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Near-Infrared and Visible Light Periocular Recognition with Gabor Features using Frequency-Adaptive Automatic Eye Detection

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Abstract

Periocular recognition has gained attention recently due to demands of increased robustness of face or iris in less controlled scenarios. We present a new system for eye detection based on complex symmetry filters, which has the advantage of not needing training. Also, separability of the filters allows faster detection via one-dimensional convolutions. This system is used as input to a periocular algorithm based on retinotopic sampling grids and Gabor spectrum decomposition. The evaluation framework is composed of six databases acquired both with near-infrared and visible sensors. The experimental setup is complemented with four iris matchers, used for fusion experiments. The eye detection system presented shows very high accuracy with near-infrared data, and a reasonable good accuracy with one visible database. Regarding the periocular system, it exhibits great robustness to small errors in locating the eye centre, as well as to scale changes of the input image. The density of the sampling grid can also be reduced without sacrificing accuracy. Lastly, despite the poorer performance of the iris matchers with visible data, fusion with the periocular system can provide an improvement of more than 20%. The six databases used have been manually annotated, with the annotation made publicly available.

Index Terms

Biometrics, periocular, eye detection, symmetry filters, iris, Gabor filters.

I. INTRODUCTION

Periocular recognition has gained attention recently in the biometrics field [1], [2], [3] with some pioneering works already in 2002 [4] (although authors here did not call the local eye area ‘periocular’). Periocular refers

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to the face region in the immediate vicinity of the eye, including the eye, eyelids, lashes and eyebrows. While face and irises have been extensively studied [5], [6], 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 [1]. With a surprisingly high discrimination ability, this region can be easily obtained with existing setups for face and iris, and the requirement of user cooperation can be relaxed. Some studies also suggest that it may be as discriminative by itself as the face as a whole [7], [8]. Also, the periocular region appears in iris images, so fusion with the iris texture has potential to improve the overall recognition [9]. It has also another advantages, such as its availability 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) [10].

In previous research [11], we proposed a periocular recognition system based on retinotopic sampling grids positioned in the pupil center, followed by Gabor decomposition at different frequencies and orientations. This setup have been used previously in texture analysis [12], facial landmark detection and face recognition [4], and real-time face tracking and liveness assessment [13], [14], with high discriminative capabilities. The periocular system proposed, which we evaluated on two databases with near-infrared (NIR) illumination, achieved competitive verification rates in comparison with existing periocular approaches [1]. As in most studies on periocular recognition, it also relied on selecting manually the location of the periocular region. In a posterior study [15], we proposed a system for eye localization based on complex symmetry filters. This system has the advantage of not needing training. Also, by using 2D separable filters, detection can be done quite fastly by few 1D convolutions. The proposed detection system was able to accurately detect the center of the eye when using good quality iris data acquired with close-up NIR cameras, and it still worked good with most difficult data acquired with a webcam. We also used this detection system as input of our periocular recognition system [15]. Results showed that the periocular system is quite robust to inaccuracies in detecting the center of the eye. We also carried out experiments with an iris texture matcher based on 1D log-Gabor filters. Despite the poor performance of this iris matcher with webcam images, we observed that the fusion with our periocular system resulted in an improved performance.

A. Contributions

This paper extends our two previous studies [15], [11] with new developments and experiments. The eye detection and periocular recognition systems are described more formally and in greater detail. We make use of a more comprehensive set of data coming from six different databases, in contraposition to our previous works, which only made use of two databases. We also add three new iris matchers to our experimental framework. The contribution of this paper is therefore multi-fold:

- 1) *Eye localization system based on symmetry filters.* The eye detection system has been improved with the addition of two steps. The first one is concerned with frequency estimation of the iris image [16], which in this case is referred to the average transition width of the image edges. Our eye detection system relies on the computation of the orientation field of the input image, which is implemented via convolutions with sampled gaussian-derivative filters that resemble the ordinary gradient in 2D [17]. In our previous work [11], the size

of the derivative filters (which corresponds to the width of the transitions that we want to detect) was set to a fixed value. With the new developments of this project, this parameter is fixed dynamically, based on the analysis of the input image. Reported results show that this results in an increased accuracy of our eye detection system. We also add an eyelash removal step via rank filters [18]. Eyelashes appear as prominent vertical edges in the orientation field, which may mislead the symmetry filter used for eye localization. A novelty w.r.t. the system proposed in [18] is that the size of the rank filter is also adjusted dynamically according to the estimated image frequency.

- 2) *Periocular recognition system based on sampling grids and Gabor spectrum decomposition.* The eye detection system is validated by using the detected eye center as input to our periocular recognition system. Two different sampling grid configurations are evaluated within the periocular recognition system, with dense and coarse sampling respectively. Based on our experiments, the density of the grid can be reduced without sacrificing too much accuracy, allowing computational savings in the feature extraction process. Although not directly comparable due to the use of different databases for the experiments, our system achieves competitive verification rates in comparison with existing periocular recognition approaches [1]. It is also shown that, when eye detection is done with sufficient accuracy, the recognition performance does not suffer a significant drop. This demonstrates that the periocular recognition system can tolerate small deviations in the position of the sampling grid. These results are in line with our previous observations [15], [11], that are validated here with a bigger test set. Lastly, a novel observation in this paper is that the periocular system is able to cope with certain degree of variation in the scale (size) of the eye.
- 3) *Fusion of periocular and iris information.* We evaluate four iris matchers based on 1D log-Gabor filters (LG) [19], local intensity variations in iris texture proposed by Christian Rathgeb et al. (CR) [20], Discrete-Cosine Transform (DCT) [21], and cumulative-sum-based grey change analysis proposed by Ko et al. (KO) [22], which are also fused with the periocular matcher. With NIR images, the iris matchers are, in general, considerably better in our experiments. On the other hand, they show a poorer performance with challenging images with VW illumination, but the fusion of iris and periocular systems can result in a considerable improvement. Despite the adverse acquisition conditions of the VW databases and the lower image resolution, it is worth noting that the (even smaller) iris texture is still able to provide complementary identity information to the periocular system.
- 4) *Evaluation on multiple databases captured both with near-infrared (NIR) and visible (VW) illumination.* In our previous papers [11], [15], we used only two databases on each case. Here, we use six different databases: BioSec baseline [23], CASIA-Iris Interval v3 of the Institute of Automation, Chinese Academy of Sciences (CASIA) [24], IIT Delhi v1.0 (IITD v1.0 database) of the Indian Institute of Technology (IIT) [25], MobBIO [26], UBIRIS v2 [27] and Notre Dame ND-IRIS-0405 [28]. Five of them have been captured with NIR sensors, while the other two, with sensors in VW range. These provide a comprehensive and heterogeneous test set, allowing extensive validation experiments of our developments.
- 5) *A ground-truth database of iris segmentation data.* The databases used in this paper have been annotated

manually by an operator, enabling accurate evaluation of the eye localization system. The annotation is also used as input of the periocular recognition system, allowing to test its robustness against inaccuracies in the detection of the eye center given by small errors of the eye detection system. The iris segmentation ground-truth have been made available to the research community ¹ under the name of Iris Segmentation Database (IRISSEG) [29].

