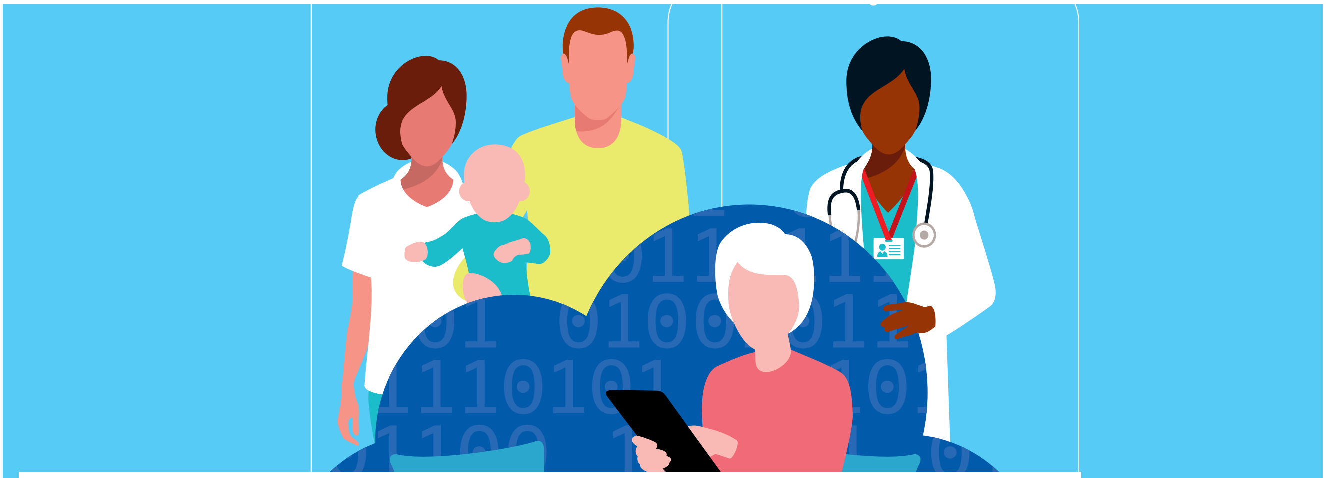

Periocular Biometrics: A Modality for Unconstrained Scenarios

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This article discusses the state of the art in periocular biometrics, presenting an overall framework encompassing the field's most significant research aspects, which include ocular definition, acquisition, and detection; identity recognition; and ocular soft-biometric analysis.

The ocular region consists of several organs, including the cornea, pupil, iris, sclera, lens, retina, and eyelid, among others (Figure 1). Among these, the iris, sclera, retina, and periocular entities have been studied as biometric modalities, particularly the iris.[1] However, iris recognition systems primarily operate with near-infrared (NIR) illumination and controlled close-up acquisition. In visible illumination, their performance significantly degrades. Moreover, real-world conditions present challenges, such as occlusion, subjects' poses, unfavorable illumination, and low resolution, which may even hinder iris localization or the acquisition of suitable iris images. Face recognition technologies have also seen significant progress over the past two decades, but unconstrained recognition remains difficult. Partial faces became an issue, even in controlled setups, during the pandemic, due to the mandatory use of masks in some places, negatively impacting state-of-the-art facial recognition systems.[2]

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In this context, periocular biometrics has rapidly evolved as a promising approach for unconstrained biometrics. Several recent survey papers,[1,3,4] including those specifically addressing mask-related challenges,[5] have contributed to this field. Several competitions have also been organized over the years.[6] The ocular region by itself has demonstrated effectiveness in identity recognition,[3] soft-biometrics estimation,[7] and expression analysis.[5] It appears both in iris and face images, so it is easily obtainable with existing sensors. It also remains visible at various distances, even when face occlusion occurs due to close acquisition (for example, selfies[8]) or when the standoff distance prevents high-resolution iris imaging. Moreover, in many uncooperative scenarios, it may be the only visible area, involuntarily or voluntarily (for example, criminals concealing their faces). Even in cooperative situations, the use of facial masks during the pandemic obstructed most of the face, revealing only the eyes and their immediate surrounding, affecting all kinds of applications employing face technologies in security, health care, border control, education, and other domains.

