Face Recognition in Adverse Conditions

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Chapter 12
Using Ocular Data for Unconstrained Biometric Recognition

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ABSTRACT

There are several scenarios where a full facial picture cannot be obtained nor the iris properly imaged. For such cases, a good possibility might be to use the ocular region for recognition, which is a relatively new idea and is regarded as a good trade-off between using the whole face or the iris alone. The area in the vicinity of the eyes is designated as periocular and is particularly useful on less constrained conditions, when image acquisition is unreliable, or to avoid iris pattern spoofing. This chapter provides a comprehensive summary of the most relevant research conducted in the scope of ocular (periocular) recognition methods. The authors compare the main features of the publicly available data sets and summarize the techniques most frequently used in the recognition algorithms in this chapter. In addition, they present the state-of-the-art results in terms of recognition accuracy and discuss the current issues on this topic, together with some directions for further work.

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1. INTRODUCTION

The face and the iris are among the most popular traits for biometric recognition, and are – together with the fingerprint – the most frequently reported in the specialized literature (Bowyer, Hollingsworth, & Flynn, 2008; Zhao et al. 2000).

The iris has a predominantly randotypic morphogenesis, unique for each individual, and allows very high recognition accuracy. Also, it is a protected organ visible from the exterior, justifying the efforts on "relaxing" its acquisition setup (Santos & Hoyle, 2012; Shin et al., 2012; Tan, Zhang, Sun, & Zhang, 2012).

The face has been traditionally regarded as the main trait to perform recognition under less controlled conditions. However, several drawbacks significantly decrease the effectiveness of face-based recognition systems: 1) due to its 3D structure, substantial differences in appearance are expected with respect to subjects' poses; 2) large regions of the face are often occluded, in case of non-orthogonal data acquisition; 3) facial expressions notoriously affect the appearance of the face; 4) disguising is particularly easy.

According to the above, growing attention has been paid to other traits potentially useful for biometric recognition. Among these, the use of information in the vicinity of the eye (the periocular region) has been gaining in popularity. Being particularly useful on less constrained scenarios, when image acquisition is unreliable, or to avoid iris pattern spoofing, the periocular region does not require constrained close capturing or user cooperation, it's relatively stable, when compared to the whole face, and rarely occluded. Due to the proximity with the iris, both can be easily acquired with a single camera and fused at the score level to compensate for environmental adversities and uncooperative subjects.

The usage of periocular information has even proven itself to be of importance in scenarios where the face has been *reshaped* (*e.g.* plastic surgery), with interesting results (Jillela & Ross, 2012; Bhatt, Bharadwaj, Singh, & Vatsa, 2013).

The idea of *periocular recognition* came from the ability of humans to recognize someone by his / her eyes, which are known to provide substantial amounts of discriminating information that is relatively stable over lifetime. Hence, the term periocular biometrics refers to the development of recognition methods that analyze not only the iris structure, but also the shape of eyelids, the distribution of eyelashes, the texture of the sclera and of the skin surrounding the eye to perform recognition.

This chapter provides an overview of the most relevant attempts to perform biometric recognition in uncontrolled acquisition environments, using information in the periocular area. We summarize the most relevant methods in the literature and compare the techniques most frequently reported for each of the typical processing phases: segmentation, quality assessment, feature encoding and matching. Next, we describe the data sets that are publicly available and used in the evaluation of algorithms, and report the state-of-the-art recognition rates that act as reference values for further improvements on this technology.

The remainder of this chapter is organized as follows: Section 2 overviews the anatomic and biological features of the periocular region. Section 3 compares the main characteristics of the data sets used in periocular recognition experiments. A comprehensive review of the most relevant papers published in this scope is given in Section 4. Section 5 reports the current state-of-the-art results and Section 6 discusses the issues and challenges that are currently associated to the periocular recognition process. Finally, Section 7 concludes this chapter.

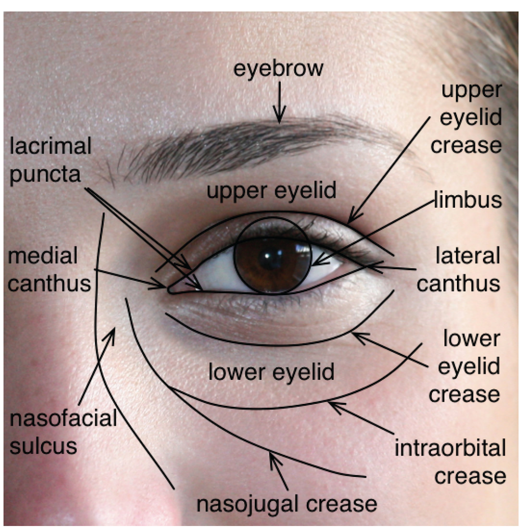
2. PERIOCULAR ANATOMY AND STRCTURES

Not only the superficial features of the skin determine the facial appearance, but also the concavities and convexities conferred by the underlying bones and muscles play a significant role. In particular, the periocular region comprises many anatomic features and landmarks that potentially fit for recognition purposes (Figure 1).

Centered on the eye, which is located on the orbital aperture, the periocular region has its creases and sulcus decided essentially by four bones: 1) the frontal bone, ending with the supraorbital process where the eyebrow is located and which affects its appearance; 2) the nasal bone, defining the upper part of the nose; 3) the lacrimal bone, that forms the cavity for the tear gland; and 4) the zygomatic bone, also known as cheek bone.

Although bone structure directly impacts facial appearance, most of the studied features rely more on muscle and skin specifications, and less on bone level properties, which would be less prone to both natural (*e.g.* aging) and external changes (*e.g.* plastic surgery).