Approach	Features	Training	Database	Best accuracy
Smeraldi, Bigun [4]	Gabor filters	M2VTS (202 VW images)	M2VTS (349 VW images) XM2VTS (2388 VW images)	99.3% (M2VTS) 99% (XM2VTS)
Uhl, Wild [30]	Viola-Jones detector of face sub-parts (OpenCV)	yes (n/a)	CASIA distance v4 (282 NIR images) Yale-B (252 VW images)	96.4% (NIR) 99.2% (VW)
Jillela <i>et al.</i> [10]	Correlation filter	1000 eye images	FOCS (404 NIR images)	95%
Our approach	Symmetry filters	no	6 iris datasets: 4 NIR, 2 VW (6932 NIR images, 3050 VW)	96% (NIR) 27% (VW)

TABLE I
OVERVIEW OF EXISTING AUTOMATIC EYE DETECTION WORKS.

B. Literature Review

1) *Eye Detection and Iris Segmentation:* Most studies of periocular recognition have not focused on detection of the periocular region (it is manually extracted), but on feature extraction only. Only Park *et al.* [2] used a Viola-Jones face detector [39] plus heuristics measurements (not specified) to extract the periocular region, so successful extraction relied on an accurate detection of the whole face. Traditional iris segmentation techniques based on edge information, such as the integro-differential operator [40] or the Hough transform [41], may not be reliable under challenging conditions either. Jillela *et al.* [10] evaluated these two iris segmentation approaches, together with newer approaches designed to handle challenging iris images, such as Geodesic Active Contours [42], Active Contours Without Edges [43], or Directional Ray Detection [44]. They used the difficult Face and Ocular Challenge Series (FOCS) database of periocular images, which were captured from subjects walking through a portal with NIR illumination in an unconstrained environment. With the traditional segmentation approaches [40], [41], segmentation accuracy was below 55%, whereas the other approaches were in the range 85-90%. The latter methods, however, are much more computationally expensive, as noted in [10].

Many iris segmentation techniques include rough location of dark pixels of the pupil by image thresholding [45]. However, this may not work in the presence of nonuniform illumination, or other adverse conditions where the periocular modality is precisely intended to achieve its highest potential. Some works deal with the issue of locating the eye position without relying on a full-face detector, with a summary of them given in Table I. The

¹http://islab.hh.se/mediawiki/index.php/Iris_Segmentation_Groundtruth and www.wavelab.at/sources

Approach	Features	Test Database	Best accuracy (single eye)		
				EER	Rank-1
Smeraldi, Bigun [4]	Gabor filters	M2VTS: Gabor (349 VW images)	M2VTS: Gabor	0.3%	n/a
Park <i>et al.</i> [2]	HOG, LBP, SIFT	FRGC v2.0 (1704 VW images)	FRGC: HOG	21.78%	66.64%
			FRGC: LBP	19.26%	72.45%
			FRGC: SIFT	6.96%	79.49%
Miller <i>et al.</i> [31]	LBP	FRGC (1230 VW images)	FRGC: LBP	0.09%	89.76%
		FERET (162 VW images)	FERET: LBP	0.23%	74.07%
Adams <i>et al.</i> [32]	GEFE+LBP	FRGC (820 VW images)	FRGC: GEFE+LBP	n/a	86.85%
		FERET (108 VW images)	FERET: GEFE+LBP	n/a	80.80%
Juefei-Xu <i>et al.</i> [33], [34]	LBP, WLBP, SIFT, DCT Walsh masks, DWT, SURF Law Masks, Force Fields Gabor filters, LoG	FRGC (16028 VW images)	FRGC: LBP+DWT	n/a	53.2%
		FG-NET (1002 VW images)	FRGC: LBP+DCT	n/a	53.1%
			FRGC: LBP+Walsh	n/a	52.9%
			FG-NET: WLBP	0.6%	100%
Bharadwaj <i>et al.</i> [35]	ULBP, GIST	UBIRIS v2 (7409 VW images)	UBIRIS: ULBP	n/a	54.30%
			UBIRIS: GIST	n/a	63.34%
			UBIRIS: ULBP+GIST	n/a	73.65%
Woodard <i>et al.</i> [8]	RG color histogram LBP	FRGC (4100 VW images)	FRGC: RG	n/a	96.1%
		MBGC (911 NIR images)	FRGC: LBP	n/a	95.6%
			FRGC: RG+LBP	n/a	96.8%
			MBGC: LBP	n/a	87%
Woodard <i>et al.</i> [9]	LBP	MBGC (1052 NIR images)	MBGC: LBP	0.21%	92.5%
Padole, Proença [36]	HOG, LBP, SIFT	UBIPr (10950 VW images)	UBIPr: HOG+LBP+SIFT	n/a	~20%
Hollingsworth <i>et al.</i> [37]	Human observers	NIR (120 subjects)	NIR: Human	n/a	92%
Hollingsworth <i>et al.</i> [3]	Human observers	VW (210 subjects)	VW: Human	n/a	88.4%
		NIR (210 subjects)	NIR: Human	n/a	78.8%
Mikaelyan <i>et al.</i> [38]	Symmetry patterns (SAFE)	BioSec (1200 NIR images)	BioSec: SAFE	12.81%	n/a
		MobBIO (800 VW images)	MobBIO: SAFE	11.96%	n/a
Our approach	Gabor features	BioSec (1200 NIR images)	BioSec: Gabor	10.56%	66%*
		Casia Interval v3 (2655 NIR images)	Casia: Gabor	14.53%	n/a
		IIT Delhi v1.0 (2240 NIR images)	IITD: Gabor	2.5%	n/a
		MobBIO (800 VW images)	MobBIO: Gabor	12.32%	75%*
		UBIRIS v2 (2250 VW images)	UBIRIS: Gabor	24.4%	n/a

TABLE II

OVERVIEW OF EXISTING PERIOULAR RECOGNITION WORKS. * RESULTS REPORTED IN [15].

work by Smeraldi and Bigun [13] made use of sampling grids and Gabor features in a similar manner that our periocular recognition system, but for eye detection and face tracking purposes. More recently, in [30], Uhl and Wild used the OpenCV implementation of Viola-Jones detectors of face sub-parts [39]. An accuracy of 96.4/99.2% in the combined detection of face parts was reported using NIR/VW face images, respectively. Eye detection can be also a decisive pre-processing task to ensure successful segmentation of the iris texture in difficult images. In [10], Jillela *et al.* used a correlation filter [46] to detect the eye center in their experiments with iris segmentation

algorithms mentioned above, achieving a 95% success rate. Despite this good result in indicating the approximate position of the eye, the accuracy of iris segmentation algorithms in the challenging FOCS database were between 51% to 90%, as indicated above.