Our scope is, thus, the ocular region. This article aims to provide insights into key aspects of periocular biometrics, covering the entire pipeline, from the definition of the ocular region to its acquisition, detection, and identity recognition. We also discuss aspects such as combining with other modalities to enhance recognition accuracy (typically, face or iris), recognition in different spectra,[9] or estimating demographic attributes (gender, age, and ethnicity) from ocular images. The article concludes by highlighting current challenges and future directions. Existing recent surveys[1,4,5,6] primarily describe specific feature methods, algorithms, datasets, and benchmarks. This article takes a more practical approach, focusing on technical aspects but omitting detailed algorithmic specifics (found in referenced surveys). We mention only the achieved accuracy for a specific task whenever relevant, referring interested readers to papers dedicated to systematic reviews of datasets and benchmarks.[6] In addition, due to the magazine's limitation on the number of references, original works cannot always be cited directly. In such cases, we refer readers to survey papers for comprehensive details about the mentioned issues. This mostly applies to older papers.

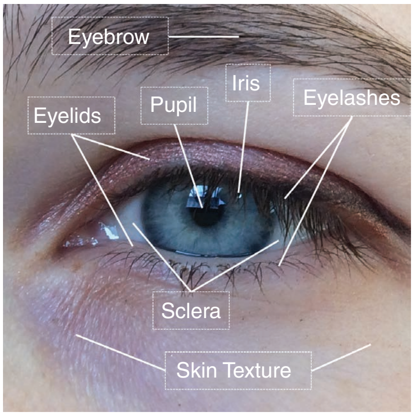

FIGURE 1. An eye image labeled with some parts of the ocular region.

THE PERIOCULAR 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, the term is used loosely to refer to the externally visible region of the face around the eye socket, and sometimes it is used interchangeably with the term "ocular." Thus, periocular systems employ the entire eye image as input, as depicted in Figure 1. While components such as the iris and sclera are present, they are not necessarily used in isolation or may not have sufficient quality to be processed reliably on their own. It is important to note that there is no standardized definition for the periocular region of interest (ROI), resulting in variations across papers. Additionally, some authors use the eye center as the reference, while others use the eye corners, which are less sensitive to gaze variations.[4]

Initial research employed face or iris datasets, due to limited availability of periocular ones. Sensing devices included digital cameras, webcams, video cameras, or close-up iris sensors. As research progressed, specific datasets emerged. A detailed description of face, iris, and periocular databases can be found in existing surveys[1,3,5,6] and newer papers.[10] Figure 2 shows sample images from periocular databases and the best-reported accuracy on those datasets. They are categorized into NIR and visible databases. Most visible databases (CSIP, MICHE, VSSIRIS, VISOB, and UFPR) have been captured using mobile devices by volunteers themselves, introducing variabilities, such as blur, defocus, reflections, eyeglasses, off-angle gazes, poses, makeup, or expressions. These databases also include different sensors and environments (indoor/outdoor, natural light/office light, and so on) Some are with long-range devices (FOCS and CASIA distance) or zoomable digital cameras (UBIPr), and there are a few multiple-spectra sets, enabling cross-spectral periocular analysis.[9] Also, although several sets involve different acquisition distances (for example, MIR 2016, CASIA Iris Mobile, and UBIPr), subjects usually stand at predetermined

