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Periocular Biometrics: A Modality for Unconstrained Scenarios

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Abstract—Periocular refers to the region of the face that surrounds the eye socket. This is a feature-rich area that can be used by itself to determine the identity of an individual. It is especially useful when the iris or the face cannot be reliably acquired. This can be the case of unconstrained or uncooperative scenarios, where the face may appear partially occluded, or the subject-to-camera distance may be high. However, it has received revived attention during the pandemic due to masked faces, leaving the ocular region as the only visible facial area, even in controlled scenarios. This paper discusses the state-of-the-art of periocular biometrics, giving an overall framework of its most significant research aspects.

■ **THE OCULAR AREA** is comprised of several organs, such as the cornea, pupil, iris, sclera, lens, retina, optical nerve, eyelids, etc. Figure 1 depicts some of them. Among these, the iris,

sclera, retina, and periocular have been studied as biometric modalities, especially the iris [1]. However, iris systems mostly operate with near-infrared (NIR) illumination and controlled close-

up acquisition. In visible (VIS) illumination, iris recognition performance significantly degrades [2]. In addition, difficult covariates found in real-world conditions (occlusion, subjects' pose, illumination, resolution, etc.) may even prevent the location of the iris itself or the obtention of an iris image suitable for operation. Facial technologies have also seen significant progress in the last decades, but unconstrained recognition is still elusive. Partial faces have become an issue even in controlled setups during the pandemic due to the mandatory use of masks. Even after years of pandemic, their negative effect on state-of-the-art facial recognition systems has been systematically documented [3].

In this context, periocular biometrics rapidly evolved for unconstrained biometrics, with several survey papers [4], [1], [5], [2], [6], and more recently due to the use of masks [7]. Several competitions have also been organized across the years [8]. The ocular region by itself has shown to hold powerful keys to estimating identity [5], soft-biometrics [9], or expression [7]. An advantage is that it appears both in iris and face images so that it can be easily obtained with existing sensors. This part of the face is available over a wide range of distances, even if the face is partially occluded due to a close acquisition (e.g. selfie) or if the distance is high enough to prevent high-resolution iris acquisition. It may also be the only visible area in many unconstrained or uncooperative situations, involuntarily or voluntarily (e.g. criminals concealing the face). Even in cooperative situations, the pandemic has produced by law that the eyes are the only visible area in nearly all public situations, affecting all kinds of applications employing face technologies.

THE PERIOCCULAR REGION: DEFINITION, ACQUISITION AND DETECTION

The medical definition of “periocular”, according to the Merriam-Webster dictionary, is “surrounding the eyeball but within the orbit”. In biometrics contexts, the term is used loosely to refer to the externally visible region of the face that surrounds the eye socket, and sometimes it is used interchangeably with the term “ocular”. Thus, periocular systems employ as input images of the whole eye, such as the one in Figure 1.

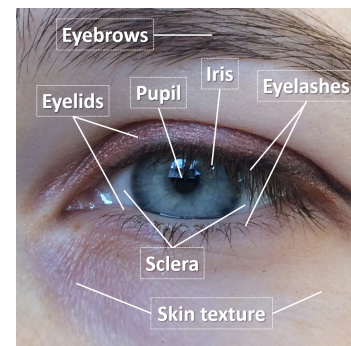


Figure 1. Eye image labeled with some parts of the ocular region.

While the iris, sclera, and other elements are presents, they are not necessarily used in isolation, or they may not have sufficient quality to be reliably processed stand-alone. On the other hand, there is no standard definition of the periocular region of interest. Some authors use the eye center as reference, while others use the eye corners, which are less sensitive to gaze variations [6]. The significance of the various elements of the ocular region and the size of the region around the eye have also been subjects of scrutiny [7].

Initial research employed face or iris datasets due to the limited availability of periocular ones. Sensing devices included digital cameras, webcams, video cameras, or close-up iris sensors. As research progressed, specific datasets appeared. A detailed description and reference papers of face, iris, and periocular databases can be found in existing surveys [5], [2], [8], [7]. Some sample images of periocular databases are shown in Figure 2. They are divided into NIR and VIS databases. The majority have been captured with mobile devices. Some are with long-range devices (FOCS, CASIA distance) or zoomable digital cameras (UBIPr), and there are a few multiple spectra sets. Although many include different acquisition distances (e.g. MIR 2016, CASIA Iris Mobile, UBIPr), subjects stand at determined stand-off distances. The only database with true mobility is FOCS, from subjects walking through an acquisition portal.