2) *Features for Periocular Recognition*: An overview of existing approaches for periocular recognition is given in Table II. A recent review article has also been published in [1]. The most widely used approaches include Local Binary Patterns (LBP) [47] and, to a lesser extent, Histogram of Oriented Gradients (HOG) [48] and Scale-Invariant Feature Transform (SIFT) keypoints [49]. The use of different experimental setups and databases make difficult a direct comparison between existing works. The study of Park *et al.* [2] compares LBP, HOG and SIFT using the same data, with SIFT giving the best performance (rank-one recognition accuracy: 79.49%, Equal Error Rate (EER): 6.95%), followed by LBP (rank-one: 72.45%, EER: 19.26%) and HOG (rank-one: 66.64%, EER: 21.78%). Other works with LBPs, however, report rank-one accuracies above 90% and EER rates below 1% [31], [8], [9]. Gabor features were also proposed in a seminal work of 2002 [4], which has served as inspiration for our periocular system, although this work did not call the local eye area ‘periocular’. Here, the authors used three machine experts to process Gabor features extracted from the facial regions surrounding the eyes and the mouth, achieving very low error rates ($EER \leq 0.3\%$). We also have recently proposed a new system based on detection of local symmetry patterns (which we call SAFE features) [38], with reported EER rates of $\sim 12\%$. Lastly, in the extensive experiments of this paper with our Gabor-based periocular system, we report EER rates of 2.5-14.53% (NIR data) and 12.32-24.4% (VW data); and rank-one accuracies of 66% (NIR data) and 75% (VW data) [15]. Another important set of research works have concentrated their efforts in the fusion of different algorithms. For example, Bharadwaj *et al.* [35] fused Uniform LBPs (ULBP) with a global descriptor (GIST) consisting of perceptual dimensions related with scene description (image naturalness, openness, roughness, expansion and ruggedness). The best result, obtained by the fusion of both systems, was a rank-one accuracy of 73.65%. Juefei-Xu *et al.* [33], [34] fused LBP and SIFT with other local and global feature extractors including Walsh masks [50], Laws Masks [51], DCT [52], DWT [53], Force Fields [54], SURF [55], Gabor filters [56], and Laplacian of Gaussian. The best result obtained was a rank-one accuracy of 53.2% by fusion of DWT and LBP. Finally, Hollingsworth *et al.* [3] evaluated the ability of (untrained) human observers to compare pairs of periocular images, resulting in a rank-one accuracy of 88.4% (VW data) and 78.8% (NIR data).

Comparison of periocular with face or iris is also done in some cases. For example, Park *et al.* [2] reported a rank-one accuracy of 99.77% using the whole face, but when the full face is not available (simulated by synthetically masking the face below the nose region), accuracy fell to 39.55%. This points out the strength of periocular recognition when only partial face images are available, for example in criminal scenarios with surveillance cameras, where it is likely that the perpetrator masks parts of his face. In the same direction, Miller *et al.* [7] found that, at extreme values of blur or down-sampling, periocular recognition performed significantly better than face. On the other hand, both face and periocular matching using LBPs under uncontrolled lighting were very poor, indicating that LBPs are not well suited for this scenario. Finally, Woodard *et al.* [9] fused periocular and iris information from near-infrared (NIR) portal data. Using a traditional iris algorithm based on Gabor filters [40], they found that

periocular identification performed better than iris, and the fusion of the two modalities performed best. In most of these studies, periocular images were acquired in the VW range (see third row of Table II). Hollingsworth et al. [3] compared the use of visible-light and NIR light images in periocular and iris recognition. According to this study, periocular on VW images works better than on NIR because visible-light images show melanin-related differences that do not appear in NIR images. This is supported by other studies which use VW and NIR data simultaneously in the experiments [8], but this is not the case in the present paper, with our periocular system achieving better performance on some NIR periocular databases than on the VW ones. On the other hand, many iris systems work with NIR illumination due to higher reflectivity of the iris tissue in this range [40]. Unfortunately, the use of more relaxed scenarios will make NIR light unfeasible (e.g. distant acquisition, mobile devices, etc.) so there is a high pressure in the research field to the development of iris algorithms capable of working with visible light [57].

C. Paper Organization

This paper is organized as follows. Section II describes our eye detection system. The periocular recognition system and iris matcher used in this paper are described in Sections III and IV, respectively. Section V describes the evaluation framework, including the databases and protocol used. Results obtained are presented in Sections VI and VII, followed by conclusions in Section VIII.

Fig. 1. Example of symmetric patterns. Each column represents one family of patterns differing only by their orientation (given in column 2). The associated filter suitable to detect each family (Equation 2) is also indicated in row 2.

II. EYE LOCALIZATION

We propose the use of symmetry features for eye localization. Symmetry features enable the description of symmetric patterns such as lines, circles, parabolas, and so on (Figure 1). These features are extracted via symmetry filters, Equation 1, which output how much of a certain symmetry exist in a local image neighborhood [58], [17]. An overview of the system proposed for eye localization is shown in Figure 2.

Fig. 2. Eye detection using symmetry filters. The hue in color images encodes the direction, and the saturation represents the complex magnitude. To depict the magnitude, they are re-scaled, so the maximum saturation represents the maximum magnitude, while black represents zero magnitude. Zero angle is given by red color. It can be observed that I_{20} shows a prominent region in red color around the neighborhood of the eye center. The detected eye center is marked in the original iris image too. Iris image is from CASIA-Iris Interval v3 database.

A. Symmetry filters

Symmetry filters are a family of filters computed from symmetry derivatives of Gaussians. The n^{th} symmetry derivative of a Gaussian, $\Gamma\{n, \sigma^2\}$, is obtained by applying the partial derivative operator $D_x + iD_y = (\partial/\partial x) + i(\partial/\partial y)$, called 1st symmetry derivative, to a Gaussian:

$$\Gamma\{n, \sigma^2\} = \begin{cases} (D_x + iD_y)^n g(x, y) & (n \geq 0) \\ (D_x - iD_y)^{|n|} g(x, y) & (n < 0) \end{cases} \quad (1)$$

Since $D_x + iD_y$ and $(-\frac{1}{\sigma^2})(x + iy)$ behave identically when acting on a Gaussian [58], [17], Equation 1 can be rewritten as

$$\Gamma\{n, \sigma^2\} = \begin{cases} (-\frac{1}{\sigma^2})^n (x + iy)^n g(x, y) & (n \geq 0) \\ (-\frac{1}{\sigma^2})^{|n|} (x - iy)^{|n|} g(x, y) & (n < 0) \end{cases} \quad (2)$$

The interest is that these symmetry derivatives of Gaussians are able to detect patterns as those of Figure 1 through the computation of the second order complex moment of the power spectrum via [17]

$$I_{20} = \langle \Gamma\{n, \sigma_2^2\}, h \rangle \quad (3)$$

where h is the complex-valued orientation tensor field given by

$$h = \langle \Gamma\{1, \sigma_1^2\}, f \rangle^2 \quad (4)$$

and f is the image under analysis [17]. Parameter σ_1 defines the size of the derivation filters used in the computation of image h , whereas σ_2 , used in the computation of I_{20} , defines the size extension of the sought pattern.

For each family of symmetric patterns, there is a symmetry filter $\Gamma^{\{n,\sigma^2\}}$ (indexed by n) suitable to detect the whole family [59]. Figure 1 indicates the filters that are used to detect each family. The local maxima in $|I_{20}|$ gives the location, whereas the argument of I_{20} at maxima locations gives the group orientation of the detected pattern (except for the first family in Figure 1, $n=-2$, where the ‘orientation’ represents the chirality of the curves). Therefore, I_{20} encodes how much of a certain type of symmetry exists in a local neighborhood of the image f . In addition, a single symmetry filter $\Gamma^{\{n,\sigma^2\}}$ is used for the recognition of the entire family of patterns, regardless of their orientation (or chirality). Symmetry filters have been successfully applied to a wide range of detection tasks such as cross-markers in vehicle crash tests [60], core-points and minutiae in fingerprints [61], [62], or iris boundaries [63]. The beauty of this method is even more emphasized by the fact that I_{20} is computed by filtering in Cartesian coordinates without the need of transformation to curvilinear coordinates (which is implicitly encoded in the filter).