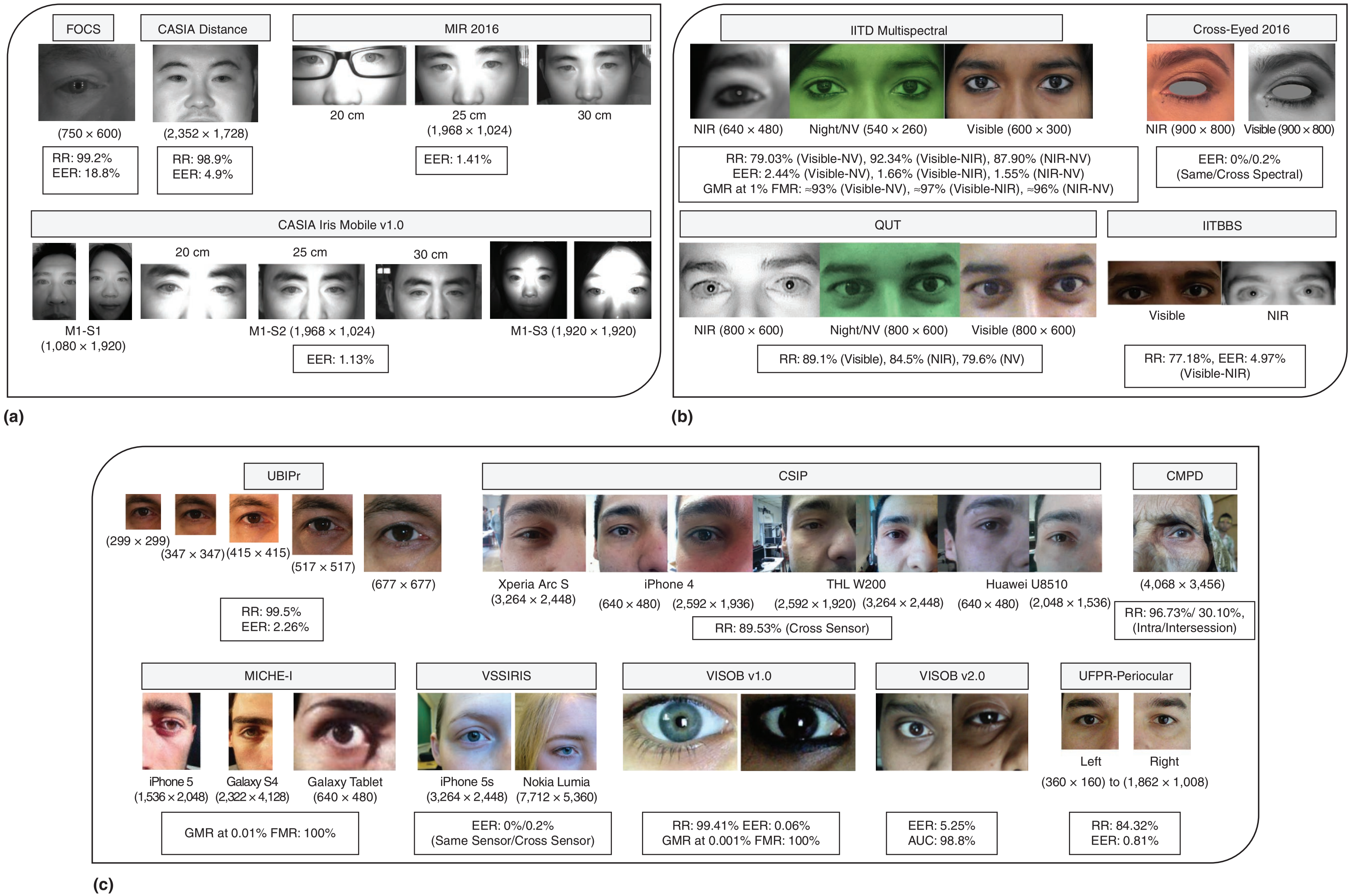

FIGURE 2. Samples of periocular databases and the best results in the literature with a periocular modality: (a) near-infrared (NIR) spectrum, (b) multispectral, and (c) visible (VIS) spectrum (results adapted from references in Sharma and Ross[5] and Zanlorensi et al.[6] and other newer references[10]). RR: recognition rate; EER: equal error rate; GMR: genuine matching rate; FMR: false matching rate; AUC: area under the curve; NV: night vision.

standoff distances. The only database with true mobility is FOCS, with subjects walking through an acquisition portal. This introduces significant challenges, such as motion blur or scale changes, resulting in lower accuracy (equal error rate: 18.8%) compared to other databases. Such results highlight on-the-move operation as an open challenge in periocular recognition. Certain databases serve specific purposes. For example, CMPD contains subjects before/after cataract surgery, a common procedure among elderly people. The reported results comparing images before/after the procedure (recognition rate: 30.1%) indicate that cataract surgery significantly impacts periocular recognition.

In research studies, automatic detection of the ocular region has not been a primary focus. Instead, the emphasis has been on feature extraction for recognition or other tasks, such as soft biometrics.[11] Initially, manual marking of the ROI or extraction after full-face detection was commonly used. In comparison to face detection research, which has spanned several decades, very few methods have been proposed to locate the eyes directly without the support of the nose-to-chin region.[3] State-of-the-art face detectors, including those based on deep learning (DL), are designed to detect the entire face. Occlusion is present in training databases but is not specifically controlled, nor are the methods trained or evaluated on their capabilities when only the ocular area is visible. Occluded face detection has been attracting research recently, including methods that locate the visible parts of the face.[12] However, these approaches primarily focus on analyzing face subregions (mouth, nose, and so on) to infer the potential location of the full face. Detecting the ocular region directly without relying on full-face detection or a systematic analysis of expected subparts is, thus, an underresearched area.

