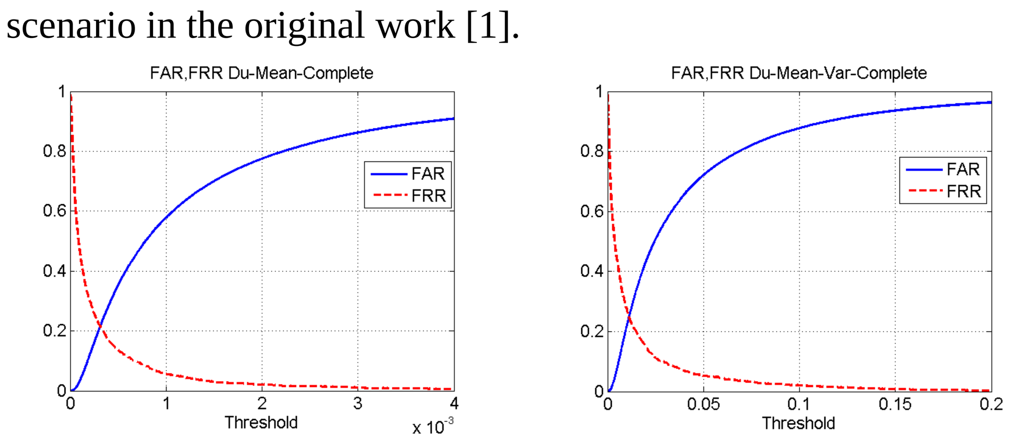

Fig. 2. ROC of Original Du vs. variance "enhanced" version (EER 0.22 vs. 0.25)

Figure 2.b displays the ROC curve for a variant of the Du algorithm using 1D signatures. Employing LTP row variance instead of mean is obviously not a good idea as previous results show. Even when combining both mean and variance signatures as shown in Figure 2.b, the results is still worse as compared to the original version.

Experimental Results – Du2D

When turning to 2D signatures, we compare different fusion strategies and histogram resolutions in Table 1 with respect to their EER. While it is obvious that too many histogram bins lead to poor results (important histogram properties are concealed by noise), also a reduction to 20 bins results in lower EER as compared to 100 bins. When comparing the two fusion strategies, accumulating distances (AD) at a row basis is clearly superior to simple histogram concatenation (HC) at a reasonable histogram resolution. In this scenario, we are clearly able to improve EER as compared to the original Du algorithm (from 0.22 down to 0.16).

# bins	1500450	255	100	20
HC	0.3	0.2	0.18	0.19
AD	0.32	0.16	0.16	0.18

Table 1 EER for two assessment variants and different histogram resolutions.

Note also, that histgram resolution up to 255 is beneficial for accumulating errors fusion while it is not for histogram concatenation. This is an intuitive result, since in case of histogram concatenation the vectors to be compared in the Du measure are already fairly long overall, while this is not the case for accumulating errors fusion.
Table 2 compares three weighting strategies for the accumulated errors fusion strategy. The best results are obtained when using weight 4 for the LTP row closest to the pupil. This result confirms the assumption, that "inner" iris information is most important for recognition purposes.

histogram bins	255	100	20
no weight	0.16	0.16	0.18
weight 2	0.15	0.15	0.19
weight 4	0.15	0.15	0.16

Table 2 EER for three weighting variants and different histogram resolutions.

We display ROC curves for the best settings for each fusion strategy in Figure 3. Especially the weighted case for accumulated errors fusion shown in Figure 3.b exhibits a much better behaviour of the FAR curve in proximity of zero which documents also the improved behaviour.

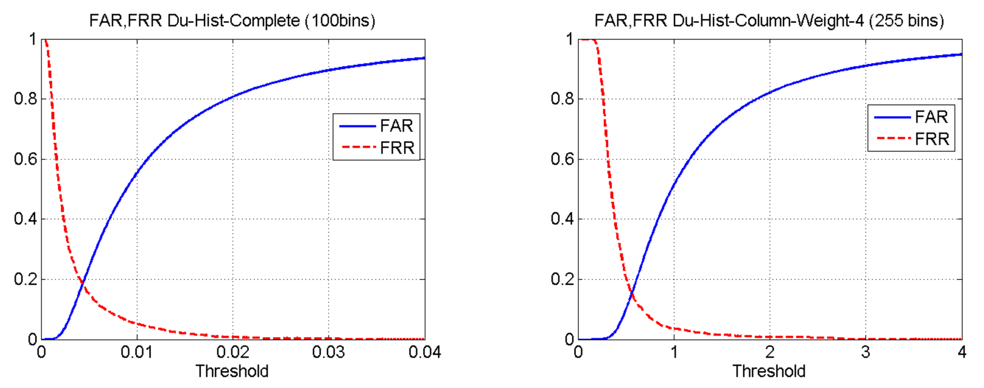

Fig. 4. ROC curves of Du2D (concatenated histograms, 100 bins - EER 0.18 vs. accumulated errors, weight 4, 255 bins - ERR 0.15).

Conclusion and Future Work

In this work we have improved an iris recognition algorithm based on 1D signatures extracted from the spatial domain by including histogram based information instead of mean values. While we succeeded in maintaining rotation invariance in our improved version, FAR and FRR are still significantly worse compared to state of the art identification techniques which limits this improvement to the employment in a similarity ranking scheme as it is the case for the original version.
One reason for the still disappointing behaviour is as follows: when shifting the different rows in the polar iris image with a different amount against each other, the 2D signatures (as well as the 1D signatures of course) are preserved. Our results indicate that indeed information about the spatial position of frequency fluctuations in iris imagery is crucial for effective recognition.
Since the proposed scheme excels by its low computational cost, we aim at improving it in future work by further reducing the amount of template data by combining several rows into a single histogram in an optimal manner and also adapting the histogram resolution to the importance of the row index.

References

[1] Y. Du, R.W. Ives, D.M. Etter, and T.B. Welch. Use of one-dimensional iris signatures to rank iris pattern similarities. *Optical Engineering*, 45(3):037201–1 – 037201–10, 2006.

[2] R.W. Ives, A.J. Guidry, and D.M. Etter. Iris recognition using histogram analysis. In *Conference Record of the 38th Asilomar Conference on Signals, Systems, and Computers*, volume 1, pages 562–566. IEEE Signal Processing Society, November 2004.

[3] J.-G. Ko, Y.-H. Gil, J.-H. Yoo, and K.-I. Chung. A novel and efficient feature extraction method for iris recognition. *ETRI Journal*, 29(3):399 – 401, 2007.