ROTATION-INVARIANT IRIS RECOGNITION
Boosting 1D Spatial-Domain Signatures to 2D

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Keywords: Biometric authentication, iris recognition, rotation invariance.

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.

1 INTRODUCTION

With the increasing usage of biometric systems in general the interest in non-mainstream modalities rises naturally. 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. An interesting fact is that the iris recognition market is strongly dominated by Iridian Inc. based technology which is based on algorithms by J. Daugman (Daugman, 2004). The corresponding feature extraction algorithm employes 2D Gabor functions. However, apart from this approach, a wide variety of other iris recognition algorithms has been proposed in literature, most of which are based on a feature extraction stage involving some sort of transform (see e.g. (Ma et al., 2004; Zhu et al., 2000) for two examples using a wavelet transform).

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. (Ko et al., 2007)) 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. For example, the matching stage of the Daugman scheme involves multiple matching stages using several shifted versions of the template data which is a typical approach. As a consequence, rotation invariant iris features are highly desired to avoid these additional computations.

Global iris histograms (Ives et al., 2004) 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 (Du et al., 2006) uses rotation invariant 1D signatures with radial locality extracted from the spatial domain. Still, also the latter technique suffers from unsatisfactory FAR and FRR and thus is only recommended to be used in a similarity ranking scheme (i.e. determining the n closest matches). In this work we aim at improving this algorithm.

In Section 2, we will review the original version of the algorithm and then describe the improvements conducted. Section 3 provides experimental results. We first describe the experimental settings (employed data and software used). Subsequently, we present and discuss our experimental results providing EER improvements over the original version of the algorithm. Section 4 concludes the paper and gives outlook to future work.

Matschitsch S., Stögner H., Tschinder M. and Uhl A. (2008).
ROTATION-INVARIANT IRIS RECOGNITION - Boosting 1D Spatial-Domain Signatures to 2D.
In *Proceedings of the Fifth International Conference on Informatics in Control, Automation and Robotics - SPSMC*, pages 232-235
DOI: 10.5220/0001480102320235

2 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. Note that the ISO/IEC 19794-6 standard defines two types of iris imagery: rectilinear images (i.e. images of the entire eye like those contained in the CASIA database) and polar images (which are basically the result of iris detection and segmentation). As a further preprocessing stage, we compute local texture patterns (LTP) from the iris texture as described in (Du et al., 2006). 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.

2.1 The Original 1D Case

The original algorithm (Du et al., 2006) 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 (Du et al., 2006) which we apply in all variants.

2.2 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 (Ives et al., 2004)). 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. These weights are applied to the "accumulated errors" fusion strategy by simply multiplying the distances obtained for each row by the corresponding weight.

3 EXPERIMENTAL STUDY

3.1 Setting and Methods

For all our experiments we considered images with 8-bit grayscale information per pixel from the CASIA[1] 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.

The employed iris recognition system builds upon Libor Masek's MATLAB implementation[2] of a 1D version of the Daugman iris recognition algorithm. First, this algorithm segments the eye image into the iris and the remainder of the image ("iris detection"). Subsequently, the iris texture is converted into a polar iris image. Additionally, a noise mask is generated indicating areas in the iris polar image which do originate from eye lids or other non-iris texture noise.

Our MATLAB implementation uses the extracted iris polar image (360×65 pixels) for further processing and applies the LTP algorithm to it. Following the

[1] http://www.sinobiometrics.com

[2] http://www.csse.uwa.edu.au/~pk/studentprojects/libor/sourcecode.html

suggestion in (Du et al., 2006), 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.

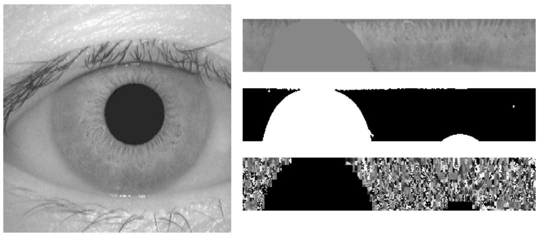


Figure 1: CASIA iris image and the corresponding iris template, noise mask, and LTP patch.