B. Eye detection process

We use the filter of order $n = -2$ to detect the eye position in a given image. By assuming that iris boundaries can be approximated as circles, the eye can be detected with the pattern of concentric circles shown in Figure 1 (top left). Despite the inner (pupil) and outer (sclera) boundaries of the iris are not concentric, we exploit the evidence that the pupil is fully contained within the sclera boundary, with the center of both circles in close vicinity [40]. Due to the separable property of 2D gaussians, the filter can be re-written as

$$\Gamma^{\{-2,\sigma^2\}} = \left(-\frac{1}{\sigma^2}\right)^2 (x - iy)^2 g(x) g(y) = \left(-\frac{1}{\sigma^2}\right)^2 (x^2 g(x) g(y) - y^2 g(y) g(x) - i2xg(x) yg(y)) \quad (5)$$

so the 2D convolutions can be computed by several 1D convolutions, achieving a considerable higher speed. Also, in computing h , 1D convolutions can be used, since

$$\Gamma^{\{1,\sigma^2\}} = \left(-\frac{1}{\sigma^2}\right)^2 (x + iy) g(x) g(y) = \left(-\frac{1}{\sigma^2}\right)^2 (xg(x) g(y) + iyg(y) g(x)) \quad (6)$$

After the computation of I_{20} , we search for local maxima in $|I_{20}|$ with a window of size 7×7 . The maximum with highest magnitude is selected as the center of the eye. Evidence of the pattern of concentric circles is given by an argument of the complex filter response equal to zero (2π in Figure 1). Thus, only maxima with absolute angle below a certain threshold are considered. An example of the detection process can be seen in Figure 2.

C. Image frequency estimation

Computation of the orientation field via Equation 4 is achieved by convolution of the input image f with the first order gaussian-derivative filter:

$$\Gamma\{1, \sigma^2\} = (D_x + iD_y)g(x, y) = \left(-\frac{1}{\sigma^2}\right)^2 (x + iy)g(x, y) \quad (7)$$

This symmetry derivative filter resembles the ordinary gradient in 2D [17]. Parameter σ controls the size of the derivation filters in the computation of the image h . This size, in turn, is related with the width of the edge transition that the filter will be able to detect (Figure 3, right). We give in Figure 4 an example of the orientation field obtained from an iris image with different σ . As can be observed, using a low value of σ results in parts of the sclera edge undetected. It also results in too much noise in the image, since the derivative filter is sensitive to edges of small width, which typically are the product of quick noisy oscillations. On the contrary, using a high value of σ has the undesirable effect of making the detected edges too wide, which may merge some edges which are close to each other. This can be appreciated in the pattern of light reflections within the pupil, which become blurred.

In our previous work [15], the value of σ was set heuristically to a fixed value. In this paper, we propose a method to estimate the average width of the transitions found in the edges of the image, which will be used to set σ . This will allow to customize the size of the derivative filters to each individual image. For this purpose, we make use of the method proposed in [16] to compute the image frequency map. This method is tailored to compute the local frequency of 2D sinusoidal waves (Figure 3, left). Here, we model the target edge transitions in iris images as a Cumulative Distribution Function (CDF) of a gaussian, which in 1D is given by (Figure 3, right):

$$\Phi(x) = 0.5 \left[1 + \operatorname{erf} \left(\frac{x}{\sqrt{2}\sigma} \right) \right] \quad (8)$$

It can be seen in Figure 3 that the width T of the CDF transition corresponds to approximately $3 \times \sigma$ to each side of the origin. Therefore, we define:

$$T = 6 \times \sigma \quad (9)$$

The algorithm of [16] is used to estimate the width of the CDF transition as follows. We provide as input a set of 2D CDFs as those shown in Figure 3, right, with different transition widths $(T_1, T_2, \dots, T_N)$, for which we obtain an estimated frequency value $(F_1, F_2, \dots, F_N)$ in the point marked with '+'. The correspondence between the output and the input parameters is then found by training a second-order polynomial: $T'(F) = aF^2 + bF + c$. We allow the parameter T_i to vary between 2 and 22, which is a reasonable range for edge transitions in an iris image. Given an input iris image, we then apply this algorithm pixel-wise, see an example in Figure 2. A global edge transition value of the whole image is finally computed by averaging the value of each pixel.

D. Eyelash removal

Eyelashes appear as prominent vertical edges in the orientation field, which may mislead the symmetry filter used for eye localization. We incorporate an eyelash removal step based on the method proposed in [18]. For this purpose, prior to computation of the orientation field (Equation 4), a 1D rank filter is applied to the image. A rank filter is

Fig. 3. Left: planar 2D sinusoid with absolute frequency $\omega_o = 2\pi/12$. Right: 2D gaussian Cumulative Distribution (CDF) with transition of width $T=24$ ($\sigma=24/6=4$). On the right part of each subplot, it is shown the cross-section across the horizontal red line. For the CDF, cross-sections with different values of σ are also shown.

Fig. 4. Computation of the complex orientation field with different sizes of the derivation filters. $T=8.23$ is the average width of the image edges found with the algorithm of Section II-C.

a filter whose response is based on ranking (ordering) the pixels contained in the image area encompassed by the filter. A 1D rank- p filter of length $1 \times L$ will replace the center pixel by the p th gray level in the L -neighborhood of that pixel. After applying this filter, most eyelashes will be weakened or even eliminated (Figure 2). A value of $L = 7$ and $p = 2$ is proposed in [18], which will be used in this paper. In addition, we propose to use a value of L proportional to the estimated image frequency of the previous step.

III. PERIOULAR RECOGNITION SYSTEM

For periocular recognition, we use the system proposed in [11], which is based on the face detection and recognition system of [13], [4]. Input images are analyzed with a retinotopic sampling sensor, whose receptive fields consist in a set of modified Gabor filters designed in the log-polar frequency plane. The system is described next.

A. Sampling Grid

Our periocular system makes use of a sparse retinotopic sampling grid positioned in the eye center. The grid has rectangular geometry, with sampling points distributed uniformly (Figure 5). At each point, a Gabor decomposition of the image is performed, see Section III-B. The sparseness of the sampling grid allows direct Gabor filtering

in the image domain without needing the Fourier transform, with significant computational savings [4] and even feasibility in real time [14]. We evaluate two different grid configurations (see Figure 5 and Table III), one with a dense sampling, and another with a coarse sampling. Parameter d_i indicates the distance between adjacent sampling points. This distance is constant for all images of the same database, so dimensions of the grid are not adapted to the scale of the input eye image. Due to different image size (Table IV), dimensions of the sampling grid are set accordingly for each database. Images in UBIRIS show the eyebrows in many cases, so the grid has been made large in both vertical and horizontal directions to capture such region. With the other databases, the grid has been designed in such way that the eyelids and eyelashes (vertical direction) and the eyelids corners (horizontal direction) are sufficiently covered, whenever possible. The latter cannot be achieved with CASIA and IITD however, since eyelids corners fall outside the image limits in most cases.

B. Gabor Decomposition of the Power Spectrum

The local power spectrum of the image is sampled at each cell of the grid by a set of modified Gabor filters organized in 5 frequency channels and 6 equally spaced orientation channels. For a filter tuned to orientation φ_0 and angular frequency $\omega_0 = \exp(\xi_0)$:

$$G(\xi, \varphi) = A \exp\left(-\frac{(\xi - \xi_0)^2}{2\sigma_\xi^2}\right) \exp\left(-\frac{(\varphi - \varphi_0)^2}{2\sigma_\varphi^2}\right) \quad (10)$$

where A is a normalization constant and (ξ, φ) are the log-polar frequency coordinates, with $\xi = \log|\vec{\omega}|$ and $\varphi = \tan^{-1}(\omega_x, \omega_y)$. Gabor responses are grouped into a single complex vector with $n=5 \times 6$ values per sampling grid, which is used as identity model. Matching between two images is done using the magnitude of complex values. Prior to matching with magnitude vectors, they are normalized to a probability distribution (PDF) by dividing each element of the vector by the sum of all vector elements, and matching is done using the χ^2 distance [64]. In our previous works [15], [11], we accounted for rotation by shifting the sampling grid of the query image in counter- and clock-wise directions, and selecting the lowest matching distance. However, we observed that no significant improvement is achieved, allowing computational savings by removing such step. Therefore, rotation compensation will not be performed in this paper.

