Periocular Biometrics and its Relevance to Partially Masked Faces: A Survey

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ABSTRACT

The performance of face recognition systems can be negatively impacted in the presence of masks and other types of facial coverings that have become prevalent due to the COVID-19 pandemic. In such cases, the periocular region of the human face becomes an important biometric cue. In this article, we present a detailed review of periocular biometrics. We first examine the various face and periocular techniques specially designed to recognize humans wearing a face mask. Then, we review different aspects of periocular biometrics: (a) the anatomical cues present in the periocular region useful for recognition, (b) the various feature extraction and matching techniques developed, (c) recognition across different spectra, (d) fusion with other biometric modalities (face or iris), (e) recognition on mobile devices, (f) its usefulness in other applications, (g) periocular datasets, and (h) competitions organized for evaluating the efficacy of this biometric modality. Finally, we discuss various challenges and future directions in the field of periocular biometrics.

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1. Introduction

Biometrics is the automated or semi-automated recognition of individuals based on their physical (face, iris), behavioral (signature, gait), or psychophysiological (ECG, EEG) traits (Jain et al., 2011; Ross et al., 2019). The COVID-19 pandemic has ushered in a number of considerations for biometric systems. For example, in the context of fingerprint recognition, researchers are now investing more effort in designing contactless fingerprint systems (Yin et al., 2020; Lin and Kumar, 2019). Similarly, the prevalent use of face masks and social distancing protocols has refocused attention on occluded face recognition and, inevitably, ocular biometrics. The ocular region refers to the anatomical structures related to the eyes, and biometric cues in this region include pupil, iris, sclera, conjunctival vasculature, periorcular region, retina, and oculomotor plant (comprising eye globe, muscles, and the neural control signals).

The term “periocular” has been used to refer to the region surrounding an eye consisting of eyelids, eyelashes, eye-folds, eyebrows, tear duct, inner and outer corner of an eye, eye shape, and skin texture (Figure 1). While many articles in the biometric literature include the sclera, iris, and pupil in the context of periocular recognition (Park et al., 2009; Miller et al., 2010; De Marsico et al., 2017; Smereka and Kumar, 2017; Luz et al., 2018), others have excluded these regions (Woodard et al., 2010a,b; Park et al., 2011; Proena and Neves, 2018). The periocular region may be biocular (the periocular regions of both eyes are considered to be a single unit) (Jillela and Ross, 2012; Juefei-Xu and Savvides, 2012) or monococular (either left or right periocular) (Park et al., 2009, 2011) or a fusion of the two monococular regions (combination of left and right periocular regions) (Bharadwaj et al., 2010; Woodard et al., 2010a,b; Boddeti et al., 2011). Earlier work (Park et al., 2009, 2011) on periocular biometrics studied its feasibility as a standalone biometric trait. Other researchers (Woodard et al., 2010a,b; Park et al., 2011; Juefei-Xu and Savvides, 2012) established its relevance by comparing it with the face and iris modalities. In some non-ideal conditions, the periocular region even shows higher performance than face (Miller et al., 2010; Park et al., 2011; Juefei-Xu and Savvides, 2012) and iris (Boddeti et al., 2011) modalities. Hollingsworth et al. ascertained its usefulness as a biometric trait by conducting human analysis on near-infrared (Hollingsworth et al., 2010; Hollingsworth et al., 2011; Hollingsworth et al., 2012) and visible (Hollingsworth et al., 2012) spectrum images.

Periocular recognition has numerous applications that go beyond the current pandemic (Figure 2). This includes (a) operat-
In the literature, there are previous surveys that focused on periocular biometrics (Santos and Proena, 2013; Nigam et al., 2015; Alonso-Fernandez and Bigun, 2016; Rattani and Derakhshani, 2017; Badejo et al., 2019; Behera et al., 2019; Kumar and Seeja, 2019). Santos and Proena (2013) summarized the significant papers on periocular recognition before 2013. The authors in (Nigam et al., 2015; Rattani and Derakhshani, 2017) discussed the research advances of various ocular biometric traits such as iris, periocular, retina, conjunctival vasculature and eye movement, and their fusion with other modalities. Alonso-Fernandez and Bigun (2016) described periocular recognition methodologies in terms of pre-processing, feature extraction, fusion, soft-biometric extraction, and other applications. Behera et al. (2019) focused on cross-spectral periocular recognition. Zanlorensi et al. (2021) provided detailed information on periocular and iris datasets, and competitions based on some of these datasets. A recent survey on periocular biometrics is in (Kumari and Seeja, 2019). Figure 3 shows a visualization of various research work on periocular biometrics. The main contributions of this paper lie in the detailed categorization of periocular techniques. We also describe periocular techniques specifically useful for human recognition in the COVID-19 pandemic.

