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Postprint

This is the accepted version of a paper presented at *3rd International Workshop on Biometrics and Forensics, IWBF 2015, Gjøvik, Norway, 3-4 March, 2015*.

Citation for the original published paper:

Alonso-Fernandez, F., Mikaelian, A., Bigun, J. (2015)

Comparison and Fusion of Multiple Iris and Periocular Matchers Using Near-Infrared and Visible Images.

In: *3rd International Workshop on Biometrics and Forensics, IWBF 2015* (pp. Article number: 7110234-). Piscataway, NJ: IEEE Press

<http://dx.doi.org/10.1109/IWBF.2015.7110234>

N.B. When citing this work, cite the original published paper.

Permanent link to this version:

<http://urn.kb.se/resolve?urn=urn:nbn:se:hh:diva-28021>

COMPARISON AND FUSION OF MULTIPLE IRIS AND PERIOCLAR MATCHERS USING NEAR-INFRARED AND VISIBLE IMAGES

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ABSTRACT

Periocular refers to the facial region in the eye vicinity. It can be easily obtained with existing face and iris setups, and it appears in iris images, so its fusion with the iris texture has a potential to improve the overall recognition. It is also suggested that iris is more suited to near-infrared (NIR) illumination, whereas the periocular modality is best for visible (VW) illumination. Here, we evaluate three periocular and three iris matchers based on different features. As experimental data, we use five databases, three acquired with a close-up NIR camera, and two in VW light with a webcam and a digital camera. We observe that the iris matchers perform better than the periocular matchers with NIR data, and the opposite with VW data. However, in both cases, their fusion can provide additional performance improvements. This is specially relevant with VW data, where the iris matchers perform significantly worse (due to low resolution), but they are still able to complement the periocular modality.

Index Terms— Iris, periocular, biometrics, near-infrared data, visible data, fusion.

1. INTRODUCTION

Periocular recognition has gained attention recently in the biometrics field, with a surprisingly high discrimination ability [1]. While face and irises have been extensively studied [2, 3], the periocular region has emerged as a promising trait for unconstrained biometrics, following demands for increased robustness of face or iris systems under less constrained conditions. Periocular refers to the face region in the immediate vicinity of the eye, including the eye, eyelids, lashes and eyebrows. It is available over a wide range of distances even when the iris texture cannot be reliably obtained due to low resolution (high distances) or under partial face occlusion (close distances) [4]. Also, the periocular region appears in iris images, so fusion with the iris texture has potential to improve the overall recognition. Woodard et al. [5] fused periocular and iris information from NIR portal data. Using a iris algorithm based on Gabor filters [6], they found that periocular identification performed better than iris in the difficult conditions of portal data (at-a-distance and

in-motion subjects); and the fusion of the two modalities performed best. Also, Alonso-Fernandez and Bigun. [7] fused iris and periocular modalities using close-up NIR camera and VW webcam data. With NIR data, the iris matcher performed much better, and the fusion did not improve performance. With VW data, due to low image resolution, the iris matcher performed worse; however, the fusion of iris and periocular improved the recognition performance.

In this paper, we carry out an extensive comparison of the iris and periocular modality, as well as their fusion. We use three periocular and three iris matchers based on different features, and a comprehensive set of data coming from five different databases (three acquired with a close-up NIR camera, and two in VW light with a webcam and a digital camera). In our experiments, iris matchers are in general better than periocular matchers with NIR data, and the opposite with VW data. Previous studies indicate that the iris modality is more suited to the NIR illumination due to higher reflectivity of the iris tissue in this range [6], while the periocular modality is best for VW illumination due to the appearance of melanin-related differences of the skin that does not appear in the iris region [8, 9]. This is also mirrored in our fusion experiments, where we have observed that with NIR data, the fusion of iris systems alone produces the biggest performance improvement; on the contrary, with VW data, this happens by fusing periocular systems alone. Nevertheless, our results show that the fusion of periocular and iris modalities provide additional, non-negligible improvements both with NIR and VW data.