Figure 1. Anatomic features on the periocular region



Eyebrows constitute the foundation for eyelids, and are straighter on men and more arched on women. Eyebrow thickness changes among ethnicities and, with the aging process, their orientation and height also change. Concerning the eyelids, their contours depend on gender, ethnic group and age, and dimension intervals are defined in previous studies (Tan, Oh, Priel, & Korn, 2011).

Even considering this richness of ocular elements, the features actually being used on periocular biometrics algorithms are quite simple and can be divided into two levels, as suggested by Woodard, Pundlik, Lyle, and Miller (2010a): 1) the first level comprises eyelids, eye folds, and eye corners, and 2) the second level comprises skin texture, wrinkles, color and pores. This simplicity might be due to the relative novelty of the field: having passed only a couple of years since the first relevant study on periocular recognition, the earliest recognition algorithms firstly employed classical techniques in the computer vision domain-of-knowledge, before attempting more sophisticated / specific methods.

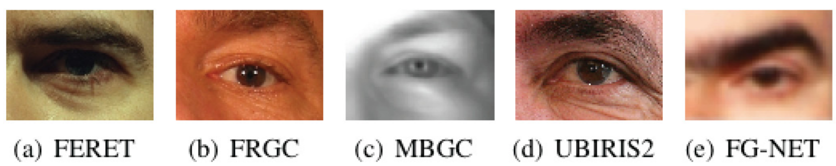
3. DATA SETS

Due to the novelty of the use of the periocular region to perform biometric recognition, only a few data are publicly available. Hence, an issue is the lack of datasets specifically designed for the development of periocular recognition methods. Due to this, researchers usually resort to face and iris databases, being the most relevant given on Table 1 and illustrated on Figure 2. We report the number of images and subjects available per dataset, the dimensions of the images and the

Table 1. Summary of dataset specifications. Variations abbreviations refer to Distance (D), Expression (E), Illumination (I), Occlusion (O) and Pose (P)

Name	# of Images	# of Subj.	Image Dimension	Variations
FERET	14051	1199	512×768	E, I, P
FRGC	36818	741	$\approx 1200 \times 1400$	E, I
MBGC	149 AVI	114	2048×2048	D, E, I, O, P
UBIRIS.v2	11102	261	800×600	D, O, I
UBIPr	10950	261	Multiple	D, O, I, P
FG-NET	1002	82	$\approx 400 \times 500$	D, E, I, P

Figure 2. Sample images that illustrate the datasets typically in the evaluation of periocular algorithms



main variability factors in each one, which play an extremely important role in the evaluation of the robustness of recognition algorithms.

- **FERET:** The Facial Recognition Technology (FERET) database (Phillips, Moon, Rizvi, & Rauss, 2000), designed as a standard for developing face recognition methods, was acquired at George Mason University over eleven sessions and a three years period (1993 to 1996). It was initially released as low resolution (256×384 pixels) grayscale data, and only later a high-resolution color version was also disclosed. Contains a total of 14051 images, gathered from 1199 different subjects within a semi-controlled acquisition protocol with strict expression, pose and illumination changes.
- **FRGC:** Collected at the University of Notre Dame, the Face Recognition Grand Challenge (FRGC) database (Phillips et al., 2005) consist of high resolution ($\approx 1200 \times 1400$ pixels) color still images, captured on both controlled and uncontrolled environments. The controlled setup was assembled at a studio with uniform illumination, where subjects were requested to stand still, look strait at the camera, and essay sequentially both neutral and smiling expressions. As for the uncontrolled acquisition, images were shoot in different scenarios, disregarding both background and illumination.
- **UBIRIS.v2:** The UBIRIS.v2 is a unconstrained iris database (Proença, Filipe, Santos, Oliveira, & Alexandre, 2010), captured on the visible wavelength from moving subjects, at different distances and challenging illumination conditions, thus simulating realistic acquisition issues and the related noise factors. Data from both eyes is separately available, as well as the surrounding periocular data, thus allowing to stress out periocular methods, and even their fusion with iris recognition techniques.
- **UBIPr:** As an effort to advance periocular biometric research, the UBI Periocular

Recognition (UBIPr) dataset (Padole & Proença, 2012) allows to evaluate periocular methods at "higher levels of heterogeneity," as noise factors were actually introduced on the acquisition setup: varying acquisition distance, irregular illumination, pose and occlusion. In addition, manual database annotation includes regions-of-interest and essential landmarks. Image dimensions vary accordingly to the acquisition distance, and range from 501 × 401 pixels (at 8m) to 1001 × 801 pixels (at 4m).

- **FG-NET:** The FG-NET is a facial aging database with around one thousand images from 82 subjects, up to 69 years old. Captured at different acquisition setups and many years apart, it is clear how subjects were shoot under very irregular illumination, pose and expression conditions.
- Images are 400 × 500 pixels in size, captured on the visible wavelength, and for each one a 68 landmark points annotation is also provided.

Recently, Cardoso et al. (2013) developed an algorithm for synthesizing degraded ocular images. Considering that the collection of data for biometric experiments is particularly hard due to security / privacy concerns of volunteers and the substantial amounts of data required, they described a stochastic method able to generate a practically infinite number of iris images with a singular characteristic: simulating image acquisition under uncontrolled conditions. Hence, the generated images have eight varying factors: optical defocus, motion blur, iris occlusions, gaze, pose, distance, levels of iris pigmentation and lighting conditions (Figure 3). Particular attention was paid for mimicking the dynamic conditions in uncontrolled lighting environments, by using "cube-maps" that replicate different environments that (potentially) surround the simulated subjects. Also, authors announced the availability of an online platform[1] where anyone has the possibility to adjust the levels of variability desired for each of the above factors, and define the main properties of the artificial data sets. This tool might constitute a valuable resource for the evaluation of the robustness of iris segmentation / recognition algorithms, and is available in a completely free and anonymous way.

