COMPUTATIONALLY EFFICIENT SERIAL COMBINATION OF ROTATION-INVARIANT AND ROTATION COMPENSATING IRIS RECOGNITION ALGORITHMS

Mario Konrad, Herbert Stögner
School of Communication Engineering for IT, Carinthia Tech Institute, Austria
mario.konrad@edu.fh-kaernten.ac.at

Andreas Uhl, Peter Wild
Department of Computer Sciences, University of Salzburg, Austria
{uhl, pwild}@cosy.sbg.ac.at

Keywords: Iris recognition, Multibiometrics, Serial classifier combination, Rotation compensation.

Abstract: Rotation compensation is one of the computational bottlenecks in large scale iris-based identification schemes, since a significant amount of Hamming distance computations is required in a single match due to the necessary shifting of the iris codes to compensate for eye tilt. To cope with this problem, a serial classifier combination approach is proposed for iris-based identification, combining rotation-invariant pre-selection with a traditional rotation compensating iris code-based scheme. The primary aim, a reduction of computational complexity, can easily be met - at comparable recognition accuracy, the computational effort required is reduced to 20% or even less of the fully fledged iris code based scheme. As a by-product, the recognition accuracy is shown to be additionally improved in open-set scenarios.

1 INTRODUCTION

Iris recognition technology has been dominated over years by the commercially successful algorithm of J. Daugman (Daugman, 2004). This algorithm basically extracts local iris features from polar iris images by convolution with 2-dimensional complex Gabor atoms, quantizing the resulting phase information into 2 bits per coefficient. The basic idea of extracting local intensity variations from iris texture has been followed employing other types of transforms and methods as well, e.g. in the spatial domain or in the wavelet domain. All these approaches share the property of being sensitive against eye tilt, i.e. they are intrinsically not rotation invariant due to the usage of local spatial information. Therefore, in order to compensate potential rotation, in all these algorithms the templates in the matching process are shifted against each other for a certain amount, and taking the minimal template distance among all shifted versions as the actual distance. Obviously, depending on the amount of shift that is required for a certain application (i.e. the amount of rotation that is to be expected), these operations may amount to a significant number of matching operations performed, which can become prohibitive in an identification scenario.

Rotation-invariant iris features therefore represent an attractive alternative. Due to the significant computational demand associated with transform domain processing, spatial domain techniques working directly on the iris texture are of specific interest in our context. Du et al. (Du et al., 2006) employ first order moments of the iris texture line-histograms. While this technique is successful in providing rotation invariance and consequently fast matching procedures independent of the eye's position, it fails in terms of recognition accuracy.

This is where our approach comes in. In this work we combine a spatially-based rotation invariant iris recognition approach with a traditional local-feature based scheme into a serial classifier combination.

The aim is to result in reduced overall computational demand as compared to classical rotation compensating schemes while at least maintaining their recognition accuracy. This is achieved by using the first scheme to determine a certain amount of the highest matching ranks of the entire database (this can be done quickly due to the high speed of the first scheme), while the second (and more accurate) scheme is then only applied to this predetermined subset to determine the final matching result. Serial classifier combination aiming at a reduction of identification time is a relatively new research topic in biometrics, see (Uhl and Wild, 2009; Gentile et al., 2009) for applications in hand biometrics and iris biometrics. This work is the first multi-algorithm multibiometric (Ross et al., 2006) approach combining rotation-invariant with rotation compensating iris recognition algorithms serially to reduce computational demands. Besides the aimed reduction in computational effort it is of particular interest, if the combination of two very different feature types can also lead to improved recognition results. Since features used in classifier combinations need to be as uncorrelated as possible to result in better results as compared to their single classifier counterparts, a recognition improvement might be expected as well in our case, since the features of the two classifiers used are of significantly different nature.

In iris recognition, several single-sensor multibiometric approaches have been suggested yet, however, mostly focussing on an improvement of recognition accuracy. Sun et al. (Sun et al., 2005) "cascade" two feature types employing global features only in addition to a Daugman-like approach if the matching value of the latter is in a questionable range. Also Zhang et al. (Zhang et al., 2004) use a similar strategy while interchanging the role of the global and the local features. Vatsa et al. (Vatsa et al., 2005) compute the Euler number of connected components as global feature, while again using an iris code as local texture feature. Park and Lee (Park and Lee, 2006) decompose the iris data with a directional filterbank and extract two different feature types from this domain. Combining the results leads to an improvement of the single techniques applied.