The rest of the paper is as follows. The periocular and iris matchers used are described in Sections 2 and 3, respectively. Section 4 describes the databases and experimental protocol. Results are presented in Sections 5 (individual systems) and 6 (fusion). Finally, conclusions are given in Section 7.

2. PERIOCLAR RECOGNITION SYSTEMS

This section describes the basics of the three machine experts used for periocular recognition.

Based on Symmetry Patterns (SAFE)

This system, recently presented in [10], is based on the Symmetry Assessment by Feature Expansion (SAFE) descriptors

Fig. 1. SAFE periocular matcher. Feature extraction process for one filter radius. The hue encodes the direction, and the saturation represent the complex magnitude.

proposed in [11]. An overview is given in Figure 1. The feature extraction method employed describes neighborhoods around keypoints by projection onto harmonic functions which estimates the presence of various symmetric curve families (Figure 2, top) around such keypoints. Keypoints are selected on the basis of a rectangular-shaped grid positioned in the eye center (Figure 3), with sampling points uniformly distributed. We use a relative low dense grid, since more dense grids do not necessarily lead to better performance [12], also allowing smaller feature sets and faster processing. We start by extracting the complex orientation map of the image. We then project $N_f = 9$ ring-shaped areas of different radii around selected keypoints onto an space of $N_h = 9$ harmonic functions. We use the result of scalar products of harmonic filters ψ_{mk} with the orientation image to quantify the amount of presence of pattern families as those shown in Figure 2 around each keypoint. The feature vector dimension describing a keypoint is given by an array **SAFE**. The elements $SAFE_{mk}$ are complex-valued and their magnitudes represent the amount of reliable orientation field within the annular ring $k = 1 \dots N_f$ explained by the $m = 1 \dots N_h$ symmetry basis. To match two complex-valued feature vectors $SAFE^r$ and $SAFE^t$, we use the triangle inequality as $M = \angle \langle SAFE^r, SAFE^t \rangle / \langle |SAFE^r|, |SAFE^t| \rangle$, with $M \in \mathbb{C}$. The argument $\angle M$ represents the angle between $SAFE^r$ and $SAFE^t$ (expected to be zero when the symmetry patterns detected coincide for reference and test feature vectors). The confidence is given by $|M|$. To include confidence into the angle difference, we use $MS = |M| \cos \angle M$. The resulting matching score $MS \in [-1, 1]$ is equal to 1 for coinciding symmetry patterns in the reference and test vectors (full match). Matching between two images is done by computing the score MS between corresponding points of the grid. All matching scores are then averaging, resulting in a single score between two given images.

Based on Gabor Features (GABOR)

This matcher is described in [12], which is based on the face detection and recognition system of [13]. It makes use of the same sampling grid of Figure 3, so features are extracted in the same keypoints. The local power spectrum of the image is sampled at each keypoint by a set of Gabor filters organized in 5 frequency channels and 6 equally spaced orientation chan-

Fig. 2. *Top:* Sample patterns of the family of harmonic functions used as basis of the SAFE matcher (with $m=-4:3$). *Mid-*
dle: One pattern per original (top) but in selected ring support $|\psi_{mk}|$. *Bottom:* Filters ψ_{mk} used to detect patterns above.

Fig. 3. Sampling grid showing different configurations with the databases used (images resized to the same height). Parameter d is the distance between adjacent points.

nels. The Gabor responses from all grid points are grouped into a single complex vector, which is used as identity model. Matching between two images is using the magnitude of complex values. Prior to matching with magnitude vectors, they are normalized to a probability distribution (PDF), and matching is done using the χ^2 distance [14].

Based on SIFT Keypoints (SIFT)

This matcher is based on the SIFT operator [15]. SIFT keypoints are extracted only in the region given by the square retinotopic sampling grid (Figure 3). The recognition metric is the number of matched keypoints, normalized by the average number of detected keypoints in the two images under comparison. We use a free implementation of the SIFT algorithm¹, with the adaptations described in [16]. Particularly, it includes a post-processing step to remove spurious matching points using geometric constraints (Figure 4).