IV. BASELINE IRIS MATCHERS

We conduct matching experiments of iris texture using four different systems based on 1D log-Gabor filters (LG) [19], local intensity variations in iris textures (CR) [20], Discrete-Cosine Transform (DCT) [21], and cumulative-sum-based grey change analysis (KO) [22]. We have used the LG implementation of Libor Masek [19], while the other three algorithms are from the USIT - University of Salzburg Iris Toolkit software package [65]. In the four algorithms, the iris region is first unwrapped to a normalized rectangle using the Daugman's rubber sheet model [40]. Normalization produces a 2D array (of 20×240 , height $\times$ width, in the LG and 64×512 in the other three algorithms), with horizontal dimensions of angular resolution and vertical dimensions of radial resolution. Feature

Fig. 5. Sampling grid showing different configurations with the databases used in this paper (images are resized to the same height).

	BIOSEC	CASIA	IITD	MOBBIO	UBIRIS
DENSE SAMPLING					
distance (d_1)	30	30	30	16	16
points	$13 \times 19 = 247$	$9 \times 11 = 99$	$9 \times 13 = 117$	$9 \times 13 = 117$	$19 \times 23 = 437$
COARSE SAMPLING					
distance (d_2)	60	60	60	32	32
points	$7 \times 9 = 63$	$5 \times 5 = 25$	$5 \times 7 = 35$	$5 \times 7 = 35$	$9 \times 11 = 99$

TABLE III

CONFIGURATIONS OF THE SAMPLING GRID WITH THE DATABASES USED IN THIS PAPER.

encoding is implemented according to the different extraction methods employed. The CR algorithm employs a template of integer values, which is matched via square differences, whereas the other three algorithm employ binary iris codes, which are matched using the Hamming distance.

V. DATABASES AND PROTOCOL

As experimental dataset, we use data from the following six databases in our experiments: BioSec baseline [23], CASIA-Iris Inverval v3 [24], IIT Delhi v1.0 [25], MobBIO [26], UBIRIS v2 [27] and Notre Dame ND-IRIS-0405 [28]. A summary of the used subset of these databases is given in Table IV. There are four databases acquired with near-infrared (NIR) illumination, and two databases with visible (VW) light. All NIR databases use a close-up iris sensor, and they are mostly composed of good quality, frontal view images. MobBIO database has been captured with a Tablet PC, with two different lightning conditions, variable eye orientation and occlusion levels (distance to the camera was kept constant, however). UBIRIS v2 has been acquired with a digital camera, with the first

session performed under controlled conditions, simulating an enrollment stage. The second session, on the other hand, was captured 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 six databases have been annotated manually by an operator [29], meaning that the radius and center of the pupil and sclera circles are available, which are used as input for the experiments. Similarly, the eyelids are modeled as circles, which are used to build the noise mask of the iris matchers. Examples of annotated images are shown in Figure 6. This segmentation groundtruth has been made available for the research community under the name of Iris Segmentation Database (IRISSEG) [29], and can be freely downloaded².

Fig. 6. Example of images of the BioSec database with the annotated circles modeling iris boundaries and eyelids.

We carry out verification experiments in this paper. We consider each eye as a different user (the number of available eyes per database is shown in Table IV). Genuine matches are as follows. When the database has been acquired in 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 experiments, the first image of a user is used as enrolment sample, and it is matched with the second image of the remaining users. When the database has been acquired in two sessions, the enrolment sample is selected from the first session, and query samples are selected from the second session. The exact number of matching scores per database is given in Table IV. For the Notre Dame ND-IRIS-0405 database, there are few subjects which have been manually segmented. For this reason, this database has not been used in the verification experiments (note the ‘-’ in Table IV).

Some fusion experiments are also done between different matchers. The fused distance is computed as the mean value of the distances due to the individual matchers, which are first normalized to be similarity scores in the $[0, 1]$ range using tanh-estimators as $s' = \frac{1}{2} \left\{ \tanh \left(0.01 \left(\frac{s - \mu_s}{\sigma_s} \right) \right) + 1 \right\}$. Here, s is the raw similarity score, s' denotes the normalized similarity score, and μ_s and σ_s are respectively the estimated mean and standard deviation of the genuine score distribution [66].

VI. EYE DETECTION RESULTS

A. Setup

In Figure 7, we give the performance of our eye detection system on the six databases used in this paper. The histograms of average width of the edge transitions (using the algorithm of Section II-C) are shown in Figure 8, and the histograms of pupil and sclera radius of each database (as given by the groundtruth) are shown in Figure 9.

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

database	subjects	eyes	sessions	images	image size	sensor	lightning	other information	Matching scores	
									genuine	impostor
Biosec [23]	75	150	2	1200	480 × 640	LG EOU3000	NIR	4 images/eye/session, indoor	2400	22350
Casia Interval v3 [24]	249	396	2	2655	280 × 320	close-up camera	NIR	images per eye/session not constant, indoor	9018	146667
IIT Delhi v1.0 [25]	224	448	1	2240	240 × 320	JIRIS JPC1000	NIR	5 images/eye, indoor	4800	200256
MobIO [26]	100	200	1	800	200 × 240	Asus TE300T	visible	4 images/eye; variable light, orientation, occlusion	1200	39800
UBIRIS v2 [27]	104	208	2	2250	300 × 400	Nikon E5700	visible	≤ 15 images/eye/session; variable light, orientation, occlusion	15750	22350
ND-IRIS-0405 [28]	30	-	-	837	480 × 640	LG 2200	NIR	no user information available, indoor	-	-

TABLE IV

DATABASES USED AND EXPERIMENTAL PROTOCOL.

The eye detection system is evaluated under the following four scenarios, which have a different degree of adaptability to the width of the edge transitions of the input image. A ranked performance of the scenario 4 is also given in Table V, with results of the other three scenarios also shown for comparative purposes:

- 1) not including eyelashes removal, and parameter σ of the first order gaussian-derivative filter (Equation 7) fixed to $\sigma=7/6$ for all input images; this corresponds to a CDF transition of width $T=7$ (Equation 9), which is the value used in our previous paper [15];
- 2) including eyelashes removal ($L=7$, based on [18]), and $\sigma=7/6$;
- 3) not including eyelashes removal, and $\sigma=T'/6$, with T' being the edge transition width of the input image given by Section II-C
- 4) including eyelashes removal (with L adapted to the input image as $L=T'$), and $\sigma=T'/6$

The symmetry filter used is designed to cover 75% of the shortest image side. This is to ensure that it captures the different size of the eyes present in the databases due to variations in the distance to the sensor. Detection accuracy is evaluated by the distance of the detected eye center with respect to the annotated pupil and sclera centers [67]. Distances are normalized by the radius of the annotated circles for size and dilation invariance, as shown in the inner sub-figure of Figure 7 (bottom right). This way, a normalized distance nd lower than 1 means that the detected point is inside the circle, and the opposite if $nd > 1$. Also, since the sclera radius is always lower than the pupil radius, the normalized distance w.r.t. the sclera center will be smaller than w.r.t. the pupil center, as can be observed in Figure 7.