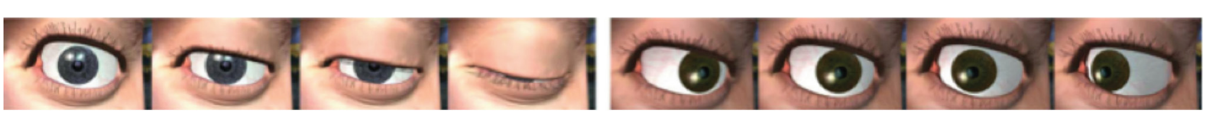
4. RELEVANT RESEARCH

In this section we summarize the most relevant techniques published in the scope of periocular recognition. Also, we overview the algorithms published in adjacent areas, that can potentially be used to improve periocular recognition algorithms, such as iris segmentation, image quality assessment, feature extraction and matching on ocular data.

4.1 Periocular Recognition

The pioneering approach for periocular biometrics dates back to Park, Ross, & Jain (2009), proposing to extract features at two different levels: local and global, as information concerns patches of the periocular area, or is extracted from the whole image. For global feature extraction, images are properly aligned, using the location of the iris and its dimensions as reference, and defining a 7

Figure 3. Examples of artificial images of the ocular region generated by the NOISYRIS platform



× 5 grid of square regions-of-interest. Although authors acknowledge eye corners to be more fit for such task (Park, Jilela, Ross, & Jain, 2011), they claim that such points cannot be reliably determined. Then, two well-known distribution-based descriptors, namely Histogram of Oriented Gradients (HOG) (Dalal & Triggs, 2005) and Local Binary Patterns (LBP) (Ojala, Pietikäinen, & Harwood, 1996; Ojala, Pietikäinen, & Harwood, 1994), are computed for each region-of-interest independently, and quantized into 8-bin histograms combining shape and texture information. The array comprising such histograms is easily matchable to an identical one (from another image), by simply computing the Euclidean distance. As for the local features, Scale-Invariant Feature Transform — SIFT (Lowe, 2004) allows the detection of a set of key-points, encoded with their surrounding pixels information, and compared against their counterparts from another image. This descriptor offers invariance to translation, scaling and rotation. The authors conducted their tests over a "small" (899 images, 30 subjects, 2 sessions) database of frontal periocular images acquired in the visible wavelength of the electromagnetic spectrum, and reported performances ranging from 62.5% using only HOG features to 80.8% when fusing them with SIFT results. Curiously, combining the three features didn't improved those results, setting joint performance at 80%. Recognition using the whole face, for the same database, achieved 100% Rank-1 accuracy.

On a later work, Park, Jilela, Ross and Jain (2011) went further on stressing periocular recognition by analyzing performance impact of several factors: eyebrow inclusion or disguising, automatic segmentation, side information, iris and sclera masking and expression variation. Their results showed that adding eyebrow information improved SIFT results in almost 19%, although automatic OpenCV segmentation exhibited better performance with "eyebrow-less" data. Face side information, by other side, is almost irrelevant, with performance variations of about 1%. From the stressed variations, expression has a significant impacting over periocular recognition potential, except for SIFT, because of its robustness to distortion. On the other side, this descriptor was the most disfavored on iris/sclera occlusion. Top accuracy for single classifiers was 79.45%, achieved using SIFT over unmasked data, manually segmented and including the eyebrow, when compared to images from the same side and expression. Compared to their previous work (Park et al., 2009), score level fusion didn't present a significant improvement. Recognition over non-ideal situations was also a concern, and authors compared their results with FaceVACS[2] face recognition system marks — 99.77% recognition accuracy on "clear" facial images. Occlusions, for instance, led to significant performance drops (about 60% when occluding the lower part of the face), even for small occlusions on the periocular area. Without score fusion, the encoding methods singlehanded led to accuracies no greater than 25.97%, 20.51% and 10.12% respectively for 10%, 20% and 30% of periocular occlusion. Eyebrow modifications were also subject of testing, using the TAAZ[3] tool to simulate makeover, and leading to 7.5% (LBP) to 10% (other descriptors) performance decay.

When facing subjects shoot with 15º to 30º head rotation, a 35% to 45% performance deterioration was registered. Finally, authors pointed out another issue associated with the periocular region — its lack of stability over time. Images captured three months apart from each other appear to perform 15% worst, and 30% when captured with half-year gap. As further work, authors suggest several possible improvements: better alignment and matching methods; multi-spectral analysis; and the possibility of fusion with iris (or face) recognition methods.

Miller, Rawls, Pundlik, and Woodard (2010b) analyzed the skin texture by applying an Uniform-LBP (ULBP), with further insights on each region's impact on the recognition process. This LBP-based approach achieves "improved rotation invariance with uniform patterns and finer quantization on the angular space" (Ojala, Pietikainen, & Maenpaa, 2002). Similarly to the previous approach, the periocular region is cropped proportionally to intra-eye distance, scaled to 100 × 160 pixels, and divided in a 7 × 4 region-of-interest grid. To avoid iris and sclera information influencing the results, an elliptical neutral mask is overlapped to the image. After histogram normalization, ULBP is computed for each region on an 8-pixel neighborhood, producing 59 possible results that populate a histogram and the periocular signature array. Finally, Manhattan distance is used for matching. Experiments were conducted on subjects of FRGC and FERET datasets, for both eyes separately and combined, reporting 84% and 71% and 90% and 74% recognition rates respectively.