PERIOCULAR BIOMETRICS AS A STAND-ALONE MODALITY

One of the earliest papers on periocular biometrics was by Park et al., in 2009.[13] Simple texture operators were used to encode the periocular region. Subsequently, in 2011 (see Alonso-Fernandez and Bigun[3]), a more detailed analysis was conducted, exploring the effectiveness of incorporating eyebrows, the possibility of fusing face and periocular modalities, the impact of varying poses and illumination, masking the iris and eye region, and so on. In particular, the authors demonstrated the benefits of the periocular modality when the face was partially occluded.

Since then, various methods have been employed to encode the periocular region. These include classical texture operators [local binary pattern (LBP), binarized statistical image feature, binary robust invariant scalable key point, histogram of oriented gradients (HOG), scale-invariant feature transformation (SIFT), speeded-up robust feature, and so on] and filters (Gabor, Leung–Malik, and so forth).[34] The importance of different elements within the ocular region and the size of the region around the eye have been subjects of scrutiny as well.[5] For example, texture and color information (skin, wrinkles, pores, and so on) are more useful in the visible spectrum. In the NIR spectrum, such cues are obfuscated (see Figure 2), so ocular geometry information (eyelids, lashes, brows, and so forth) becomes more relevant.

More recently, due to the prevalence of DL techniques, convolutional neural networks (CNNs) have gained popularity,[5] either employing off-the-shelf CNN features or training networks using autoencoders or attention mechanisms to guide the network to focus on relevant regions, such as eyebrows and eyelashes.[10] The current state of the art is given by DL models. However, one drawback of these models is their reliance on large-scale databases, which are currently lacking in periocular research. Most of the datasets mentioned in the previous section contain only a few thousand images at most. The largest available dataset (VISOB v1.0) consists of 158,000 images, which is one or two orders of magnitude lower compared to the datasets available in other modalities, such as face biometrics. Therefore, the scarcity of large-scale periocular databases poses a challenge in advancing the field of periocular biometrics.

COMBINATION WITH OTHER MODALITIES

From the beginning, the periocular region has been considered valuable for unconstrained data acquisition in visual surveillance scenarios.[14] However, data obtained in such settings often lack intrasubject permanence and discriminability among subjects, which is the main rationale for fusing the periocular region with other biometric traits to improve the overall performance.

The iris, due to its biological proximity, is frequently chosen for fusion. This combination is especially useful when the iris has insufficient quality due to reflections, an off-axis gaze, motion, low resolution, and so on. Different texture descriptors are used in existing works, such as classical Gabor kernels for the iris and the LBP, HOG, or Leung–Malik for the periocular region.[5] Fusion is typically performed at the score level. More recently, DL models have also been employed, leveraging joint attention mechanisms to learn relevant features of each region.

Fusing descriptions from the entire face and the periocular region is also common. This is beneficial when the face is partially occluded, exhibits significant pose variation, or is captured at a close distance. As in the case of the iris, the idea is to obtain independent feature representations from the face and periocular region, delimited using hard-attention mechanisms and fused at the feature or score levels. Earlier attempts included traditional features, such as Gabor wavelets, the LBP, HOG, or SIFT.[3] Recent works explore DL solutions, such as shared backbones or Siamese models, with an independent stream for each one.

Finally, the sclera region should also be mentioned as another trait frequently advocated for fusion with the periocular region.[5] Various features and methods for sclera detection and segmentation have been proposed over the years. The sclera is particularly advantageous in the visible spectrum, where its prominent blood vessels are easily observable.

In conclusion, most studies highlight the benefits of fusing periocular information with other neighboring traits. The exception is due to Proença and Neves,[15] who argued that recognition performance in the visible spectrum is optimized when components within the ocular globe (iris and sclera) are discarded, and the recognizer's response is solely based on the surrounding eye information.