B. Frequency Estimation

An analysis of the groundtruth histograms (Figure 9), reveals that all databases acquired with NIR illumination have approximately the same range of pupil and sclera radius, despite the use of sensors from different manufacturers. This is consistent with the fact that acquisition with this type of close-up sensors is done in a controlled manner, with the user always positioning the eye approximately at the same distance from the sensor. Only the Notre Dame database has slightly higher values. This explains that the histogram of edge transitions of this database is the right-most one (Figure 8), meaning wider edge transitions, since the eye is closer to the camera. The case of IITD

is particular, since its histogram of edge transitions is the left-most one (meaning shorter transitions on average). Images of IITD, however, shows a very crisp details of the iris texture and surrounding regions (see Figure 5), which may result in many short edge transitions due to iris texture details that are captured by the frequency estimation algorithm. Having iris images with more clear details seems a consistent explanation, since the best verification rates are obtained with IITD (as will be seen later in this section); however, this should be confirmed by additional studies. Concerning databases acquired with visible illumination, the pupil and sclera radius have lower values on average, meaning that the eye appear smaller in the image (see Figure 5). With MobBIO, the range of radii is small, since it was acquired with constant distance to the camera [26]. In addition, the histogram of edge transitions in Figure 8 appears towards the left (shorter transitions due to smaller eyes). UBIRIS, on the other hand, was intentionally acquired from various distances [27]. This is reflected in the spread of the histogram of sclera radii, which is wider than any other database.

Fig. 7. Performance of automatic eye detection. Inner sub-figure (bottom right): relative distance in terms of the radius of the target circle. The distance is normalized by the radius of the annotated circle for size and dilation invariance.

C. Eye Detection

Regarding the performance of the eye detection system (Figure 7), databases acquired with NIR illumination show in general higher accuracy. These are databases that are acquired in a more constrained manner, controlling the illumination and the positioning of the person being captured [45]. Also, NIR images show a more detailed iris texture due to its higher reflectivity in this range [3]. This results in sharper iris boundaries, which are the features used by our eye detection algorithm. The detected eye center with NIR databases usually falls within the pupil, i.e.

Fig. 8. Histograms of average width of edge transitions in iris images using the algorithm of Section II-C.

Fig. 9. Histograms of pupil and sclera radius of the databases used, as given by the groundtruth [29].

the solid curves in Figure 7 reaches more than 95% for $nd \leq 1$. Moreover, for most images, the detected point is relatively close to the pupil center ($nd \leq 0.3$ for $\sim 90\%$ of the database). The only exception to this is (again) IITD. An explanation is that the sclera circle in this database is, in many cases, as big as the image itself (height of IITD images is 240 pixels, see Table IV, and half of the database has a sclera radius higher than 105 pixels, see Figure 9). Since we are using a symmetry filter that covers 75% of the shortest image side (corresponding to a radius of 90 with IITD), there are a great amount of images in which the filter is not able to cover the (outer) sclera circle, relying on the (inner) pupil circle only.

With the databases acquired in visible range, eye detection is not so accurate: the detected eye center falls within the pupil in about 80%/60% of the images (MobBIO/UBIRIS, respectively). With MobBIO, however, it is worth noting that the detected point is within the sclera for nearly the whole database (with UBIRIS, this happens in 90% of the images). This is a good result considering the more adverse conditions in which these databases have been acquired [26], [27]. Also, it should be considered that in these two databases, the eye appear smaller in the image, meaning that a displacement of few pixels in the detected eye position has higher impact in the normalized distance. Some examples of eye detection in images from MobBIO are given in Figure 10. The three examples where detection occur in the vicinity of the eye center (top) show cases of off-angle image (left), occluded eye

database	Scenario 1		Scenario 2		Scenario 3		Scenario 4		rank
	pupil accuracy	sclera accuracy	pupil accuracy	sclera accuracy	pupil accuracy	sclera accuracy	pupil accuracy	sclera accuracy	
biosec (nir)	88.80	95.00	94.92	98.75	93.30	97.25	96.42	99.83	1
notredame (nir)	91.28	98.69	94.74	99.64	93.91	99.76	95.94	99.88	2
casia (nir)	83.88	88.70	89.91	95.59	91.56	95.18	91.22	97.21	3
iitd (nir)	40.36	40.63	60.72	61.65	55.36	55.71	77.32	78.39	4
mobbio (vw)	32.50	91.13	24.50	90.25	29.00	91.88	26.75	91.25	5
ubiris (vw)	15.42	76.58	14.93	82.93	15.64	79.78	15.38	82.22	6

TABLE V

PERFORMANCE OF AUTOMATIC EYE DETECTION (RANKING BASED ON RESULTS OF SCENARIO 4). RESULTS CORRESPOND TO A DETECTION ERROR EQUAL OR LESS THAN 40% ($nd=0.4$ IN THE x -AXES OF FIGURE 7). THE RANKING IS DONE BASED ON ACCURACY W.R.T. THE PUPIL CENTER.

(center) and reflections due to glasses (right). The images below are examples of unsuccessful detection. Further examination of the first case (left) reveal that the inner (pupil) iris boundary is hardly visible and as a result, the filter response is weakened. The same happens in the second case (center) due to occlusion. The third example (right) shows a maxima in the region of interest, but a stronger maxima occur due to curve-shaped boundaries given by the glasses of the contributor. Some other examples with images from UBIRIS are also given in Figure 10. The first case of successful detection (top left) shows an image with glasses and uneven illumination. The second (center) is an off-angle image, and the third (right) is an example with very low contrast. Concerning the examples of unsuccessful detection (bottom), in the first case (left) there is a stronger maxima due to curve-shaped boundaries of glasses. In the second case (center), the eye is hardly visible due to occlusion, while the third (right) is an example of extreme off-angle combined with low contrast. As a result, in the latter image, the circular shape of the eyelids produces a stronger maxima.

Considering the four scenarios defined at the beginning of this section, it can be seen in Figure 7 that in all cases, except MobBIO, the first scenario (grey curve) is the worst case. This is the scenario without eyelashes removal and with parameter σ constant, meaning that including any preprocessing in form of eyelash removal and/or adaptation to the width of the image edges is beneficial. The fourth scenario (black curve), when all preprocessing is adaptive to the estimated image frequency, is the best scenario with BIOSEC, CASIA and IITD, and it is always on top with the other three databases (except for the pupil curves of MobBIO). The case of IITD is representative. As explained before, the sclera circle is, in many cases, nearly as big as the image. It means that part of this circle will fall outside the image limits (see Figure 5) due to displacements in eye positioning during acquisition. As a result, the eye detection system is more prone to errors with this database. A great amount of images, however, can be recovered by adding some kind of preprocessing, with the biggest benefit obtained by making adaptive both the

Fig. 10. Examples of eye detection with MobBIO. Top: successful localization in the vicinity of the eye center. Bottom: unsuccessful localization. Image I_{20} is also given. The detected eye center is marked with a prominent red cross.

Fig. 11. Examples of eye detection with UBIRIS. Top: successful localization in the vicinity of the eye center. Bottom: unsuccessful localization. Image I_{20} is also given. The detected eye center is marked with a prominent red cross.

eyelash removal step and the parameter σ of the derivative filter (scenario 4). This extreme case shows the benefits of the two new steps added to our eye detection system.