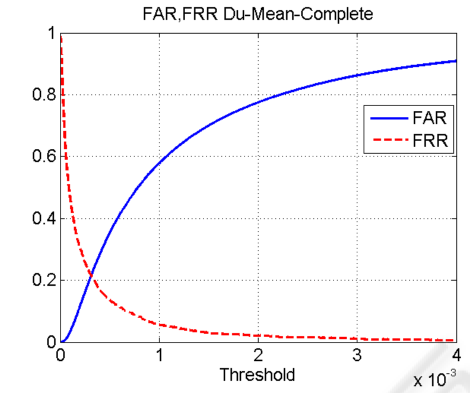
Figure 1 shows an example of an iris image of one person (CASIA database), together with the extracted polar iris image, the noise mask, and the LTP patch (template, noise mask, and LTP patch have been scaled in y-direction by a factor of 4 for proper display).

3.2 Experimental Results

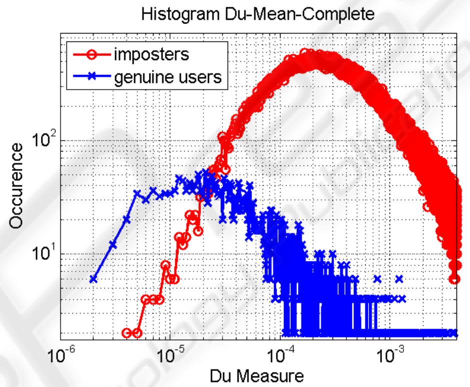
In Figure 2.a, we show the ROC curve of the original version of the Du approach employing 1D signatures based on LTP row mean vectors. EER is rather high with 0.22 and especially the concave shape of the FAR curve for the Du algorithm depicts a steep slope close to zero which means that low FAR values cause unrealistically high FRR. The latter result illustrates the reason why this algorithm is restricted to the similarity ranking scenario in the original work (Du et al., 2006).

The reasons for the respective behaviour can be seen in Figure 2.b. The overlap between genuine users and imposters distributions is is very large for the Du approach, obviously causing the high EER.

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).



(a) ROC-plot: ERR 0.22



(b) Genuine users and imposters distributions

Figure 2: Behaviour of the original DU algorithm.

Table 1: EER for two assessment variants and different histogram resolutions (2D signatures).

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

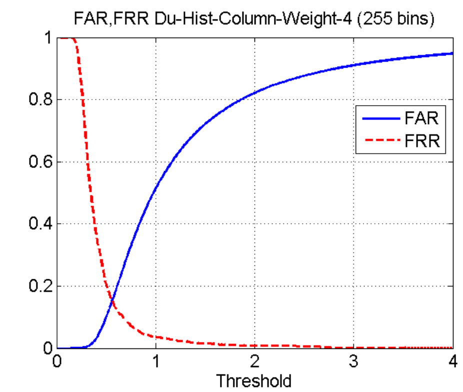
Note also, that histgram resolution up to 255 is beneficial for accumulating errors fusion while it is not for histogram concatenation. This is an intuitive result, since in case of histogram concatenation the vectors to be compared in the Du measure are already fairly long overall, while this is not 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.

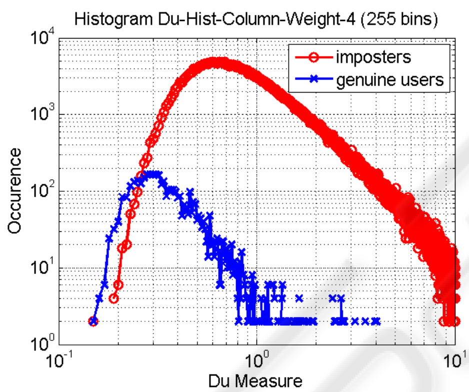
We display the ROC curve for the best setting for accumulted error fusion strategy in Figure 3.a. The graph exhibits a much better behaviour of the FAR

Table 2: EER for three weighting variants and different histogram resolutions (2D signatures).

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



(a) ROC-plot: EER 0.15



(b) Genuine users and imposters distributions

Figure 3: Behaviour of best 2D Du variant (accumulated errors (weight 4, 255 bins)).

curve in proximity of zero as compared to the original one which documents also the improved behaviour.

Finally, we visualize genuine users and imposters distributions the same 2D variant of the Du algorithm in Figure 3.b which confirms improvements with respect to the original algorithm.

4 CONCLUSIONS

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. This operation corresponds to the rotation of concentric circles of iris pixels by an arbitrary amount – still, the signatures for all those artificially generated images are identical. Our results indicate that indeed information about the spatial position of frequency fluctuations in iris imagery is crucial for effective recognition.

ACKNOWLEDGEMENTS

Most of the work described in this paper has been done in the scope of a semester project in the master program on “Communication Engineering for IT” at Carithia Tech Institute.

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