3. IRIS RECOGNITION SYSTEMS

We conduct matching experiments of iris texture using three different systems based on 1D log-Gabor filters (LG) [17], Discrete-Cosine Transform (DCT) [18], and the SIFT operator [15] (SIFT). The LG implementation is from Libor Masek code [17] and the DCT is from USIT - University of Salzburg Iris Toolkit software [19]. In the LG and DCT algorithms, the iris region is first unwrapped to a normalized rectangle using the Daugman's rubber sheet model [6]. Normalization produces a 2D array of 20×240 , height $\times$ width, (LG) and 64×512 (DCT), with horizontal dimensions of angular res-

¹ <http://vision.ucla.edu/vedaldi/code/sift/assets/sift/index.html>

Fig. 4. Matching of two iris images using SIFT operators without and with removing false matches by geometrical constraints (left and right, respectively). Trimming is done by removing matching pairs whose orientation and length differ substantially from the predominant orientation and length computed from all the matching pairs.

olution and vertical dimensions of radial resolution. Feature encoding is implemented according to the different extraction methods. Both the LG and DCT algorithms employ binary iris codes, which are matched using the Hamming distance. The SIFT iris matcher is the same of Section 2, but with the keypoints extracted from the iris region only.

4. DATABASES AND EXPERIMENTAL PROTOCOL

As experimental dataset, we use data from the following databases: BioSec [20], CASIA-Iris Interval v3 [21], IIT Delhi v1.0 [22], MobBIO [23] and UBIRIS v2 [24]. A summary of the used subset of these databases is given in Table 1. Three are acquired with NIR illumination, and two with visible light. All NIR databases use a close-up iris sensor, and are mostly composed of good quality, frontal view images. MobBIO database has been captured with a Tablet PC (Asus TE300T), with two different lightning conditions, variable eye orientation and occlusion levels (distance to the camera was kept constant). UBIRIS v2 has been acquired with a digital camera (Nikon E5700), with the first session under controlled conditions, simulating an enrollment stage; and the second session under a ‘real-world’ setup, with natural luminosity, heterogeneity in reflections and contrast, defocus, occlusions and off-angle images. Also, images of UBIRIS v2 have been captured from various distances. The five databases have been annotated manually by an operator [25], meaning that the radius and center of the pupil and sclera circles are available, which are used as input for the experiments. The groundtruth histograms are given in Figure 5. This segmentation groundtruth is available for download² under the name of Iris Segmentation Database (IRISSEG) [25].

We carry out verification experiments. We consider each eye as a different user (the number of available eyes per database is shown in Table 1). Genuine matches are as follows. When the database has two sessions, we compare all images of the first session with all images of the second session. Otherwise, we match all images of a user among them, avoiding symmetric matches. Concerning impostor

Fig. 5. Histograms of pupil and sclera radius of the databases used, as given by the groundtruth [25].

experiments, the first image of a user is used as enrolment sample, and is matched with the second image of the remaining users. When the database has two sessions, the enrolment sample is selected from the first session, and query samples from the second session. The number of matching scores per database is given in Table 1. For the fusion experiments between different matchers, we use linear logistic regression fusion. Given N matchers which output the scores $(s_{1j}, s_{2j}, \dots, s_{Nj})$ for an input trial j , a linear fusion of these scores is: $f_j = a_0 + a_1 \cdot s_{1j} + a_2 \cdot s_{2j} + \dots + a_N \cdot s_{Nj}$. The weights $a_0, a_1, \dots, a_N$ are trained via logistic regression as described in [26]. We use this trained fusion approach because it has shown better performance than simple fusion rules (like the mean or the sum rule) in previous works [26].

database	subjects	eyes	sessions	images	image size	lightning	Matching scores	
							genuine	impostor
Biosec	75	150	2	1200	480 × 640	NIR	2400	22350
Casia Interval v3	249	396	2	2655	280 × 320	NIR	9018	146667
IIT Delhi v1.0	224	448	1	2240	240 × 320	NIR	4480	200256
MobBIO	100	200	1	800	200 × 240	visible	1200	39800
UBIRIS v2	104	208	2	2250	300 × 400	visible	15750	22350

Table 1. Databases used and experimental protocol.