VII. RECOGNITION RESULTS

A. Setup

Next, we report verification results using the periocular system of Section III (Table VI). Results are given in the following two situations: *i*) using as input the groundtruth pupil center (‘manual eye detection’), and *ii*) using the detected eye position given by our detection system (‘automatic eye detection’). The latter are done with the eye detection system working under the fourth scenario defined in Section VI-A. Due to different image size, Gabor filter wavelengths of the periocular system span the range 4-16 with MobBIO and UBIRIS, and 16-60 with the other databases. For each database, this covers approximately the range of pupil radius of all its images, as given by the groundtruth (Figure 9). Configuration of the sampling grid, including the number of sampling points per database, is given in Figure 5 and Table III. We consider two cases with the periocular system: *a*) using the original iris images

(Section VII-B), and *b*) resizing the iris images to have a constant (average) sclera radius (Section VII-C). Finally, iris verification results and its fusion with the periocular matcher are provided respectively in Tables VII and VIII, which are analyzed in Section VII-D.

B. Periocular Recognition

As can be observed in Table VI (top), results with automatic eye detection shows some degradation w.r.t. using groundtruth in databases where eye detection is less accurate (IITD, MobBIO and UBIRIS, according to Table V). It is relevant however that, with MobBIO, no reduction in accuracy is observed with the coarse grid (compare results of ‘d2’ columns). Recall that, with this database, the detected eye center is within the sclera circle for nearly all images (Figure 7). An explanation can be that since the dense grid has more points which are closer to each other, it is more sensitive to spatial displacements given by a errors in the detection of the eye. This result is encouraging, since it shows that the periocular recognition system is able to cope with certain degree of error in estimating the eye center when an appropriate grid configuration is chosen.

The degradation with IITD is specially significant, given its much worse results in eye detection observed in Figure 7. It is also worth noting the very low EER of IITD with manual eye marking, which could be explained by the very crisp details observed in the iris texture and surrounding regions of the image, as mentioned before. Being able to improve the results in automatic eye detection with this database would result in a very powerful recognition system using our algorithm. On the other hand, UBIRIS shows a very high EER, which will be analyzed in the following section. It is also worth noting the degradation observed in CASIA, despite the good results in eye detection with this database.

With respect to the use of dense or coarse grids, there is no appreciable differences in performance, either with manual or automatic eye detection (compare columns 2-3 and 3-4 in Table VI, respectively). This is good, considering that the dense grid has four times more points (Table III). The only appreciable reduction in performance with a coarse grid is observed in MobBIO (apart from UBIRIS), which could be attributed either to the smaller size of the eye (Figure 9) or the more adverse acquisition conditions in visible range, showing more variability in illumination, eye orientation and occlusion [26]. This should need additional experiments, however.

C. Image Resize

From Table VI (top), we observe a very poor performance in UBIRIS using the original iris images (EER of 36% or more). Our assumption is that, apart from being the database acquired with the most adverse perturbations in terms of illumination, off-angle, occlusions, etc. (Section V), there is also a wide variability in eye resolution (see Figure 9) due to acquisition at different distances. As a result, the points of the grid used by our periocular algorithm (which is of constant dimensions) are not capturing consistently the same region of the image (observe Figure 12, top).

Motivated by this fact, we have conducted verification experiments where all images of the database have been resized via bicubic interpolation to have the same sclera radius. For each database, we choose as target radius

Fig. 12. Top: example of grid positioning in two images from the same user having different eye resolution. Bottom: images resized to have the same sclera radius. Distance between sampling points is 32. Images are from UBIRIS.

the average sclera radius of the whole database, as given by the groundtruth. Verification results after this procedure are given in the bottom part of Table VI. As it can be observed, EER with UBIRIS is reduced significantly with this strategy. It is also of relevance that for the other databases, there is no substantial change in performance after images have been resized. This means that the periocular recognition is 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 present in this database (lightning changes, off-angle, etc.)

D. Fusion with the Iris Modality

Results of the iris matcher and fusion with the periocular system are shown in Tables VII and VIII. Concerning the iris matchers, it is observed that their performance is, in general, much better than the periocular matcher with NIR databases (BIOSEC, CASIA, IITD). This is expected, since iris systems usually work better in NIR range [40], and it confirms our previous results using only BIOSEC and MobBIO databases [15]. The KO iris matcher shows similar performance than the periocular matcher with NIR databases, and the CR iris matcher performs worse with BioSec and IITD. Regarding absolute performance numbers, it is relevant that LG and DCT matchers have the best performance with NIR data, but DCT matcher does much worse than LG with VW data (see MobBIO and UBIRIS).

Also, despite the worse performance of CR and KO with NIR data, their performance is comparable to LG with VW data. Although it is not the scope of this paper, these results seem to suggest that some of the iris features used are more suitable for NIR than for VW data, and vice-versa. It should be remarked however that the iris matchers have been executed without any image enhancement step (e.g. reflections removal or contrast equalization), so the incorporation of such pre-processing, or the use of other software implementations, may lead to different results.

As regards to the fusion experiments (Table VIII), the best iris matchers with NIR data (LG and DCT) do not result in performance improvement when fused with the periocular matcher. One reason could be the big difference in performance between iris and periocular found in these cases. On the other hand, fusion using the CR or KO matchers (which have comparable performance with the periocular matcher using NIR data, see Table VII) results in performance improvements of up to 32%. It is therefore obvious in our experiments that there is more benefit in fusing two modest matchers than in fusing one matcher that is already very good with another with a modest performance. This, however, should not be taken as a general statement. Other fusion rules different than the one employed here may lead to different results, specially if the supervisor is data quality and/or expert adaptive [68], [66], see for example the fingerprint experiments of [69].

It is of relevance that on the other hand, the periocular system works better than the iris matchers with VW databases (with UBIRIS, this happens after images are resized). One reason could be that the eye has a smaller size in these databases (see Figure 9), so it is more difficult to extract reliable identity information from the (even smaller) iris texture. In such conditions, the periocular region is able to provide a rich source of identity data, as evidenced in our experiments. It is worth noting, however, that even in the adverse conditions of the VW databases, the iris texture is still able to complement the periocular system, as shown in the fusion results. Using the LG iris matcher, for example, EER improvements of 20% or more can be achieved by the fusion. On the other hand, despite the performance of CR and KO is comparable to LG, the fusion of CR/KO with the periocular system does not have similar performance improvements in many cases. Only CR with MobBIO shows consistent performance improvements of 15-20%. Finally, the DCT iris matcher (which performs the worst with VW data) does not provide any improvement when fused with the periocular system.

VIII. CONCLUSIONS

Periocular recognition has emerged as a promising trait for unconstrained biometrics [1], [2], [3], following demands for increased robustness of face or iris systems, with suggestions that it may be as discriminating by itself as the face as a whole [7], [8]. Periocular refers to the region in the immediate vicinity of the eye, including the eye, eyelids, lashes and eyebrows. It has shown a surprisingly high discrimination ability [1], and it can be easily obtained with existing setups for face and iris. A primary consequence is to drastically reduce the need of user cooperation. It is also available over a wide range of distances even when the iris texture cannot be reliably obtained (e.g. low resolution, blinking or closed eyes, off-angle poses, inappropriate illumination) or when portions of the face are occluded (e.g. close distances) [10]. Most face detection and recognition systems use a holistic approach, i.e. they require a full face image, so the performance is negatively affected in case of occlusion [5]. Also, the

Periocular system					
		Manual eye detection		Automatic eye detection	
		d1	d2	d1	d2
database		ORIGINAL IMAGE SIZE			
biosec (nir)		10.69	10.77	10.18	10.65
casia (nir)		14.53	14.81	17.06	16.45
iitd (nir)		2.5	2.67	10.62	10.76
mobbio (vw)		12.65	15.16	14.31	15.15
ubiris (vw)		41.72	36.15	45.27	44.59
database		RESIZED IMAGES			
biosec (nir)		10.56	10.91	10.24	10.24
casia (nir)		15.55	15.4	17.71	17.07
iitd (nir)		2.85	3.04	10.99	11.06
mobbio (vw)		12.32	13.96	14.9	15.15
ubiris (vw)		24.81	24.4	35.49	35.44

TABLE VI
VERIFICATION RESULTS IN TERMS OF EER (PERIOCLAR SYSTEM).

periocular region appears in iris images, so the fusion of the information present in the periocular region with the iris texture has a potential to improve the overall recognition [9].