The impact of image quality was addressed by Miller, Lyle, Pundlik, & Woodard, 2010a, over three factors: blur, resolution and illumination. Image preprocessing included a similar periocular crop and resizing (251 × 251 pixels), grayscale conversion, histogram equalization and eye masking, but instead of ULBP a base LBP was used. When blurring the data with a Gaussian filter convolution, the periocular performance over face was evidenced for high blur levels. A similar conclusion was reached when down sampling to 40% of the original size. As for uncontrolled illumination conditions, performance degrades to low levels, as local approaches (*e.g.* LBP) are not suited for irregular lighting conditions.

The authors also compared the discriminant capabilities of the different color channels. The green channel leads to higher differentiation (23% higher accuracy than the red channel), and has similar texture information as the blue channel. Globally, authors concluded that performance achieved on the periocular region was better than using the whole face, having suggested the use of different classification methods, in particular Support Vector Machines (SVM) (Savvides et al., 2006).

Adams et al. (2010) extended Miller et al. (2010b) work, having used a Genetic & Evolutionary Computing (GEC) method to optimize the original feature set, namely the Steady-State Genetic Algorithm (SSGA) as implemented by *NASA's eXploration Toolset for Optimization of Lauch and Space Systems*[4] (X-TOOLSS). Authors reported 86% accuracy for either eye on the FRGC dataset and 80% on FERET data, and top results of 85% and 92% for those databases respectively. Using only 49~52% of the original features improved on, at least, 10%. Nonetheless, the chosen algorithm was not proven to be the optimal for that specific periocular features.

Inspired by Park et al. (2009), Juefei-Xu et al. (2010) expanded their experiments to less ideal imaging environments, having analyzed the performance of different feature schemes on the FRGC dataset.

In addition to LBP and SIFT, both local and global feature extraction schemes were stressed: Walsh masks (Beer, 1981); Laws' masks (Laws, 1980); Direct Cosine Transform (DCT) (Ahmed, Natarajan, & Rao, 1974); Discrete Wavelet Transform (DWT) (Mallat, 1989); Force Fields (Hurley, Nixon, & Carter, 2000); Speed Up Robust Features (SURF) (Bay, Ess, Tuytelaars, & Van Gool, 2008); Gabor Filters (Clausi & Jernigan, 1996) and Laplacian of Gaussian (LoG). The LBP itself was fused with other methods, yielding the results given in Table 2.

Table 2. Rank-1 identification accuracy obtained with the fusion of LBP with other methods (Juefei-Xu et al., 2010)

Fused Methods	Accuracy (%)
LBP + LBP	42.5
Walsh Masks + LBP	52.9
Laws' Masks + LBP	51.3
DCT + LBP	53.1
DWT + LBP	53.2
Force Field Transform + LBP	41.7
Gabor Filters + LBP	12.8
LoG filters + LBP	30.9

Authors show local descriptors to register better results, with the post-application of LBP translated into a performance boost. Although top accuracy was attained with DWT + LBP (53.2%), results were very similar when using DCT and Walsh or Laws' masks. SIFT and SURF verification rate was surprisingly low (<1%), most likely due to low image resolution.

Juefei-Xu, Luu, Savvides, Bui, and Suen (2011) addressed the aging effect on periocular recognition, previously reported as an issue (Park et al. (2011)). Their approach starts by performing two types of corrections: pose, using Active Appearance Models (AAM); and illumination, through anisotropic diffusion model. The periocular region was normalized from the provided landmark points, and features extracted using Walsh-Hadamard transform encoded LBP (WLBP). On a final stage, the unsupervised discriminant projection (UDP) technique (J. Yang, Zhang, Yang, & Niu, 2007) boosted results to very high performance levels. This method was tested on the FG-NET database, with images taken years apart at different acquisition setups (non-uniform illumination, pose and expression). The reported results showed improvements in performance by 20%, and WLBP to perform 15% better than raw pixel intensity matching. UDP also delivers better accuracy (up to 40%) than Principal Component Analysis (PCA) or Locally Preserving Projections (LPP). All the stages together resulted in 100% identification accuracy.

Bharadwaj, Bhatt, Vatsa, and Singh (2010) research on periocular biometrics was focused on unconstrained visible wavelength captured data (UBIRIS.v2 dataset), and tackled the question combining ULBP with a global matcher — GIST — consisting on the combination of five perceptual scene descriptors (Oliva & Torralba, 2001): naturalness, openness, roughness, expansion and ruggedness.

ULBP was computed over 64 patches of the original image and, for the GIST, local contrast normalization was achieved with Fourier transform and the special envelope computed using a set of Gabor filters. For match computation, $X2$ distance and min-max normalized results from both eyes are fused by a weighted sum. GIST gave best performance than ULBP, and fusing both results led to 73.65% rank-1 accuracy.

To establish the slice of the electromagnetic spectrum that most favor periocular recognition, Woodard, Pundlik, Lyle, and Miller (2010a) evaluated second level features on both NIR (MBGC) and visible-wavelength (FRGC) data. To avoid biased results, an elliptical mask was overlapped to the eye, removing the iris and sclera information. On both datasets texture information was encoded using LBP over a ROI grid, and on the visible wavelength data this information was fused at score level with color information drawn from the red and green channels histograms. At the matching stage Manhatan distance was used for LBP histograms, and Bhattacharya distance for color histograms. Results suggest texture information to be more discriminant, and only a slight improvement was registered after the fusion. As for the electromagnetic spectrum, visible wavelength data delivered better results (88~90% accuracy) than NIR (81~87%).

Subsequently, Woodard, Pundlik, Miller, Jillela, and Ross (2010b) assessed how periocular texture information could improve iris data reliability, so that difficulties when dealing with non-ideal imaging could be dealt with. Tests were conducted over MBGC data, which although being a NIR dataset, had challenging conditions for iris recognition. Iris processing was as of Daugman (1993), except with manual segmentation, and after encoding texture information as above described, information from both traits was fused with a simple weighted sum after min-max normalization. Their work showed how iris' low performance on such difficult data benefits from periocular fusion, raising rank-1 accuracy in over 80%, to 96.5%.