Automatic detection of the ocular region has not been a fundamental issue addressed in research studies. Instead, the core focused on feature extraction for recognition or other tasks, such as soft-biometrics. Initial studies relied on

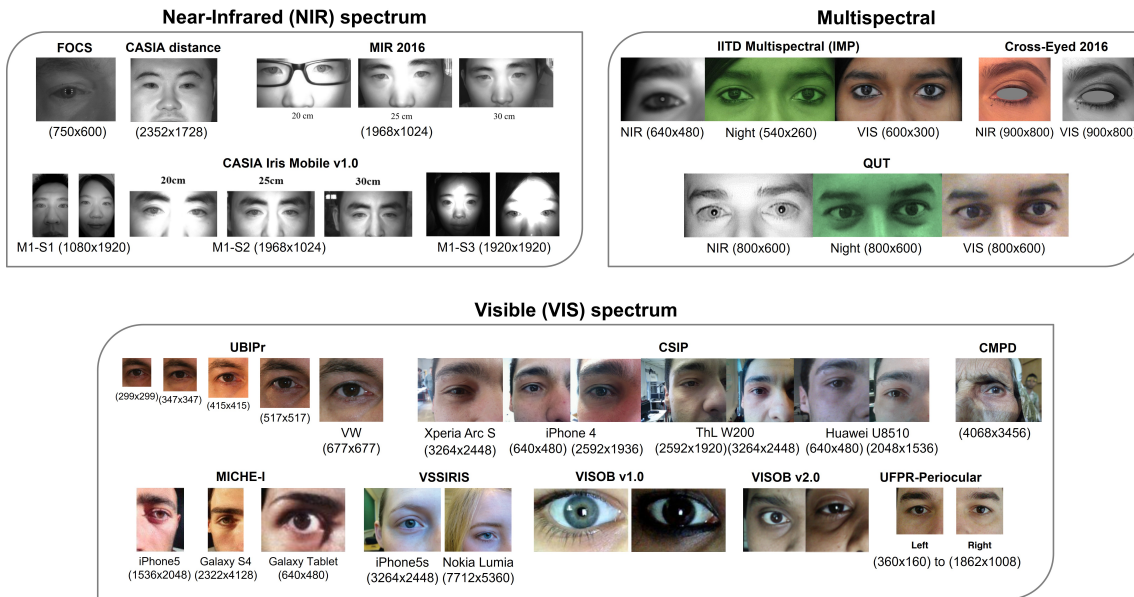


Figure 2. Samples of images from periocular databases.

manual marking of the region of interest or extraction after full-face detection. In comparison to research on face detection, which spans several decades, very few methods have been proposed to locate the eyes directly without the support of the nose-to-chin region [5]. State-of-the-art face detectors, including in the *deep-learning* (DL) era, aim at detecting the entire face. Occlusion is present in training databases but is not specifically controlled, nor the methods are trained or evaluated on their capabilities when only the ocular area is visible. Occluded face detection is attracting research recently, including methods to locate which parts of the face are visible [10]. Still, they focus on face-subregions analysis that looks for their different parts (mouth, nose, etc.) to compose the potential location of the full face. Detecting the ocular region directly without relying on full-face detection or on a systematic analysis of their expected subparts is thus an under-researched area.

PERIOCCULAR BIOMETRICS AS A STANDALONE MODALITY

One of the earliest papers on periocular biometrics was by Park et al. in 2009 [11]. Simple texture operators were used to encode the periocular region. Subsequently [12], a more detailed analysis was conducted where the authors

investigated the effectiveness of incorporating the eyebrows, the possibility of fusing face and periocular modalities, the effect of varying pose and illumination, the effect of masking the iris and eye region, etc. In particular, the authors demonstrated the benefits of the periocular modality when the face was partially occluded. Since then, a number of methods have been used to encode the periocular region. These include features extracted using classical texture operators (LBP, BSIF, BRISK, HOG, SIFT, SURF, etc.) and filters (Gabor, Leung-Malik, etc.) [5], [6]. More recently, with the deep-learning paradigm, Convolutional Neural Networks (CNNs) have been used [7], either applying off-the-shelf CNN features or trained networks based on autoencoders and attention models.

COMBINATION WITH OTHER MODALITIES

From the beginning, the periocular region has been regarded as an interesting possibility for unconstrained data acquisition associated with visual surveillance scenarios [13]. In such settings, the obtained data frequently lacks not only intra-subject permanence but also discriminability between subjects, which is the main rationale for fusing the periocular region to other biometric traits to improve the overall performance.