Approaches closer related to our work are quick screening or pre-classification techniques. Several authors have developed techniques to divide iris data into a certain number of categories in order to achieve a rough pre-classification before applying a more accurate matching technique. Qui et al. (Qui et al., 2007) use iris textons to generate five classes, and Yu et al. (Yu et al., 2006) use fractal dimension to generate four classes. The approach as described in this work is different from the techniques proposed so far in several ways. First, it is different compared to the single-sensor multibiometric approaches combining global and local features suggested since we

- mainly focus on a reduction of computational effort by limiting the required rotation compensation in matching instead of aiming at better recognition accuracy and
- we apply a specific type of serial classifier combination to accomplish this (i.e. contrasting to many other approaches not both classifiers are applied to the entire dataset).

Second, it is different to the developed screening approaches since we

- do not partition the templates into a certain number of classes and do therefore not limit the actual matching to the common class of database template and sample template and
- we actually combine our "screening approach" with a classical technique in serial manner and provide actual computational performance and classification accuracy results.

In contrast to recently introduced serial iris feature combinations (Gentile et al., 2009), we employ a rotational-invariant pre-selecting feature making bitshifts in the first classifier unnecessary.

Section 2 describes the iris recognition techniques, which are part of our serial matching approach and explains the applied serial classifier combination technique. In Section 3, the experimental setup is discussed and experimental results are provided. First, we illustrate the results of the classical approach using local features and rotation compensation. Subsequently, we discuss and present the experimental results for the serial classifier combination for the open-set scenario with respect to time consumption as well as recognition performance of the different approaches. Section 4 concludes the paper.

2 SERIAL CLASSIFIER COMBINATION IN IRIS RECOGNITION

The applied serial classifier combination mainly aims at reducing computation demand in identification scenarios. The basic idea is to employ a faster recognition scheme with rotation invariant (more global) features for a first screening sweep across the entire database. The screening procedure does not result in a certain number of classes, which can then be used to restrict the subsequent search to a single class, but results in a ranking of the enrolled database templates. This ranking is subsequently used to determine actually two classes, where the subsequent search is limited to one of these classes then – obviously this is the class with the highest ranks. An important parameter of this approach is the amount of top ranked templates that is contained in the class subject to further search. We denote this parameter p and it is expressed in percent of the database, e.g. if $p = 25$, the 25% top ranked templates are subject to further processing by the second, computationally more expensive approach (which relies on local texture features and requires rotation compensation). Obviously, for increasing p the computational demand is increased. The main question addressed in the experimental section is whether the recognition accuracy can be maintained for decreasing p, or otherwise, in how far the decrease of p is coupled to a decrease of recognition accuracy.

In the next two subsections we will briefly review the two iris recognition schemes, which we use to combine into a serial classifier combination.

2.1 Rotation-invariant Screening

Du et al. (Du et al., 2006) have proposed a rotation invariant 1D signature approach, which we employ as the first screening stage. As preprocessing, local texture patterns (LTPs) are generated, which substract a localized mean value from the data. By averaging LTP values of an entire row of the LTP polar iris image (which is generated in a first preprocessing stage after iris detection), one value of the 1D signature is generated. While the upper and lower three rows of the polar iris data are discarded, the remaining rows are used to create the final 1D signature. In recent work (Matschitsch et al., 2008) this approach has been extended by using entire row histograms instead of first order moments only, which results in 2D signatures in some sense. Clearly, both the original 1D and the extended 2D signatures are rotation invariant.

Two 1D signatures are compared by using the Du measure (Du et al., 2006). For the extension to 2D signatures, we apply the "accumulated errors" approach (Matschitsch et al., 2008), where the Du measure is computed for each row between the single histograms and the resulting distances are accumulated afterwards for all rows. We apply the accumulated errors strategy using 256 histogram bins. Moreover, a weighting factor > 1 is used for the distance of polar image rows, which are close to the pupil and a factor $= 1$ is proposed for rows, which are close to the sclera of the eye. The weighting factors for the rows in between are obtained by linear interpolation.