In Woodard, Pundlik, Miller, and Lyle (2011), both studies were unified and extended, providing a closer insight to their previous results. Once again, authors conclude periocular region performance to be comparable to the one obtained using similar features on the whole face.

Jillela and Ross (2012) take advantage of periocular region features to improve the identification performance of two commercial face recognition software over subjects that have submitted to plastic surgery. Inspired by Park et al. (2009), authors also use SIFT and LBP, even though this last one is computed for all color channels. Fusion is achieved at score-level, where all outputs are combined after a single score for LBP is averaged from individual color scores.

Tests were conducted over a plastic surgery database (Singh et al., 2010) consisting of images downloaded from plastic surgery information Websites, and thus with considerable changes in resolution, scale and expression. Results show periocular methods to have 63.9% rank-1 accuracy, and even though face recognition software overcomes that with 85.3%, the best result is obtained when fusing both: 87.4%.

On stressing noise factors impact on periocular recognition, Padole and Proença (2012) tested on images with four inherent variations: subjects' pose, distance to the camera (4m to 8m), iris pigmentation and occlusion. Choosing Park et al. (2009) method, they introduced some slight variations: the ROI was defined based on eye-corner position instead of iris center, which led to most significant improvements since unconstrained biometrics favor gaze variations; and at fusion stage both linear (logistic regression (Hosmer & Lemeshow, 2000)) and non-linear methods (Multi Layer Perceptron — MLP) were tested. Both fusing techniques produced similar results, being MLP slightly better though.

Interestingly, closer acquiring distances didn't seem to lead to better performance. In fact, worst results came from comparisons between subjects imaged at 4 meters, being the "optimal" distance 7m. Not so surprising was pose variation impact on recognition, with higher tilting angles resulting in lower accuracy values. Similar observations were found for the occlusion trials. Iris pigmentation was reported to also impact periocular recognition performance, with darker eyes leading to poorer results and medium pigmented irises the best ones. Subjects' gender was also reported to impact recognition rates, being female more easily identified through their periocular features. The Human ability to use contextual information and "disregard" most of noise factors, adapting itself to surrounding conditions is outstanding, marking it a hard task for machines to mimic. In fact, when designed recognition algorithms we should rather try to figure out its way of working, seeking alternate strategies to tackle the same issues.

Hollingsworth, Bowyer, and Flynn (2010) aimed at identifying which ocular elements humans find more useful for the periocular recognition task. On their essay, an iris camera was used to acquire NIR data from 120 subjects, being visible the periocular region closer to the eye although some features were missing (*e.g.* incomplete eyebrows). The iris were completely masked, to avoid biased responses, iris was masked with a circular patch, and 80 pairs of images were presented to 25 human observers, who were asked to tell apart pairs belonging to the same or different persons, indicating their degree of certainty. Further to that, subjects had to individually rate each feature's helpfulness in a three level scale.

Results pointed eyelashes to be the most helpful periocular feature, closely followed by the medial canthus and the eye shape. Participants based their responses on eyelash clusters, density, direction, length and intensity. To the inquired observers, skin was actually the less useful.

Average human accuracy on such setup was 92%.

To extend that analysis to the visible spectrum, new factors and a wider dataset, another study was conducted by Hollingsworth et al. (2012). This time, periocular (Park et al., 2009) and iris (IrisBEE biometric system from ICE (Phillips et al., 2010) recognition algorithms were also used for comparison.

Imaging 210 subjects on a controlled environment, 140 pairs of images were presented to 56 observers for each one of four setups: NIR and visible wavelength, periocular and iris data. Test subjects could then rank their certainty on a five level scale, specifying how helpful individual features were ("eye shape," "tear duct," "outer corner," "eyelashes," "skin," "eyebrow," "eyelid," "color," "blood vessels" and "other"). Due to the different pairing system and limited observation time, NIR accuracy dropped to 78.8%, and it was set on 88.4% for the visible wavelength. Machine performance was similar, within 1% difference on overall accuracy. As for the feature discrimination capacity, results were similar to the previous ones (Hollingsworth et al., 2010) for NIR data, with some differences on the visible spectrum where blood vessels, skin and eye shape were reported to be more helpful than eyelashes. Skin details are in fact more perceptible on visible wavelength data, as NIR camera illumination caused frequent skin saturation. In general, visible band was found to be preferable for periocular recognition tasks.

Human perception of iris features is greater on NIR images, with 85.6% accuracy against 79.3 on the visible wavelength. However, and unlike periocular, machine performance was 13% better than humans', with 100% and 90.7% accuracy for those same bands.

4.2 Iris Segmentation

Considering that many techniques for segmenting the iris are based on Hough-transform parameterization, Junli et al. (2013) developed a robust ellipse fitting technique robust to noisy edge-maps that likely result of degraded data. Their algorithm starts by selecting a subset of the edge points that are deemed to be more accurate. Then, considering that squaring the fitting residuals magnifies the contributions of these extreme data points, their algorithm replaces it with the absolute residuals to reduce this influence. The resulting mixed l1-l2 optimization problem is derived as a second-order cone programming one and solved by the computationally efficient interior-point methods.

Specifically concerned about the segmentation of iris images acquired at large distances, Tan and Kumar (2012) were based in the concept of Grow-cut algorithm that is able to discriminate between foreground (iris) and background (non-iris) data. The results from this phase are refined by post-processing operations: iris center estimation, boundary refinement, pupil masking and refinement, eyelashes and shadow removal and eyelid localization. Experiments were performed in well known datasets (UBIRIS.v2, FRGC and CASIA.v4 Distance) and confirmed the effectiveness of this approach. Moreover, the computational burden of the method appears to be substantially lower than of similar strategies.