RECOGNITION IN DIFFERENT SPECTRA

Image-based biometrics utilize camera sensors that measure different light wavelength ranges. The three main considered spectra are visible, NIR, and IR. Each poses advantages and restrictions for periocular biometric systems and application scenarios.[16] For example, the visible spectrum enables the use of many existing built-in cameras, offers high detail, and is suitable for scenarios such as self-verification and surveillance. NIR illumination, on the other hand, reveals details unseen in the visible spectrum (for example, in iris recognition, as the effect of melanin is negligible under NIR), is less sensitive to illumination variations, and is comfortable to the human eye because it is not perceivable. Such properties make NIR suitable for periocular recognition in combination with iris or underillumination-sensitive scenarios, such as head-mounted displays. However, it requires an active NIR invisible illumination source. IR imaging, also known as *thermal imaging*, provides less information detail and is more sensitive to environmental variations, making it less suitable for periocular recognition.

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 spectrum 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.[9]

Recognition in the visible spectrum is motivated by using existing general-purpose capture devices for self-verification (for example, smartphones[8]) or surveillance scenarios, including occluded or masked faces. Numerous databases have been collected to develop visible periocular recognition (Figure 2). NIR recognition, on the other hand, is driven by capture devices used for iris recognition and scenarios where the visible spectrum is not applicable, such as head-mounted displays in augmented and virtual reality applications.[17] Solutions for intraspectrum periocular recognition (NIR or visible) are technically similar, utilizing handcrafted features, deeply learned representations, and their fusion.[5] This interest in advancing intraspectral periocular biometrics led to the organization of a series of competitions, including the first and second International Competition on Mobile Ocular Biometric Recognition events.[6]

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. Two main directions have been followed in this regard: 1) direct comparison using features less sensitive to spectral changes or specifically learned features that produce similar representations for NIR and visible images of the same identity[10] and 2) generative transformation of the probe into the reference domain, where an intraspectral recognition algorithm is applied.[18] Given this highly challenging nature, competitions, such as the Cross-Eyed series, have focused on attracting novel solutions for cross-spectral periocular recognition.[6,9] As can be observed in Figure 2(a), the accuracy in cross-spectral datasets is typically lower than in intraspectral NIR or visible operation.

DEMOGRAPHICS FROM OCULAR IMAGES

Soft biometrics refer to ancillary information, such as age, gender, race, handedness, height, weight, hair color, and so on, that can help when recognizing a person.[11] Among these, demographic indicators (gender, age, and ethnicity) have special relevance because they can be linked to undesired discrimination among population groups.[19] Soft biometrics can be computed from the body silhouette or the face, although some have suggested computing them from fingerprints, irises, or handwriting.

In controlled scenarios, face or iris biometrics can be very effective to recognize an individual. But under difficult covariates in real-world conditions (occlusion, subjects' pose, illumination, resolution, and so on), demographic attributes can be retrieved with a higher probability of success. They can be used in isolation or complement the inconclusive decision of stronger biometric modalities. For example, combining soft biometrics with periocular features has shown enhanced overall recognition performance.[20]

Demographic attributes also find applications in targeted advertising, searching for individuals based on specific attributes, age-related access control, or child pornography detection. Although demographic estimation is often seen as relatively easy, extracting such attributes in the wild is challenging. However, research in this area primarily focuses on good quality data and frequently uses the entire face, despite likely occlusions in unconstrained setups, such as forensics or surveillance.[21]

Gender estimation (male/female) is the most widely studied attribute and considered the easiest due to its binary nature. Initial works can be traced back to 2010,[3] cropping the ocular area from well-established face recognition databases. Later works incorporated selfie images from smartphones and leveraged learned features via CNNs. Recent works achieve accuracies above 80%–90% in gender estimation.[7]

Ethnicity estimation poses challenges in defining classes consistently across databases, and some people may be severely underrepresented. Most databases have only two or three ethnic classes since they were not specifically acquired for ethnicity estimation. Initial works can be also traced back to 2010, but there is much less literature on ocular ethnicity compared to gender. Accuracies above 80%–90% are common as well, but comparing results among works is difficult due to differences in classes across databases.

Age is considered the most complex attribute due to internal (genetics) and external (health, stress, lifestyle, and so on) factors influencing the aging process. Comparatively, it is the most underresearched demographic with ocular data. Classes are often discretized (for example, children, teens, adults, and so forth), achieving higher performance compared to estimating exact age and allowing customization to requirements (for example, minors/nonminors). Pioneering works in 2015 used controlled data, followed later by selfies and in-the-wild imagery. Recent works barely exceed a 60%[7] accuracy, highlighting the difficulty of the task. It is also common to report the one-off accuracy, which considers classifications for adjacent age groups to be correct. This more tolerant framework provides accuracies above 80%.