Due to biological vicinity, the iris is the most frequently considered trait for fusion. This combination is especially useful when the iris has insufficient quality, due to reflections, off-axis gaze, motion, low resolution, etc. Different texture descriptors are used, such as classical Gabor kernels for the iris, or LBP, HOG, or Leung-Malik for the periocular region [7]. Fusion is mostly performed at the score level. More recently, due to the popularity of the deep-learning paradigm, several DL models also addressed the iris/periocular fusion exploiting joint attention mechanism to learn relevant features of each region.

Fusing descriptions from the whole face and the periocular region is also frequently reported. This is beneficial when the face is partially occluded, has a large pose variation, or is captured at a very close distance. As in the case of the iris, the idea is to obtain independent feature representations from the face and the periocular region, delimited according to hard-attention mechanism, that are further fused at the feature or score levels. Earlier attempts included traditional features such as Gabor wavelets, LBP, HOG or SIFT [5], with the most recent works also considering DL solutions, such as shared backbones for both regions, or siamese models with an independent stream for each one.

Lastly, the sclera region should also be explicitly mentioned, as it is another trait frequently advocated as a possibility for being fused to the periocular region [7]. A number of features from the sclera have been proposed across the years, including methods for its detection and segmentation [1].

Overall, most works conclude about the benefits of fusing the periocular information with other traits in the neighborhood. The exception is due to Proença and Neves [14], which argued that the recognition performance is optimized when the components inside the ocular globe (iris and sclera) are discarded, and the recognizer's response is exclusively based on the information from the surroundings of the eye.

RECOGNITION IN DIFFERENT SPECTRA

Image-based biometrics can capture characteristics by camera sensors that measure different ranges of light wavelengths. Within this scope,

the three main considered spectra are visible (VIS), near-infrared (NIR), and infrared (IR). Each poses advantages and restrictions on the periocular biometric system and the application scenario. For example, VIS allows the use of many existing built-in cameras and provides a relatively high level of detail. NIR, on the other hand, can reveal details unseen in the VIS spectrum (e.g. in iris recognition, as the effect of melanin is negligible under NIR) and is less sensitive to illumination variations. Such properties make NIR suitable for periocular recognition in combination with iris or under illumination-sensitive scenarios such as head-mounted displays. However, it commonly requires an active NIR invisible illumination source. IR imaging, which might be referred to as thermal imaging too, commonly provides much lower information details and is much more sensitive to the capture environment variations, which makes it a less suitable choice for periocular recognition. More importantly, at the algorithmic level, these spectra capture different sets of information from the periocular region. The two main periocular recognition challenges in this scope are (1) accurate recognition under each of these spectra to adapt to different use-cases and (2) accurate recognition in a cross-spectral setting, where the reference and probe are captured under different spectra.

Recognition in the VIS spectrum is mainly motivated by using existing general-purpose capture devices under self-verification (e.g. smartphones) or surveillance scenarios, including occluded or masked faces. Many databases were collected to develop VIS periocular recognition, including UBIRIS.v1 and v2, MICHE-I, and the recent large-scale UFPR-Periocular [8]. Recognition in the NIR spectrum, on the other hand, is motivated by capture devices needed for iris recognition, which enables the use of both characteristics. NIR recognition also comes in handy when VIS is not applicable, such as in head-mounted displays in augmented and virtual reality applications [15]. The development of NIR periocular recognition solutions are based on a set of databases, with CASIA-Iris-Mobile-V1.0 and its derivatives being the most widely used. Solutions for intra-spectrum periocular recognition, whether NIR or VIS, are technically similar, either based

on handcrafted features, deeply learned representations or the fusion of both [7]. This interest in intra-spectral periocular biometrics led to the organization of a series of competitions, including the VISOB 1.0 and VISOB 2.0 events [8].

Many applications restrict the biometric reference to be captured under one spectrum, but require the ability to match probes captured under other spectra. This raises the challenge of cross-spectral periocular recognition, where the information and its representation in the captured images differ between the reference and probe. Two main directions were followed in an effort to enhance the accuracy of cross-spectral periocular recognition. The first is the direct comparison, either by features that are expected to be less sensitive to the spectral change, or features that are specifically learned to produce similar representations for both NIR and VIS images of the same identity. The second direction is the generative transformation of the probe into the domain of the reference, where an intra-spectral recognition algorithm can be then applied [16]. The latter required the creation of novel cross-spectral databases such as QUT Multispectral Periocular and I-SOCIAL-DB, with a full list of recent cross-spectral databases provided in [8]. Given the highly challenging nature of the cross-spectral scenario, a series of competitions were organized to attract novel solutions, including the Cross-Eyed competition in its two versions.