5. RESULTS: INDIVIDUAL MODALITIES

Due to different image size (Table 1), filter wavelengths of the GABOR periocular system span from 4 to 16 pixels with VW and 16 to 60 with NIR databases. For each database, this covers approximately the range of pupil radius of all its images (Figure 5). For the SAFE matcher, based on [10], the range of radii of the filters is 10 to 64 with VW and 5 to 60 with NIR databases. We report verification results of the periocular and iris matchers in Table 2. We consider two cases with the periocular system: *a*) using the original images, and *b*) resizing the images so that the iris appears with constant (average) sclera radius (the latter will be analyzed later in this section). Concerning the iris matchers, their performance is, in general, much better than the periocular matchers with NIR

²http://islab.hh.se/mediawiki/index.php/Iris_Segmentation_Groundtruth and www.wavelab.at/sources

Fig. 6. Left part of each subplot: grid positioning in two images from the same user having different eye resolution. Right part: images resized to have the same sclera radius. Distance between sampling points is 32. Images are from UBIRIS.

databases. This is expected, since iris systems usually work better in NIR range [6], and it confirms other studies using only BIOSEC and MobBIO databases [7]. On the other hand, the periocular matchers perform better than the iris matchers with VW data. It can also be possible that, since the iris region appears very small in VW images, no reliable iris information can be extracted. In these cases, the (bigger) periocular region provides a much richer source of identity data, demonstrating the capability of such modality.

Regarding absolute numbers, it is relevant that LG and DCT iris matchers have the best performance with NIR data, but DCT matcher does much worse than LG with VW data (see MobBIO and UBIRIS). Concerning the SIFT matcher, it is always the best in the periocular modality (regardless of the use of NIR or VW data), but it becomes the worse with the iris modality (at least with NIR data). It is also interesting that the SIFT ‘iris’ matcher is better than the SIFT ‘periocular’ matcher with NIR data, but the opposite happens with VW data. Recall from Sections 2 and 3 that ‘iris’ keypoints are a subset of the ‘periocular’ keypoints set. Results of Table 2 suggest that the amount of keypoints from the iris region of VW images are not sufficient to provide reliable discriminative capabilities, and more keypoints from the (bigger) periocular region are needed. This has sense since the iris region in VW images is smaller, see Figure 5. On the contrary, the iris region of NIR images is big enough to provide sufficient SIFT keypoints, whereas going for the bigger periocular region actually decreases the verification performance. The case of IITD database, on the other hand, is particular, with both the iris and periocular matchers showing very low error rates. From Table 1 and Figure 5 we observe that the sclera circle in this database is in many cases as big as the image itself, therefore the iris region is occupying most of the image. In these conditions, the iris and periocular matchers are extracting features from regions with a significant overlap.

From Table 2 (top, left) we observe a very poor performance of the periocular systems with UBIRIS using the original images (EER of 32% or more). This database has a wide variability in eye resolution (Figure 5) due to acquisition at different distances. As a result, the points of the grid used by the GABOR and SAFE algorithms (which is of constant dimensions) are not capturing consistently the

same regions (observe Figure 6). Severe variations in scale can also be jeopardizing the removal of spurious matches done in the SIFT matcher (Figure 4). Motivated by these facts, we have conducted experiments where all images of the database are resized via bicubic interpolation to have the same sclera radius. For each database, we choose as target radius the average sclera radius of the whole database, given by the groundtruth. Verification results after this procedure are given in the top right part of Table 2. As it can be observed, EER with UBIRIS is reduced significantly with this strategy for all the periocular matchers. There is also a substantial reduction in the error rates of MOBBIO, which, despite attempts of capture at a constant distance, its range of sclera radii is double in size than NIR databases (Figure 5). It is also of relevance that for the NIR databases, there is no substantial change in performance after images have been resized. This means that the periocular recognition systems are able to cope with small changes in the scale (size) of the eye. On the other hand, the performance with UBIRIS after image resizing is still much worse than the other databases, which could be attributed to the remaining perturbations (lighting changes, off-angle, etc.), which are more severe than in any other database. It is also relevant that after eliminating scale influences, periocular performance with MOBBIO is comparable to the NIR databases, despite having smaller eye images. This demonstrates the possibilities of the periocular modality with low resolution images under VW illumination, an scenario where this modality is expected to show its maximum potential w.r.t the iris modality.