2.2 Local Texture Features – Iris Code

For the original iris code (Daugman, 2004), the polar images are subject to a 2D complex Gabor filtering process, subsequently the available phase information is quantized into four different levels, one for each of the four possible quadrants in the complex plane. Hence, for each pixel of the polar image, two bits are obtained, which are combined and form the iris template (i.e. iris code), which can be compared to other iris codes by computing the Hamming distance. This measure is highly localized and needs to compensate for possible rotation between irises – this is done by applying the Hamming distance calculation several times while shifting the polar images against each other. The lowest matching value then determines the final distance.

In this work, we use an open-source MatLAB implementation, which applies a 1D Gabor-filter version of the iris code strategy for iris recognition. Due to its free availability[1] and the lack of other publicly available iris recognition software, it has gained significant popularity in the community.

3 EXPERIMENTS

3.1 Experimental Setup

We use the CASIA V1.0 and the CASIA V3.0 Interval[2] as well as the MMU V1.0[3] datasets where for each database two different subsets are selected. For the CASIA V1.0, which consists of 756 images acquired from 108 eyes (7 images per eye), the first subset contains 630 iris images and the second subset comprises 126 images. For the CASIA V3.0, the first subset consists of 1705 iris images acquired from 341 different eyes (5 images for each eye). The second subset includes 117 images from 53 eyes with various numbers of images per eye. For MMU, the first dataset is composed of 400 iris images from 80 eyes, while the second set contains 50 images (again 5 images per eye). For all three databases, the first dataset is used to serve as database of enrolled persons and the second dataset contains images that are unknown to the recognition system (which are needed in the open-set scenario). Out of all datasets, we extract polar iris images with 360×65 pixels, which results in 1D/2D signatures with length 59 since only 59 out of 65 LTP rows are used.

We consider the open-set scenario (or watchlist scenario). Here it is not guaranteed that the person that should be identified is truly member of the database. Hence, an identification attempt results in

[1] `http://www.csse.uwa.edu.au/~pk/studentprojects/libor/sourcecode.html`
[2] `http://www.sinobiometrics.com`
[3] `http://pesona.mmu.edu.my/ccteo/`

a correct identification whenever an enrolled person is correctly recognized. If a not enrolled person is falsely labelled as database member, the attempt will result in a false accept. The rank-1 recognition rate as well as the false accept rate is used in order to assess this type of system.

With respect to serial classifier combination, we investigate set reductions to top-ranked $p = 1,5,10,15$ candidates subjected to further processing. Rotation compensation for the "pure" iris code technique is conducted with 2, 4, and 8 shifts of the iris code in each direction (which sums up to 17 Hamming distance calculations in the case of 8 shifts), in the context of the serial combination rotation compensation is conducted using 8 shifts in the second stage of the identification.

3.2 Results

First, we create reference results by analyzing the performance of the "pure" iris code approach. Table 1 illustrates the time consumption to search the entire database, which obviously strongly depends on the amount of shifts (AMD Athlon 2200+ processor, 512 MB RAM, Windows XP and MatLAB R2007b). For comparison, the required amount of time to search the database with the Du approach is also displayed. When conducting only a single Hamming distance computation (instead of already 5 in the case of two shifts), the iris code algorithm would be only slightly slower compared to the Du approach. Only rotation compensation degrades its performance significantly. Note, that the image segmentation and generation of the polar iris image was performed prior to the analysis and is excluded from the timing results. The time effort for these computations is 52 seconds for the CASIA V1.0 dataset and 59 seconds for the CASIA V3.0 dataset, for example.

In Figure 1, we show the effect of applying a variable amount of shifts on recognition accuracy in the iris code approach for CASIA V3.0 as an example. In accordance to literature, 8 shifts yield only slightly better results than 4 shifts overall, but this effect is more pronounced for the important case of lower false accept rates, which makes the application of 8 shifts sensible in this case as well. Therefore, further results refer to 8 shifts in the "pure" iris code approach as

Table 1: Time consumption of iris code-based identification with a various number of shifts and Du's approach.