Alonso-Fernandez and Bigun (2012) perform the segmentation of the iris based on the Generalized Structure Tensor algorithm. The key point of this strategy is that, using complex filters, authors are able to obtain both magnitude and orientation information for each edge pixel. This provides an additional amount of information that enables to more appropriately discriminate between the edges that are deemed to belong to one of the iris boundaries and spurious edges.

Xinyu et al. (2012) addressed the problem of less intrusive iris image acquisition, in terms of a segmentation algorithm able to work at very different image resolutions (from 50 to 350 pixels in iris diameter). Authors start by detecting a set of edges (Canny detector), which non-connected components are considered nodes of a graph. Next, based on the normalized cuts criterion, they discriminate between the most probable circle-like shapes that correspond to the iris boundaries.

4.3 Noise Detection

In most iris recognition methods, it is particularly important to have an estimate of the regions of the iris that are occluded by other types of information (e.g., eyelids, eyelashes or reflections), and hence should not be considered in the feature encoding phase. When such type of information is erroneously considered, most frequently the false rejection rates augment, but even the number of false acceptances can raise, if no adaptive thresholds with respect to the amount of un-occluded irises are not used.

According to the above observations, several authors addressed the problem of discriminating the useful parts of the iris images. Having considered that previous approaches are rule-based and have questionable effectiveness, Li and Savvides (2012) used Gaussian Mixture Models to model the probabilistic distributions of noise-free and noisy regions of the irises. The idea is to adjust the number of Gaussians for a distribution, by eliminating Gaussians which are not supported by the observations. Based on their experiments, authors propose Gabor filters as basic features, optimized by a simulated annealing process.

4.4 Quality Assessment

Zuo and Schmid (2013) propose three methods to improve the performance of a biometric recognition system, according to quality indexes: 1) quality-of-sample; 2) confidence in matching scores; and 3) quality sample and template features. The first two methods adaptively filter the probe biometric data and matching scores based on predicted values of Quality of Sample index (defined here as d-prime) and Confidence in matching Scores, respectively. The last method, considers that image quality measures as features for discriminating between genuine and imposter matching scores. The proposed algorithm has the advantage of being generic (suitable for other biometric modalities).

4.5 Iris Recognition

Ross et al. (2012), addressed the problem of recognizing degraded iris images, having authors considered five factors: 1) non-uniform illumination, 2) motion, 3) defocus blur, 4) off-axis gaze, and 5) nonlinear deformations. The key insight the proposed method is that a single-feature encoding schema doesn't appropriately handle all these variations, and propose three feature extraction / matching strategies: 1) gradient orientation histograms, 2) scale invariant feature transforms and a 3) probabilistic deformation model. The information extracted by each descriptor is matched independently and results are combined at the score level, using the classical sum-rule. Experiments on the FOCS and FRGC data sets encourage further work on this kind of hybrid techniques.

As with other biometric traits, most difficulties in iris recognition result from less controlled acquisition setups, that lead to severely degraded images. In this context, an interesting possibility might be to fuse periocular recognition to iris recognition algorithms that work on visible wavelength data. It has been claimed that acquire discriminating data from the iris at visible wavelengths might be to hard, due to the pigments of the human iris (brown-black Eumelanin (over 90%) and yellow-reddish Pheomelanin (Meredith & Sarna (2012) that have most of their radiative fluorescence under visible light, but this significantly varies with respect to the levels of iris pigmentation. Even though previous technology evaluation initiatives (Proença & Alexandre, 2010, 2012) confirmed the possibility of recognizing human beings in visible wavelength real-world data, the state-of-the-art algorithms have only a moderately satisfactory performance (decidability indexes of 2.5 at most). The approach that currently outperforms was developed by Tan, Zhang, Sun, and Zhang (2012) and makes fuses global color-based features and local ordinal measures to extract discriminating data from the iris region. Wang, Zhang, Li, Dong, Zhou, and Yin (2012) used an adaptive boosting algorithm to build a strong iris classifier from a set of bi-dimensional Gabor-based features, each corresponding to a specific orientation and scale and operating locally. Given the fact that the pupillary boundary is especially difficult to segment in visible wavelength data, the authors trained two distinct classifiers: one for irises deemed to be accurately segmented and another for cases in which the pupillary boundary is expected to be particularly hard to segment. Li, Liu, and Zhao (2012) used a novel weighted co-occurrence phase histogram to represent local textural features, which is claimed to model the distribution of both the phase angle of the image gradient and the spatial layout and overcomes the major weakness of the traditional histogram. A matching strategy based on the Bhattacharyya distance measures the goodness of match between irises. Marsico, Nappi, and Richio (2012) proposed the use of implicit equations to approximate both the pupillary and the limbic iris boundaries and to perform image normalization. They exploited local feature extraction techniques such as linear binary patterns and discriminating textons to extract information from vertical and horizontal bands of the normalized image.

4.6 Oculomotor-Based Recognition

One of the most original branches in the ocular biometrics domain, might be the recent attempts in performing recognition using as discriminating information the eye movements. In this scope, the work of Komogortsev, Karpov, Holland, and Proenca (2012) should be highlighted. These authors propose to fuse at the score level the oculomotor plant characteristic and the iris texture. From the eye-movement perspective, their results point out that the proposed schemes provide discriminating information between individuals. From the iris perspective, the main conclusion is that very low error rates can be obtained, even when operating on data with resolution substantially lower that the ISO/IEC 19794-6 recommendation. An extremely interesting feature of their experiments was that they were performed using low-cost COTS Webcams. Another interesting work on this scope is due to Rigas, Economou, and Fotopoulos (2012), that used cues that reflect the individual idiosyncrasies of eye movements for augmenting the robustness of the resulting pattern recognition system. Their method is based on multivariate Wald-Wolfowitz test, that compares the distributions of saccadic velocity and acceleration features. The observed identification rates reveal the efficiency of the method, even though error rates are still far of the obtained with the classical biometric traits (e.g., iris and face). To narrow this gap in effectiveness with respect to other traits, authors plan to use more dynamic features, as the combination of time and spatial information provided by eye movements.