6. RESULTS: IRIS AND PERIOCCULAR FUSION

We then perform fusion experiments of the available matchers (3 periocular and 3 iris). We choose periocular scores using image resize. We have tested all the possible fusion combinations, with the best results reported in Table 3 and Figure 7. By looking at Figure 7, it can be seen that the biggest performance improvement occurs just after the fusion of 2 systems (or 3 at most). The inclusion of additional systems does not produce the same amount of improvement. From Table 3, we observe that with NIR databases, there is tendency to choose iris systems first for the fusion; on the other hand, with VW databases, periocular systems are chosen first. This indicates that the fusion of iris systems only (NIR) or periocular systems only (VW) leads to the highest improvements in performance. As previous studies indicate, the iris modality is more suited for NIR illumination due to higher reflectivity of the iris tissue in this range [6], whereas the periocular modality work best on VW images because visible-light images show melanin-related differences of the skin that does not appear in iris images [8, 9]. Our study, which include multiple datasets captured both with NIR and VW data, and several iris and periocular matchers based on different features, supports these previous findings. However, some remarks can be done

to these tendencies. For example, the periocular matchers achieve comparable performance over some NIR (BIOSEC, CASIA) and VW (MOBBIO) databases. This indicates that with appropriate developments, they can also be used with NIR illumination, with the advantage of not needing segmentation [7]. Also, the fusion of iris and periocular modalities has the potential of improving performance. For example, the fusion of two iris systems with BIOSEC leads to an EER of 0.87% (improvement of about 22% w.r.t. the best individual system), but the fusion of five systems (which includes both iris and periocular matchers) leads up to an improvement of 33% in the EER. Similar observations can be made for the remaining databases, meaning that the fusion of periocular and iris modalities provides additional, non-negligible, improvements. This is specially relevant with VW databases. Here, iris matchers perform significantly worse than periocular matchers. One reason could be the smallest eye area (Figure 5), which makes difficult to extract reliable identity information from the (even smaller) iris texture. In such conditions, however, the iris texture is still capable of complementing the periocular systems.

When it comes to the complementarity between different systems, it can be observed in Table 3 that it is not until the SAFE system appears combined either with SIFT ‘periocular’ or GABOR (or with both) that the biggest improvements are obtained. With BIOSEC, for example, the combination of 3 systems (which includes GABOR only) has an EER improvement of 27.68% but when the three periocular systems appear in the combination, the improvement goes up to 33.04%. With MOBBIO, the best individual system is SIFT ‘periocular’, and its combination with SAFE reduces the EER in 19.87%. Same observations can be done with UBIRIS: the best individual system (GABOR) combined with SIFT ‘periocular’ reduces the EER in 25.97%, and the inclusion of SAFE allows to improve the EER up to 32.83%. These results mean that SAFE is complementary to both SIFT and GABOR systems, indicating that SAFE measures something that neither SIFT nor GABOR provides. This is a support for the view that SIFT and GABOR measure texture properties (which provides translation invariance) whereas SAFE measures object properties (iso-curve shapes in this case) in image neighborhoods [11].

7. CONCLUSIONS

Periocular recognition has emerged as a promising trait for unconstrained biometrics [1]. It can be easily obtained with existing setups for face and iris, and it appears in iris images, so its fusion with the iris texture has a potential to improve the overall recognition [5, 7]. In this paper, we evaluate three periocular matchers and three iris matchers based on different features. We use five databases for our experiments, three acquired with a close-up NIR camera, and two in VW light with a webcam and a digital camera. It is observed that the

database	PERIOCCULAR MATCHERS					
	ORIGINAL IMAGE SIZE			RESIZED IMAGE		
	GABOR	SAFE	SIFT	GABOR	SAFE	SIFT
biosec (nir)	10.77	11.59	8.5	10.91	10.75	9.08
casia (nir)	14.81	8.45	7.56	15.4	8.88	7.52
iitd (nir)	2.67	1.88	0.8	3.04	2.25	0.87
mobbio (vw)	15.17	15.86	13.7	12.66	9.87	8.73
ubiris (vw)	36.15	53.53	32.93	24.4	24.56	25.43

database	IRIS MATCHERS		
	LG	DCT	SIFT
biosec (nir)	1.12	2.31	4.44
casia (nir)	0.67	1.73	3.56
iitd (nir)	0.59	0.96	0.72
mobbio (vw)	18.81	31.1	26.95
ubiris (vw)	35.61	47.46	37.33

Table 2. Verification results in terms of EER. The best periocular and iris matcher for each database is marked in bold.