	Du	Iris code 2s	Iris code 4s	Iris code 8s
Cv1	12.5 s	77.2 s	105.8 s	176.3 s
Cv3	32.1 s	215.7 s	322.7 s	507.1 s
MMU	8.1s	48.3 s	69.3 s	111.5 s

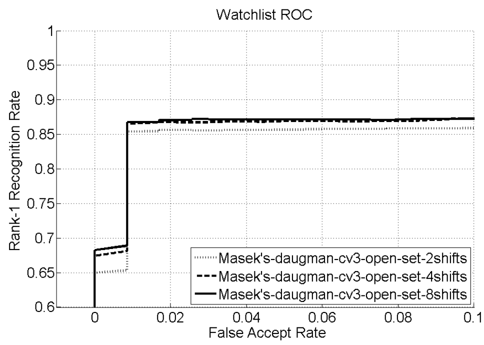


Figure 1: Performance in terms of recognition accuracy of the iris code approach for CASIA V3.0 with varying amount of shifts.

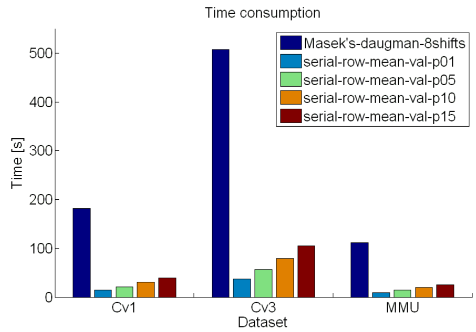


Figure 2: Time consumption (in seconds) of the iris code approach and the serial combination approach with $p = 1,5,10,15$ for 1D signatures.

well as in the second stage of the serial combination.

Figure 2 displays the time needed to perform identification over the entire datasets and compares the iris code approach using 8 shifts (denoted Masek's-daugman in this plot) with the serial approach using 1D signatures with $p = 1,5,10,15$. The time reduction achieved even for $p = 15$ is impressive.

Table 2 summarizes the time consumption of the different serial combination variants for 1D (S1DpX) and 2D signatures (S2DpX). As expected, it is confirmed that the serial approach is much faster than the classical iris code method (IC8s). Although the application of 2D signatures raises the computational effort, the results are also clearly superior. Applying a weighting factor (w=4) to the signatures does only slightly increase the computational demand in a negligible manner (not shown). For example, for 1D signatures with $p = 10$ (which is better in term of recognition accuracy in many cases compared to the iris code case as we shall see), the serial approach is faster more than a factor of 6, and still for 2D signatures the serial approach is faster by a factor of 5.

Having shown that the aim of significant reduction of the computational effort has been met, we investigate the impact of the serial classifier combination on

Table 2: Time consumption (in seconds) of the iris code approach and the serial combination approach with $p = 1, 5, 10, 15$ for 1D (above) and 2D signatures (below).

1-D signatures					
	IC8s	S1Dp1	S1Dp5	S1Dp10	S1Dp15
Cv1	181.5 s	14.1 s	21.3 s	30.3 s	39.3 s
Cv3	507.1 s	36.9 s	56.6 s	79.7 s	104.7 s
MMU	111.5 s	9.5 s	14.1 s	19.8 s	25.5 s
2-D signatures					
	IC8s	S2Dp1	S2Dp5	S2Dp10	S2Dp15
Cv1	181.5 s	19.7 s	27.0 s	35.0 s	45.0 s
Cv3	507.1 s	52.5 s	71.7 s	95.7 s	120.0 s
MMU	111.5 s	13.4 s	18.1 s	23.9 s	29.8 s

Table 3: Rank-1 Recognition Rate (RR-1) at certain False Accept Rate (FAR) values.