A competition on eye-movements biometric strategies was recently conducted by Kasprowski (2012). According to the observed results, the organizers concluded that is particularly important to be very careful in terms of the position of eyes during data capturing and also to camera calibration. Even though, further work in this scope is encouraged, having authors compared the observed recognition effectiveness to the results attained by the earliest face recognition algorithms.

5. RESULTS AND DISCUSSION

Table 3 summarizes the results obtained by the most relevant periocular recognition methods. We give the types of features extracted and the classification scheme used by each algorithm. Also, the data sets used in the experiments are summarized, together with the observed accuracy. As we can see, recently developed methods focus mainly on texture analysis and key-point extraction, and even simple algorithms lead to fair performance levels, with a noteworthy response of LBP based methods. Periocular fitness for more relaxed setups is also corroborated by these results, favoring the visible wavelength over NIR.

However, and facing the heterogeneity between test data, it's yet difficult to assess methods' relative performance in-between themselves. To bring some enlightenment on that subject, methods should be tested on the same data and

Table 3. Overview of periocular recognition methods

Approach	Features	Extract	Classifier	Dataset	Reported accuracy
(Park et al., 2009)	Shape, Texture, Key-Points	HOG, LBP, SIFT	Euclidean distance, SIFT matcher	899 images, 30 subjects, 2 sessions, visible wavel.	HOG: 62.5% LBP: 70.0% SIFT: 74.2% Best: 80.8%
(Miller et al., 2010b)	Texture	ULBP	Manhattan distance	FRGC, FERET	FRGC: 89.8% FERET: 85.1%
(Adams et al., 2010)	Texture	LBP+GEFE	Manhattan Distance	FRGC, FERET	FRFC: 92.2% FERET: 85.1%
(Woodard, Pundlik, Lyle, & Miller, 2010a)	Color, Texture	R&G ch. color hist., LBP	Bhattacharya distance, Manhattan distance	FRGC, MBGC	L FRGC: 90% R FRGC: 88% L MBGC: 81% R MBGC: 87%
(Woodard, Pundlik, Miller, Jillela, & Ross, 2010b)	Texture	Daugman's iriscode, LBP	Hamming distance, Manhattan distance	MBGC	L Iris: 13.8% R Peri: 92.5% L Fusion: 96.5% R Iris: 10.1% R Peri: 88.7% R Fusion: 92.4%
(Juefei-Xu et al., 2010)	Texture, Key-Points	Walsh Masks, Laws' masks, DCT, DWT, Force Fields, Gabor filters, LBP, SIFT, SURF	Cosine distance, Euclidean distance, Manhattan distance	FRGC	DWT+LBP: 53.2% DCT+LBP: 53.1% Walsh+LBP: 52.9% Laws' + LBP: 51.3% …
(Juefei-Xu et al., 2011)	Texture	WLBP+UDP	Cosine distance	FG-NET	100%
(Bharadwaj et al., 2010)	Naturalnes, Openness, Roughness, Expansion, Ruggedness, Texture	GIST, ULBP	X^2 distance	UBIRIS.v2	GIST: 70.82% ULBP: 63.77% Fusion: 73.65%
(Hollingsworth et al., 2010)	Human	Human	Human	NIR images, 120 subjects	92%
(Hollingsworth et al., 2012)	Human	Human	Human	NIR & visible, 210 subjects	NIR Peri: 78.8% V Peri: 88.4% NIR Iris: 85.6% V Iris: 79.3%

results analyzed side by side. Implementations of each method should reproduce papers' algorithm description as close as possible, and eventually omitted parameter chosen to maximize overall performance. As most of the literature reports results against the FRGC, that dataset is a good candidate for the evaluation stage. A total of 6225 images were selected, with the right-side periocular region manually cropped to avoid further errors, resulting in over 250 thousand matching trials with a 1:2 intra- inter-class ratio. Results from those trials can be seen at Table 4.

Some papers reported multiple results from different setups. As so, values from Table 4 may differ from the ones on Table 3, since we now chose to display the ones best fitting our test conditions.

Table 4. Tested periocular recognition methods performance indicators: Area Under ROC Curve (AUC), Equal Error Rate (EER), Computed (CA) and Reported Accuracy (RA) and Original testing dataset

Approach	Features	AUC	EER	CA	RA	Dataset
(Park et al., 2009)	LBP HOG SIFT Fusion	0.84 0.82 0.83 0.86	0.24 0.25 0.23 0.21	88.92% 88.92% 88.66% 89.69%	70.00% 62.50% 74.20% 80.80%	899 images, 30 subjects, 2 sessions, visible wav.
(Miller et al., 2010b)	ULBP	0.82	0.24	89.69%	89.80%	FRGC
(Woodard, Pundlik, Lyle, & Miller, 2010a)	ULBP Color Fusion	0.83 0.62 0.83	0.22 0.41 0.23	89.69% 35.57% 89.69%	83.40% 74.20% 87.10%	FRGC
(Woodard, Pundlik, Miller, Jillela, & Ross, 2010b)	LBP Iriscode Fusion	0.82 0.75 0.83	0.24 0.30 0.23	90.21% 69.07% 88.66%	88.70% 10.10% 92.40%	MBGC
(Bharadwaj et al., 2010)	ULBP GIST Fusion	0.76 0.87 0.88	0.30 0.21 0.19	88.40% 89.18% 87.37%	54.30% 63.34% 73.65%	UBIRIS.v2

Having Park et al. (2009) pioneering approach as comparison term, we can see how the subsequent developed algorithms introduce in fact some improvements, either by using more robust procedures (*e.g.* ULBP *vs.* LBP), by proposing different image pre-processing and ROI definition Woodard, Pundlik, Lyle, and Miller's (2010a) LBP *vs.* Park et al. (2009) LBP, or by bringing in new techniques (*e.g.* GIST). However, method performances are quite similar, with rank-1 accuracy around 89%.