DEMOGRAPHICS FROM OCULAR IMAGES

Soft-biometrics refer to *ancillary* information such as age, gender, race, handedness, height, weight, hair color, etc. Among these, demographic indicators (gender, age, ethnicity) are receiving huge attention due to their higher permanence and distinctiveness [17]. They can be captured from the body silhouette or the face, although some have suggested the use of modalities such as fingerprints, iris, handwriting, etc. [18].

In controlled scenarios, face or iris biometrics can be very effective. But under difficult covariates in real-world conditions (occlusion, subjects' pose, illumination, resolution, etc.), demographic attributes can be retrieved with a higher probability of success. They can be used in isolation, or complement the inconclusive decision of a

stronger biometric modality. They have other uses as well, such as targeted advertising, search of specific individuals fulfilling certain attributes, age-related access control, or child pornography detection. Although demographic estimation is seen frequently as relatively easy, extracting such attributes *in-the-wild* can be also challenging. However, research is mostly devoted to good-quality data. Using the entire face is also common, despite likely occlusions in real-world setups such as forensics or surveillance [17].

Gender estimation (male/female) is the most widely studied attribute and considered the easiest one due to being a binary classification. Initial works can be traced back to 2010 [5], cropping the ocular area from well-established face recognition databases. Later on, selfie images from smartphones appeared, followed by the prevalent trend of applying automatically learned features (via CNNs). Accuracies above 80-90% are common in the most recent works [19], [9].

In ethnicity estimation, the difficulty is the proper definition of classes. Ethnic classes between databases are not consistent, and some are severely under-represented. Also, most databases contain two or three classes only, since they were not acquired for ethnicity estimation specifically. Initial works can be also traced back to 2010, but the literature on ocular ethnicity is much less compared to gender. Accuracies above 80-90% are common as well [19], but a comparison between works is difficult due to the mentioned differences in classes between databases.

Age is referred to as the most complex attribute to estimate due to internal (genetics) and external (health, stress, lifestyle...) factors influencing the aging process. Comparatively, it is the most under-researched demographics with ocular data. Classes are often discretized (e.g. children, teens, adults...), achieving higher performance compared to estimating the exact age, and allowing customization to requirements (e.g. minors/non-minors). Pioneering works in 2015 used controlled data, followed later by selfie and in-the-wild imagery. The best accuracy of recent works barely exceeds 60% [19], [9], which highlights the difficulty of the task. It is also common to report the *1-off* accuracy, where classifications for groups adjacent to the true age group are also considered correct. This more tolerant framework

provides accuracies of above 80%.

CONCLUSION, CHALLENGES AND FUTURE DIRECTIONS

In the last decade, the periocular modality has rapidly evolved, surpassing face in case of occlusion or iris under low resolution. Periocular is the region around the eye, comprising the sclera, eyelids, lashes, brows, and surrounding skin. With a surprisingly high discrimination ability, it requires less constrained acquisition than the iris texture. It is also visible across a wide range of distances, even under partial face occlusion due to close distance, or low resolution due to long distances. This makes it very suitable for unconstrained or uncooperative scenarios where iris or face recognition may struggle. Beyond personal recognition, the periocular modality has been employed for other applications such as demographics or expression estimation. A graphical summary of the different aspects surrounding periocular biometrics is given in Figure 3.

Despite the mentioned advances throughout this paper, several research challenges remain. Aspects such as the size of the optimal periocular region of interest, or the minimum resolution necessary for recognition are still open questions [6], [7]. Public large-scale datasets and benchmarks are also necessary, not just to leverage the power of prevalent data-hungry deep-learning schemes, but to foster further ocular biometrics research and replication [2], [8]. A recent concern affecting all biometric modalities is demographic bias and fairness. Although face algorithms have been attracting the majority of public attention in this regard, such issues must be addressed in ocular biometrics as well. Other challenges that are worth detailing include the following:

- **Acquisition of high-quality images.** This is vital to any biometric modality. The majority of datasets in periocular research are from mobile devices and/or cooperative subjects zoomed from a relatively close distance [8]. Less cooperative scans, also including motion, and larger stand-off distances are largely under-researched factors. Several hardware solutions have been proposed, such as hyper-focal or light-field sensors that fuse images captured with different focal lengths [2], or

near-infrared walking portals [5]. However, they come at an extra cost or increased sensor size. They are also inapplicable in consumer or forensic applications.