In this paper, we present a comprehensive review of periocular biometrics. We discuss different categorizations based on (a) different anatomical cues utilized for recognition, (b) feature extraction or matching methodologies, (c) different spectral input images, and (d) fusion with different modalities. We then discuss periocular recognition techniques for mobile devices, in other applications (e.g., soft biometrics, iris presentation detection) and for recognition in special circumstances (cross-modal, gender transformation, long-distance). We also describe various periocular datasets and competitions held. Considering the COVID-19 pandemic situation, we also provide a brief review of recent face and periocular techniques specifically designed to recognize humans wearing a face mask.

The rest of the paper is organized as follows: Section 2 describes various face and periocular techniques specially applied on the masked faces for human identification, Section 3 categorizes periocular techniques based on anatomical cues utilized for recognition, Section 4 describes various periocular features extraction and matching techniques, Section 5 categorizes techniques based on input images of different spectra, Section 6 discusses fusion techniques with other biometric modalities, Section 7 provides details of periocular authentication on mobile devices, Section 8 describes periocular recognition in specific scenarios and other applications, Section 9 details periocular datasets and competitions, Section 10 focuses on various challenges and future directions, and Section 11 concludes the paper.

2. Periocular in COVID-19 Pandemic

Periocular recognition has gained relevance during the COVID-19 pandemic as some reports have documented a drop in performance of existing face recognition methods in the presence of facial masks (Damer et al., 2020; Ngan et al., 2020a; b).
Fig. 2. Various scenarios where the periocular region has increased significance: (a) girl with a mask during the covid pandemic, (b) doctors and nurses in the surgical room, (c) women in niqab, (d) partial faces in the crowd, (e) occluded face while drinking, (f) robber with face covering, (e) military personnel with face paint, (f) football player wearing a helmet, (g) cricket player wearing a helmet, (h) F1 race player in a helmet, (i) face-covering in cold weather, (j) astronauts in suit, (k) dancer with a face veil, (l) firefighter in uniform, and (m) people in motorbike helmets.

The tests conducted by NIST applied digitally tailored masks to face images for evaluation (6.2 million images from 1 million people). The first report (Ngan et al., 2020a) presented the performance of 89 algorithms that were submitted to NIST before the COVID-19 pandemic on the masked images. All 89 face recognition algorithms showed an increase in False Non-Match Rate (FNMR) by about 5% - 50% at a 0.001% False Match rate (FMR) - higher than NISTs prior study on unmasked images. The second report (Ngan et al., 2020b) published the performance of 65 new algorithms submitted to NIST after mid-March 2020 along with their previous submissions (cumulative results for 152 algorithms). The new algorithms include masked images during the enrollment stage. However, the report showed increased FNMR (5% - 40%) for all the newly submitted algorithms, though the new algorithms showed improved accuracy compared to the pre-pandemic algorithms. An earlier work by Park et al. (2011) also showed a decrease in rank-one accuracy of a commercial face recognition software from 99.77% (full-face images) to 39.55% when the lower region was occluded.

In an era of masked faces necessitated by the pandemic, periocular information can be helpful for human recognition in two ways, either by generating a full face from the periocular region or by matching using only the periocular region. Juefei-Xu et al. (Juefei-Xu et al., 2014; Juefei-Xu and Savvides, 2016) hallucinated the entire face from the periocular region using dictionary learning algorithms. Ud Din et al. (2020) detected the masked region from a face image and then performed image completion on the masked region. They used a GAN-based network for image completion, which consists of two discriminators; one learns the global structure of the face and the other focuses on learning the missing region. Li et al. (2020) also performed face completion to recover the content under the mask through the de-occlusion distillation framework. Hoang et al. (2020) emphasized the use of eyebrows for human identification. Wang et al. (2020) released three datasets for face and periocular evaluation on masked images: Masked Face Detection Dataset (MFDD), Real-world Masked Face Recognition Dataset (RMFRD), and Simulated Masked Face Recognition Dataset (SMFRD). Anwar and Raychowdhury (2020) presented an open-source tool, MaskTheFace, to create masked face images. Moreover, research work on face detection in the presence of masks (Opitz et al., 2016; Ge et al., 2017), face mask detection (Chowdary et al., 2020; Qin and Li, 2020; Loey et al., 2021) and face recognition under occlusion (Song et al., 2019; Ding et al., 2020; Geng et al., 2020; Boutros et al., 2021a, Damer et al., 2021; Harir, 2021; Montero et al., 2021) would be helpful in human identification on masked face images. Various competitions are also conducted to benchmark face recognition techniques on masked faces (Deng et al., 2021; Boutros et al., 2021b; Zhu et al., 2021).