Fig. 7. Verification results (EER) for an increasing number of fused systems. The figure shows the best EER achieved for each number of fused systems (see Table 3).

performance of the iris matchers is, in general, much better than the periocular matchers with NIR data, and the opposite with VW data. This is in tune with previous studies which indicate that the iris modality is more suited to NIR illumination [6], whereas the periocular modality is best for VW illumination [8, 9]. Another interesting findings have been also observed. For example, two of the iris matchers have the best performance with NIR data, but one is worse than the other with VW data. This and other results obtained suggest that not all features are equally suitable for the iris or periocular region, or for NIR or VW data. We have also observed that the periocular matchers are robust to a certain degree of scale changes in the eye image. We also carry out fusion experiments, with results showing that with NIR databases, there is tendency towards choosing iris systems first for the fusion; as for VW databases, periocular systems are chosen first. This supports the above observation regarding which modality is more suited to each kind of illumination. Nevertheless, the fusion of periocular and iris modalities together provides additional, non-negligible, improvements. This is specially interesting with VW databases, where the iris matchers perform

database	systems	PERIOC			IRIS			FUSION
		GABOR	SAFE	SIFT	LG	DCT	SIFT	
biosec (nir)	1				*			1.12%
	2				*	*		0.87% (-21.96%)
	3	x			*	*		0.81% (-27.68%)
	4	x	x		*	*		0.83% (-25.89%)
	5	x	x	x	*	*		0.75% (-33.04%)
	6	x	x	x	*	*	*	0.81% (-27.68%)
casia (nir)	1				*			0.67%
	2				*	*		0.57% (-14.99%)
	3				*	*	*	0.53% (-20.9%)
	4		x	x	*	*		0.52% (-22.39%)
	5		x	x	*	*	*	0.51% (-23.31%)
	6	x	x	x	*	*	*	0.51% (-23.31%)
itid (nir)	1				*			0.59%
	2			x	*			0.38% (-35.59%)
	3		x	x	*			0.38% (-35.59%)
	4	x	x	x	*			0.40% (-32.20%)
	5		x	x	*	*	*	0.42% (-27.49%)
	6	x	x	x	*	*	*	0.42% (-27.49%)
mobio (vw)	1			x				8.73%
	2		x	x				6.99% (-19.87%)
	3		x	x	*			6.83% (-21.76%)
	4	x	x	x	*			6.75% (-22.68%)
	5	x	x	x	*	*		6.75% (-22.68%)
	6	x	x	x	*	*	*	6.83% (-21.76%)
ubiris (vw)	1	x						24.4%
	2	x		x				18.07% (-25.97%)
	3	x	x	x				16.39% (-32.83%)
	4	x	x	x	*			15.67% (-35.78%)
	5	x	x	x	*	*		15.43% (-36.76%)
	6	x	x	x	*	*	*	15.17% (-37.85%)

Table 3. Verification results in terms of EER for an increasing number of fused systems. The best EER achieved for each case is given, together with the systems involved in the fusion. The relative EER variation with respect to the best individual system (shown in the last row) is given in brackets. We also mark in bold the best fusion combination for each database.

significantly worse than the periocular ones (due to very small iris size), but iris systems however are able to complement the periocular systems during the fusion.

Our future work includes the inclusion of enhancement stages to cope with adverse acquisition conditions, specially with VW databases (scale changes, off-angle, uneven lighting, etc.). Another avenue of research, with some very recent research works, is the cross-spectral matching of NIR and VW images [27, 28] or the extraction of features based on their suitability for individual periocular areas and/or illumination [29].

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