The major discrepancy between reported results and ours occur when color information is used (Woodard, Pundlik, Lyle, & Miller, 2010a). Although images from the same database were used for testing, we weren't able to reproduce such scores, and even if obtaining better accuracy on ULBP, fusing it with the color descriptors didn't bring any improvements. That happens because the score level fusion optimization technique (logistic regression) didn't give color information enough weight to make itself representative. Nonetheless, if we attend at the correlation coefficients between features, the more contrasting one is color, followed by iris and SIFT.

6. ISSUES AND PROBLEMS

Being an emerging and relatively new biometric trait, several issues arise from the use of this type of data for recognition purposes. These were grouped into five topics, based on the criteria suggested by Park, Jillela, Ross, and Jain (2011).

The first one is related with the *imaging* stage, and determining the optimal spectrum for periocular biometrics. As former research usually prefers near-infrared data, expectations aim towards the visible wavelength, where unconstrained recognition is favored. However, wouldn't the fusion from data acquired at different wavelengths, yielding multispectral data, result in relevant advantages?

The next concern is about the actual *boundaries* of the periocular region, which are yet to be settled. Even though we observe the inclusion of some traces like the eyebrows, iris or sclera, to improve overall performance, researchers sometimes disagree on whether those elements should rather be masked or cropped to avoid biased results.

Moving on to the *feature encoding* stage, new questions arise: which features are the most representative when aiming at discriminating this region? Also, the heterogeneity of the components in the periocular region may suggest that more elaborate feature schemes are required to describe such different types of information.

After settling the features, a feature *matching* scheme should be determined. We must take into account the techniques most suitable to handle data variations inherent to the less controlled acquisition process, and how to optimally handle the variations in the traditional data variation factors.

At last, how would periocular biometrics benefit from the *fusion* with other features? Even considering that the use of multiple traits might be important to compensate for acquisition adversities, and iris being a fit candidate for score level fusion during periocular recognition, the way of maximize the outcome of this (or other) association is yet to be clearly established.

Apart from the imaging, encoding, matching and fusion alternatives detailed on the previous sections, Bakshi, Sa, and Majhi (2013) addressed the *boundary* definition issue by actually studying its proportions impact on the recognition performance and the trade-off with computational cost, and proposing an *optimized* ROI with minimal template size and maximal recognition accuracy.

7. CONCLUSION

This chapter addressed the use of information in the vicinity of the eye (periocular region) to perform biometric recognition. Particularly for uncontrolled data acquisition scenarios, the periocular region is regarded as an interesting trade-off between using the entire face or using exclusively the iris. Information inside the periocular area is considered to be highly different between individuals and relatively stable over lifetime.

According to the above properties, several research groups have been concentrating their efforts in developing algorithms for periocular recognition, that usually profit of the heterogeneous types of information in this region: shapes of eyelids, texture of the skin and iris, distribution of eyelashes and skin key points (e.g., spots). This heterogeneity propitiates the fusion at different levels (data, features or scores), from various types of recognition algorithms, which is known to potentially increase robustness against degraded data.

Having presenting the publicly available data sets where experiments are being carried out, we also summarized the most relevant research on this topic and compared the state-of-the-art results in terms of recognition performance. Also, we discussed the issues and directions for further work on this topic.

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KEY TERMS AND DEFINITIONS

Commercial Off-the-Shelf (COTS): Usually refers to products that are commercially available and can be bought and used as they are, in a plug-and-play setting.

Histograms of Oriented Gradients (HOG): Texture descriptor highly popular in computer vision, to efficiently describe a broad range of images. It consists in extracting the oriented gradients in images patches, to quantize and group them into local histograms that are considered the feature sets.

IrisCode: Refers to the biometric signature extracted from the unoccluded iris ring, after segmentation and normalization. The most popular approach consists in the convolution between a set of Gabor filters and the normalized data, from where the sign of coefficients is used.

Local Binary Patterns (LBP): Extremely efficient texture descriptor, that summarizes in a single value the relationship between each pixel and its surroundings, in terms of relative intensity. Usually, histograms of these values are built and considered the feature descriptors.

Oculomotor Recognition: Emerging trait for biometric recognition, based in the observation that the movement of each subject's eyes is singular and relatively stable over lifetime.

Periocular Recognition: Emerging biometric trait that complements the iris texture, in degraded data acquisition environments. The idea is that, for bad quality data, additional discriminating information can be obtained from the shape of eyelids, and eyelashes, eyebrows and the skin texture.

Region-of-Interest (ROI): It is the first phase of any periocular recognition algorithm. After detecting the ocular components, a rectangular is superimposed in the vicinity of the eye, from where the biometric signature is extracted.

Scale-Invariant Feature Transform (SIFT): It attempts to find particular regions (keypoints) in the image that are singular, in terms of their statistical properties. It also refers to a matching strategy that tries to find correspondences among keypoints in different images.

ENDNOTES

[1] http://iris.di.ubi.pt/ NOISYRIS

[2] FaceVACS SDK available at http://www.cognitec-systems.de

[3] Free virtual makeover tool, available at http://www.taaz.com

[4] http://nxt.ncat.edu/