In the past decade, the periocular modality has rapidly evolved, surpassing the face in cases of occlusion or the iris under low resolution. The periocular region is the area around the eye, consisting of the sclera, eyelids, lashes, brows, and surrounding skin. With a surprisingly high discrimination ability, it requires less constrained acquisition than the iris texture. It remains visible at various distances, even with partial face occlusion due to close distances or low resolution due to long distances. This makes it suitable for unconstrained or uncooperative scenarios where iris or face recognition may struggle. The periocular modality gained renewed attention during the pandemic, as masks left the ocular region the only visible facial area, even in controlled situations. Apart from personal recognition, periocular biometrics have been used for demographics[7] or expression estimation.[5] Figure 3 provides a graphical summary of periocular biometrics, including aspects mentioned previously in the article and challenges discussed in the present section.

Despite the advances mentioned in this article, several research challenges remain. Questions about the optimal size of the periocular ROI and the minimum resolution required for recognition are still open.[4,5] The lack of a standardized definition for the periocular region leads to variations in the employed ROI across studies. For example, some studies exclude the sclera, iris, and pupil. Additionally, some consider the two eyes as a single instance, while others treat each eye as a separate unit. Large-scale datasets and benchmarks are needed as well to leverage data-hungry DL schemes and promote further research and replication.[1,6] A recent concern affecting all biometric modalities is demographic bias and fairness, where certain demographic groups may experience lower classification accuracy. This is not exclusive to biometrics, but it is common in automated decision-making systems.[19] Although face algorithms have attracted the majority of the public attention in this regard, proper mitigation measures are also needed in ocular biometrics. The increasing use of DL solutions also raises questions about explainability, due to their black-box nature, that is, why a recognition system makes certain decisions.

Other challenges that are worth mentioning include the following:

- *Acquisition of high-quality images*: This is vital to any biometric modality. Most periocular datasets come from mobile devices or cooperative subjects zoomed from a close distance.[6] Factors such as less-cooperative scans, motion, and larger standoff distances are underresearched. Several hardware solutions have been proposed, such as hyperfocal or light field sensors that fuse images with different focal lengths[1] or NIR walking portals