- **Smartphone authentication.** The pandemic accelerated the provision of digital services through personal devices, which have become data hubs containing sensitive information. Their inherent *on-the-move* conditions cause imaging difficulties that can severely degrade performance. Another natural property is the use of such devices in all kinds of environments entailing huge variability in pose, illumination, background, etc. A further difficulty is the availability of many different device models, each with its own camera specifications, that may not even be known. This demands proper methods to mitigate such cross-device, cross-environment operation [2].
- **Heterogeneous operation.** Despite the impressive recognition performances of periocular recognition under ideal conditions, maintaining such performance under cross-sensor, cross-spectral, and cross-resolution settings is still challenging [8], [7]. Part of this challenge is related to the lack of large-scale, e.g. multi-spectral databases, suitable to train millions of parameters in deep neural networks. This motivates the recent efforts [15] in replacing the need for authentic data with using identity-aware synthetic periocular data.
- **Deployability.** Recent works have shown the higher accuracy and generalizability of periocular recognition solutions based on deep learning when compared to handcrafted features. However, such models impose high requirements in model size and computational complexity that might make them realistically undeployable on resource-critical consumer devices. This motivates future research to work towards harvesting the knowledge learned with deeper (larger) models and transferring it into more deployable light models [20].
- **Invariance to age and other alterations.** Being a relatively recent addition to the family of biometric traits, there are different factors that might influence the performance of periocular recognition methods, such as the effect

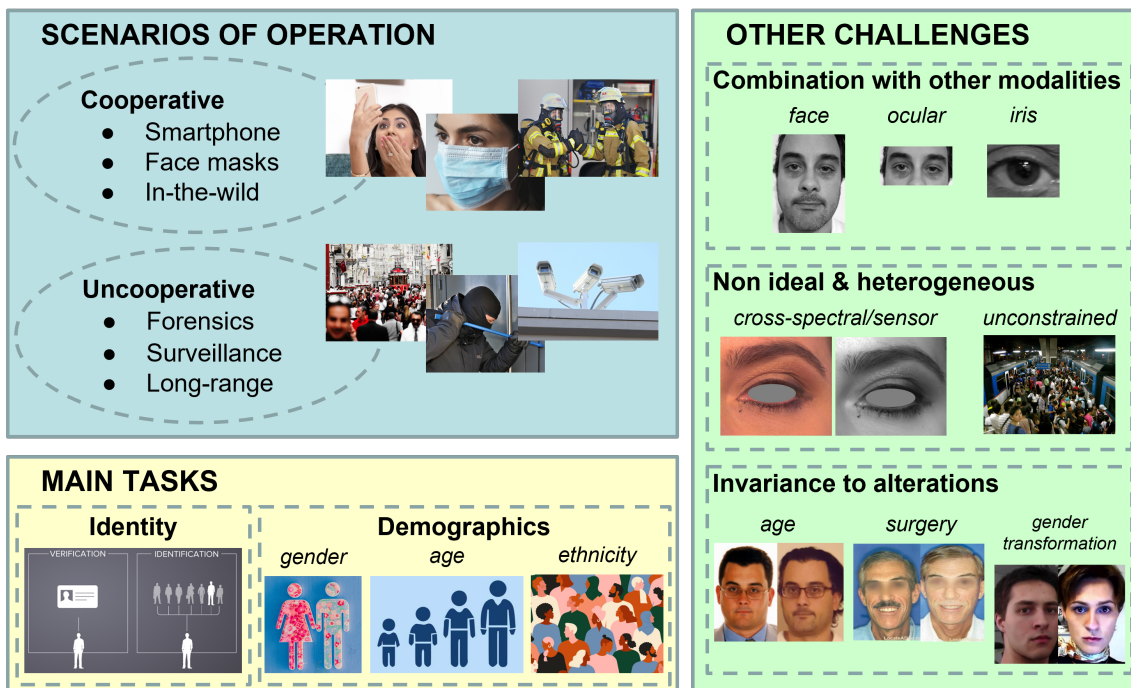


Figure 3. Graphical summary of different aspects of significance in periocular biometrics. Top left: potential scenarios of operation. Top bottom: main tasks where periocular images can be useful. Right: Some other challenges affecting periocular biometrics.

of facial expressions, the possibility of forging due to surgical procedures, and - in particular - the long-term stability of periocular features, i.e., invariance to aging [7], [5]. This analysis is a requirement to increase confidence in periocular-based recognition systems and turn this trait into an even more serious possibility when it comes to deploying a biometric recognition solution.

- **Spoofing attacks.** In parallel with the popularity of biometrics systems, their security against attacks has become paramount. The most common attack, presentation attack (also known as spoofing), consists in presenting a fake biometric sample to the sensor. This has received extensive attention with face and iris modalities to detect e.g. silicon masks, print-outs, contact lenses, or digital replays. Although several works exist with ocular images, the amount is much more limited [7], [8].

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