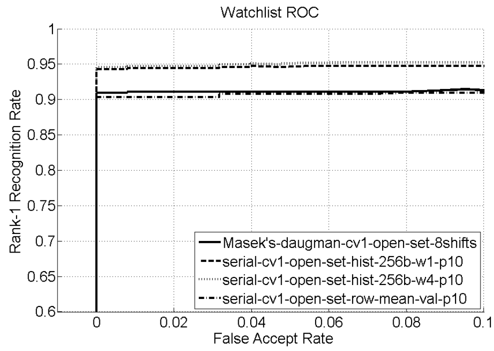
Casia V1.0					
FAR	IC8s	S1Dp1%	S1Dp5%	S1Dp10%	S1Dp15%
0%	90.9%	81.6%	88.1%	90.3%	91.9%
0.79%	91.1%	81.6%	88.6%	90.3%	91.9%
11.1%	91.1%	81.9%	89.2%	91.1%	92.5%
CASIA V3.0					
FAR	IC8s	S1Dp1%	S1Dp5%	S1Dp10%	S1Dp15%
0%	68.3%	69.2%	76.1%	65.5%	66.2%
0.85%	86.7%	77.9%	85.8%	87.7%	88.4%
11.1%	87.4%	78.4%	86.3%	88.3%	89.0%
MMU V1.0					
FAR	IC8s	S1Dp1%	S1Dp5%	S1Dp10%	S1Dp15%
0%	84.5%	49.8%	68.8%	73.8%	76.8%
0.85%	85.8%	52.5%	71.3%	75.8%	78.8%
11.1%	86.0%	53.3%	71.8%	76.3%	79.3%

the recognition results in the following. Table 3 shows the results of the serial approach with 1D signatures and using $p = 1, 5, 10, 15$ compared to the iris code 8-shifts variant for the three databases.

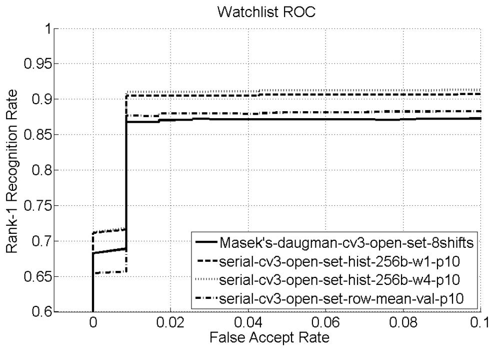
We notice, that the CASIA V1.0 dataset yields overall better results than the CASIA V3.0 and MMU V1.0 datasets. This fact may be due to the fact that the pupil areas of the CASIA V1.0 dataset have been post-processed and set to a uniformly dark gray value, which eases the segmentation process and therefore reduces errors coming from incorrect segmentation.

For the CASIA V1.0 dataset, only the $p = 15$ serial variant (S1Dp15) yields better identification rates than the iris code approach (IC8s). For higher false accept rates (FAR=11%), the $p = 10$ variant leads to similar results as compared to the iris code reference case.

For the CASIA V3.0 dataset and zero false accepts, the $p = 5$ serial variant yields the best identification rate (76.1%) and also $p = 1$ is surprisingly better than the iris code approach. The decreasing identification accuracy for increasing values of p may be surprising at first, however, these results are due to the fact that a larger set of preselected templates can increase the chance for false positives, which have been excluded for lower values of p. For higher false accept rates (FAR), the $p = 15$ percent variant produces the best results (89% @ 0.85% FAR) while also $p = 10$ performs better as compared to the iris code reference and still $p = 5$ delivers comparable recognition performance.



(a) CASIA V1.0



(b) CASIA V3.0

Figure 3: Performance of the 2D serial approach compared to the iris code approach for the CASIA datasets.

For both datasets these recognition results are not obvious since a coarse pre-selection could be expected to exclude potential genuine templates too. In contrary, the pre-selection helps to avoid false positive matches. This may be explained by the fact that the Du approach yields good results for partial iris recognition (e.g., heavy eyelid occlusion or segmentation errors) and noisy images (Du et al., 2006).

In contrast, the results for the MMU dataset are worse for the serial combinations as compared to the classical iris code approach for all values of $p = 1, 5, 10, 15$. We also notice that recognition accuracy increases monotonically with increasing p so that we can expect at least equal performance for larger values of p.

In Figure 3 we further analyze the possible improvement of the serial approach for $p = 10$ by using 2D signatures and weighting of inner rows with weight 4. For both datasets shown (CASIA V1.0 and

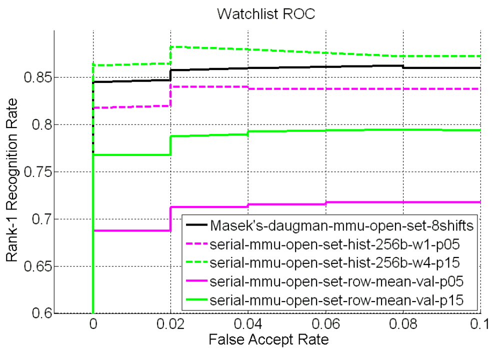


Figure 4: Performance of the 2D serial approach compared to the iris code approach for the MMU dataset.