In this paper, we propose an eye detection system based on symmetry filters. It is based on 2D separable symmetry filters tuned to detect circular symmetries, in such a way that we detect the eye center with a few 1D convolutions. One advantage of this system is that it does not need training, in contrast to other previous works making use, for example, of Gabor features [13], Viola-Jones detectors of face sub-parts [30], or correlation filters [10]. This detection system is used as input to a periocular algorithm based on retinotopic sampling grids and Gabor analysis of the power spectrum. This framework is evaluated with six databases of iris data, four acquired with a close-up NIR camera, and two in VW light with a webcam and a digital camera. This paper expands our two previous studies where we presented the eye detection [15] and the periocular recognition [11] systems. In particular, the eye detection system includes two new additions. The first one is concerned with frequency estimation of the input iris image [16], which is used to dynamically adjust the derivative filters used to compute the image orientation field. The second is an eyelash removal step [18], which also made adaptive by using the estimated image frequency. The addition of these steps has demonstrated to improve the performance of our detection system. With NIR images, the detected eye center is very close to the pupil center (measured by groundtruth [29]). The two databases in visible

database	Iris systems				Periocular
	LG	CR	DCT	KO	best case
biosec (nir)	1.12	12.93	2.31	10.64	10.56
casia (nir)	0.67	8.85	1.73	13.44	14.53
iitd (nir)	0.59	3.55	0.96	2.74	2.5
mobbio (vw)	18.81	20.56	31.10	22.81	12.32
ubiris (vw)	35.61	37.87	47.46	34.94	24.4

TABLE VII

VERIFICATION RESULTS IN TERMS OF EER (IRIS MATCHERS). PERFORMANCE OF THE PERIOCCULAR SYSTEM (BEST CASE WITH MANUAL EYE DETECTION) IS ALSO SHOWN FOR COMPARISON PURPOSES.

Fusion: periocular (d2) + iris								
Manual eye detection					Automatic eye detection			
ORIGINAL IMAGE SIZE								
database	LG	CR	DCT	KO	LG	CR	DCT	KO
biosec (nir)	2.16	7.61 (-29.34%)	4.49	8.36 (-21.43%)	1.96	7.68 (-27.89%)	4.02	7.97 (-25.09%)
casia (nir)	2.38	8.00 (-9.60%)	5.67	9.89 (-26.41%)	2.5	8.37 (-5.42%)	4.9	11.55 (-14.06%)
iitd (nir)	1.2	1.82 (-31.84%)	1.63	1.91 (-28.46%)	1.99	6.93	6.28	4.21
mobbio (vw)	11.75 (-22.49%)	12.13 (-19.99%)	15.99	14.72 (-2.90%)	12.34 (-18.55%)	12.83 (-15.31%)	17.4	15.96
ubiris (vw)	29.49 (-17.19%)	33.19 (-8.19%)	38.32	31.02 (-11.22%)	35.06 (-1.54%)	37.77 (-0.26%)	43.63 (-2.15%)	35.4
RESIZED IMAGE								
database	LG	CR	DCT	KO	LG	CR	DCT	KO
biosec (nir)	2.11	7.99 (-26.76%)	4.61	8.47 (-20.39%)	1.98	7.54 (-26.37%)	3.86	8.18 (-20.12%)
casia (nir)	2.54	8.45 (-4.52%)	6.03	10.13 (-24.63%)	2.46	8.63 (-2.49%)	5.01	11.8 (-12.20%)
iitd (nir)	1.47	2.24 (-26.32%)	2.03	2.09 (-23.72%)	2.07	6.89	5.87	4.26
mobbio (vw)	11.00 (-21.2%)	11.81 (-15.4%)	14.6	14.19	11.68 (-22.90%)	12.75 (-15.84%)	16.29	15.12 (-0.20%)
ubiris (vw)	22.41 (-8.16%)	25.47	30.44	24.3 (-0.41%)	28.05 (-20.85%)	30.94 (-12.70%)	36.19	29.42 (-15.80%)

TABLE VIII

VERIFICATION RESULTS IN TERMS OF EER (FUSION OR PERIOCCULAR AND IRIS SYSTEMS). THE RELATIVE EER VARIATION WITH RESPECT TO THE BEST INDIVIDUAL SYSTEM IS GIVEN IN BRACKETS (ONLY WHEN THERE IS PERFORMANCE IMPROVEMENT).

range shows worse performance, due to more difficult acquisition conditions which include uneven illumination, off-angle eyes, occlusions and distance changes. In one of the visible databases, however, the detected point is within the sclera for nearly the whole database. This is enough for the recognition algorithm, since no reduction in performance is observed in this database with an appropriate configuration of the sampling grid.

As far as the periocular recognition system is concerned, it is shown to be robust to a certain degree of inaccuracy in detecting the eye center, also being able to cope with small scale changes in the eye image. Dimensions of the grid are constant for all images of each database, without adaptation to the size of the input eye, so the only requirement is the availability of the eye center. We also test two different sampling grid configurations, with dense

and coarse sampling respectively. It is observed that the accuracy of the periocular matcher is not jeopardized by reducing the density of the sampling grid. This is good news for time saving purposes, considering that the dense grid has four time more less points. Lastly, we evaluate four iris matchers based on 1D log-Gabor filters (LG) [19], local intensity variations in iris textures (CR) [20], Discrete-Cosine Transform (DCT) [21], and cumulative-sum-based grey change analysis (KO) [22]. The performance of the iris matchers are, in general, much better than the periocular matcher with NIR data, and the opposite with VW data. However, there is not a general trend among all the iris matchers, suggesting that some iris of the iris features used are more suitable for NIR than for VW data, and vice-versa. Regarding fusion experiments, despite the poorer performance of the iris matchers with the VW databases, its fusion with the periocular system can provided an improved performance (of more than 20% with one of the iris matchers). This is remarkable given the smaller eye size on VW databases, resulting in an (even smaller) iris region. With NIR images, the fusion only improves if the iris and periocular matcher have comparable performance; but for the best iris matchers (EER around 1-2% or less), there is no improvement by the fusion due to the big difference in performance w.r.t. the periocular matcher. This paper also presents a new ground-truth database of iris segmentation data [29]. The six databases used in this paper have manually annotated by an operator, with the annotation being made available to the research community.

Future work includes evaluating the reliability of the proposed eye detection system in full face images. Another source of improvement will be the incorporation of a refinement stage, e.g. by pixel-wise analyzing the neighborhood of the detected point [4] to achieve a more accurate estimation of the eye center with visible images. We also plan to evaluate other existing periocular recognition algorithms [1]. Since we have observed that images in visible in general provide worse performance in our developments, we will also focus on this type of images, finding mechanisms to cope with more adverse images in terms of uneven lightning, reflections, off-angle, occlusions, or de-focus.

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