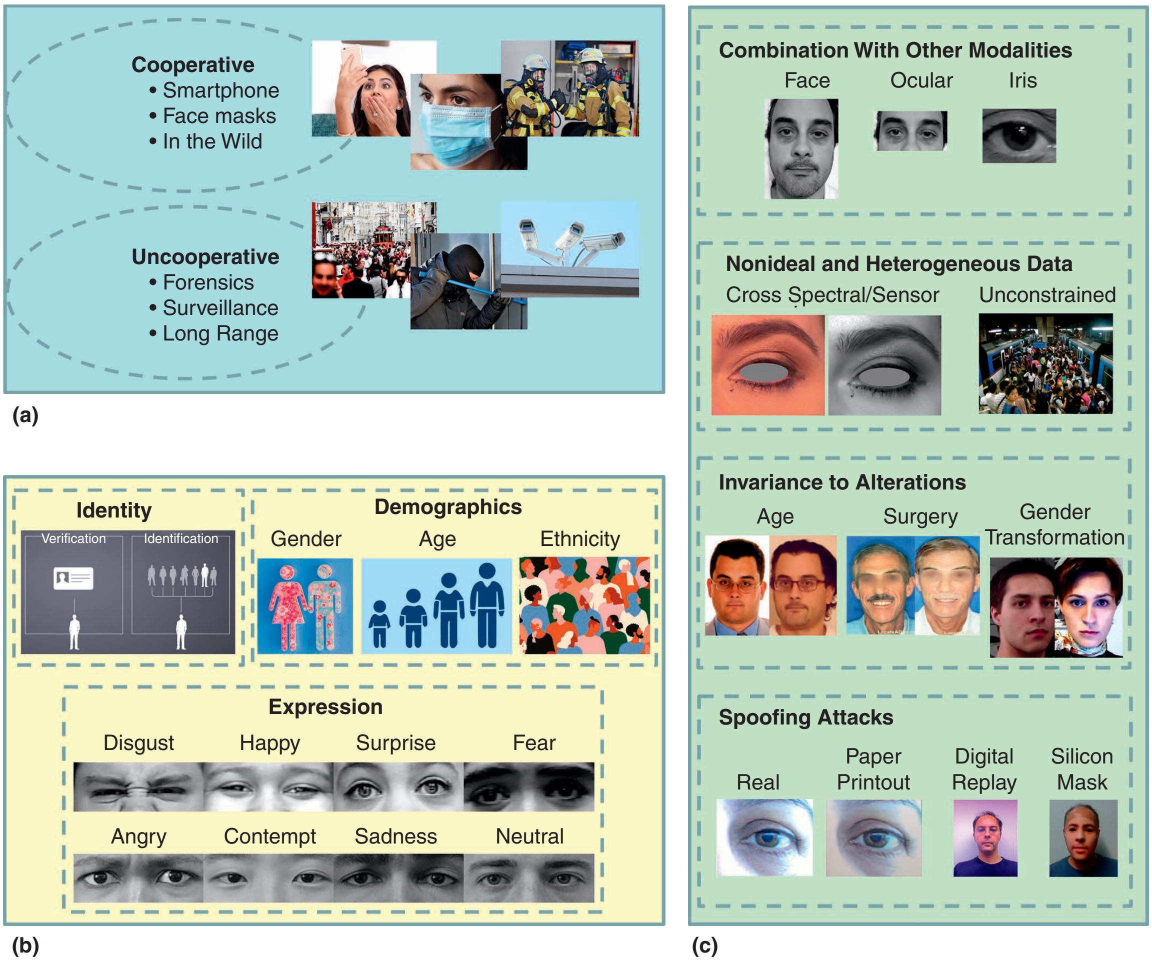

FIGURE 3. A graphical summary of different aspects of significance in periocular biometrics. (a) Potential scenarios of operation. (b) Main tasks where periocular images can be useful. (c) Some other challenges affecting periocular biometrics.

that capture approaching individuals.[3] However, they come with extra cost or increased sensor size, making them impractical for consumer or forensic applications.

- *Smartphone authentication*: The pandemic accelerated digital service provision 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. Also, device usage in diverse environments introduces variability in poses, illumination, backgrounds, and so on. The availability of different device models with unknown camera specifications further complicates operations. Operation under such circumstances is referred to as *cross device* (different devices) or *cross environment* (different acquisition environments), which demands mitigation methods to minimize adverse effects on performance.[1]
- *Heterogeneous operation*: Despite impressive periocular recognition performance under ideal conditions, maintaining those results across different sensors, spectral ranges, and resolutions remains challenging.[5,6] Part of this challenge is related to the lack of large-scale multispectral databases suitable to train deep NNs with millions of parameters. The largest ocular database (VISOB, with 550 subjects/158,000 images from three sensors) contrasts with the millions of images available to train, for example, face recognition models. This motivates recent efforts[22] that explore identity-aware synthetic periocular data as a replacement for authentic data. Generative methods have shown impressive ability in creating realistic synthetic data across various applications. In biometrics, they address privacy concerns tied to obtaining and publicly sharing benchmark databases while providing sufficient data for training DL methods.
- *Deployability*: Recent works show the superior accuracy and generalizability of DL-based periocular recognition compared to handcrafted features. However, such models impose high requirements in model size and computational complexity that make them undeployable on resource-critical consumer devices. This motivates future research to work toward harvesting the knowledge learned with deeper (larger) models and transferring it into more deployable models with reduced size and computational complexity while maintaining performance.[22]
- *Invariance to age and other alterations*: Being a relatively recent addition to the family of biometric traits, various factors can influence periocular recognition performance, such as facial expressions, potential forgery through surgical procedures, and, in particular, long-term stability of periocular features, that is, invariance to aging. Although the periocular region is relatively more stable and less affected than the entire face, few studies have examined its impact on periocular methods.[3,5] Analyzing these factors is crucial to enhance confidence in periocular-based recognition systems and establish them as a viable biometric recognition solution.
- *Spoofing attacks*: In parallel with the popularity of biometrics systems, their security against attacks has become paramount. The most common attack, the presentation attack (also known as *spoofing*), consists of presenting a fake biometric sample to the sensor. This has received extensive attention with face and iris modalities to detect, for example, silicon masks, printouts, contact lenses, or digital replays. Although several works exist with ocular images,[23] their number is much more limited.[5,6] C

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