V3.0), the 2D variant (hist-256b-w1) improves performance compared to 1D signatures considerably, while weighting (hist-256b-w4) only results in minor improvement. The performance of the serial approach with 2D signatures is better as the iris code technique for all cases for both CASIA datasets.

Figure 4 shows that also for the MMU dataset improvements in terms of recognition performance as compared to the iris-code approach are possible if 2D signatures are used and p is set sufficiently high. We observe that for $p = 15$ and 2D signatures with weighting the iris code approach is outperformed across the entire range of considered false accept rates. Note that this improvement still is achieved at a reduction of computational effort by a factor of 3.5 (compare Table 2).

4 CONCLUSIONS

As expected, we are able to reduce computational demands with our proposed serial classifier combination considerably. At a comparable recognition accuracy we suffice with 20% - 30% or even less computation time for identification (the actual value depends on the specific dataset considered). Interestingly, we are even able to outperform the recognition accuracy of iris code based recognition, since the serial classifier combination technique turns out to be more robust against false acceptances. This is especially interesting, since we reveal that the rotation-invariant first stage of the serial combination is able to exclude candidates, which lead to false accepts in the entirely rotation-compensating iris-code approach.

ACKNOWLEDGEMENTS

This work has been partially supported by the Austrian Research Promotion Agency (FFG) FIT-IT Trust in IT-Systems project 819382.

REFERENCES

Daugman, J. (2004). How iris recognition works. *IEEE Transactions on Circiuts and Systems for Video Technology*, 14(1):21–30.

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

Gentile, J. E., Ratha, N., and Connell, J. (2009). An efficient, two-stage iris recognition system. In *Biometrics: Theory, Applications and Systems (BTAS'09)*, pages 1–5.

Matschitsch, S., Stögner, H., Tschinder, M., and Uhl, A. (2008). Rotation-invariant iris recognition: boosting 1D spatial-domain signatures to 2D. In Filipe, J., Cetto, J., and Ferrier, J.-L., editors, *ICINCO 2008: Proceedings of the 5th International Conference on Informatics in Control, Automation and Robotics*, volume SPSMC, pages 232–235. INSTICC Press.

Park, C.-H. and Lee, J.-J. (2006). Extracting and combining multimodal iris features. In *Proceedings of the 1st IAPR International Conference on Biometrics (ICB'06)*, number 3832 in Lecture Notes on Computer Science, pages 389–396.

Qui, X., Sun, Z., and Tan, T. (2007). Coarse iris classification by learned visual dictionary. In *Proceedings of the 2nd IAPR/IEEE International Conference on Biometrics (ICB'07)*, number 4642 in Lecture Notes on Computer Science, pages 770–779.

Ross, A., Nandakumar, K., and Jain, A. (2006). *Handbook of Multibiometrics*. Springer.

Sun, Z., Wang, Y., Tan, T., and Cui, J. (2005). Improving iris recognition accuracy via cascaded classifiers. *IEEE Transactions on Systems, Man and Cybernetics*, 35(3):435–441.

Uhl, A. and Wild, P. (2009). Parallel versus serial classifier combination for multibiometric hand-based identification. In Tistarelli, M. and Nixon, M., editors, *Proceedings of the 3rd International Conference on Biometrics 2009 (ICB'09)*, volume 5558 of *LNCS*, pages 950–959. Springer Verlag.

Vatsa, M., Singh, R., and Noore, A. (2005). Reducing the false rejection rate of iris recognition using textural and topological features. *Int. Journal of Signal Processing*, 2(2):66–72.

Yu, L., Wang, K., and Zhang, D. (2006). A novel method for coarse iris classification. In *Proceedings of the 1st IAPR International Conference on Biometrics (ICB'06)*, number 3832 in Lecture Notes on Computer Science, pages 404–410.

Zhang, P.-F., Li, D.-S., and Wang, Q. (2004). A novel iris recognition method based on feature fusion. In *Proceedings of the International Conference on Machine Learning and Cybernetics*, pages 3661–3665.