3. Anatomical Cues in the Periocular Region

Woodard et al. (2010b) classified periocular anatomical cues into two levels: level-one cues comprise eyelids, eye folds, eyebrows, eyelashes, and eye corners, while level-two includes skin texture, fine wrinkles, color, and skin pores. Specifically, level-one cues represent geometric nature of the periocular region, while level-two embodies textural and color attributes. The authors in (Hollingsworth et al., 2010, Hollingsworth et al., 2011) Park et al. (2011), Beom-Seok Oh et al. (2012) studied the significance of various periocular components in recognizing individuals. Earlier work on face recognition (Sadr et al., 2003) suggested the eyebrows to be the most salient and stable feature of the face. Hollingsworth et al. (Hollingsworth et al., 2010, Hollingsworth et al., 2011) conducted a human analysis to identify the discriminative cues on near-infrared (NIR) images and found that eyelashes, tear ducts, shape of the eye, and eyelids are the most frequently used cues in verifying the two images of a person. The studies in (Park et al., 2011, Beom-Seok Oh et al., 2012) utilized automatic feature descriptors to determine important regions on visible (VIS) spectrum images and concluded that eyebrows, iris, and sclera are the most significant cues for periocular performance. In a subsequent work (Hollingsworth et al., 2012), the authors applied both human and machine approaches to identify discriminative regions on both NIR as well as VIS periocular images. They observed that humans and computers both focus on the same periocular cues for identification: in VIS images, blood vessels, skin region, and eye shape are more salient, whereas in NIR images, eyelashes, tear ducts, and eye shape are more promising. Other authors (Smereka and Kumar, 2013; Alonso-Fernandez and Bi-gun, 2014; Smereka and Kumar, 2017) also drew similar con-
Fig. 3. Network visualization of research articles on periocular biometrics. The size of the node represents the number of citations, and its color represents the year of publication. Figure generated using VOSviewer software.

4. Methodologies used for Periocular Recognition

A typical periocular recognition system consists of the following steps: acquisition, pre-processing of the acquired image, localization of region-of-interest (ROI), feature extraction, post-processing of extracted features, and matching of two feature sets. In the acquisition step, the periocular image is captured using a sensor or camera. We provide details of various sensors used to capture periocular images along with their datasets in Section 9. The pre-processing step aims to enhance the visual quality of an image. Commonly, pre-processing techniques are applied to normalize illumination variations, such as anisotropic diffusion (Juefei-Xu and Savvides, 2012) and Multiscale Retinex (MSR) (Juefei-Xu et al., 2014). Karahan et al. (2014) applied histogram equalization for contrast enhancement. Juefei-Xu et al. (2011) performed pre-processing schemes for pose correction, illumination, and periocular region normalization. Proena and Briceo (2014) investigated an elastic graph matching (EGM) algorithm to handle nonlinear distortions in the periocular region due to facial expressions.

The localization step extracts the periocular region from the acquired or pre-processed image. As the definition of the periocular region has not yet been standardized, the ROI used for periocular recognition varies across the literature. The authors in (Tan and Kumar, 2012; Park et al., 2009) considered the iris center as a reference point to determine the periocular rectangular region. The authors in (Padole and Proena, 2012; Nie et al., 2014) used the geometric mean of eye corners to localize the ROI since the iris center is affected by gaze, pose, and occlusion. Bakshi et al. (2013) localized the periocular region based on the anthropometry of the human face. Park et al. (2011) studied the effect of including...
eyebrows in ROI on the recognition performance by performing both manual localization (based on the centers of the eyes) and automatic localization (based on the anthropometry of the human face). Alagashaam et al. (2017b) analyzed the influence of varying periocular window sizes on periocular recognition performance. Kumari and Seeja (2021b) proposed an approach to extract optimum size periocular ROIs of two different shapes (polygon and rectangular) by using five reference points (inner and outer canthus points, two end points and the midpoint of eyebrow). Proena et al. (2014) described an integrated algorithm for labeling seven components of the periocular region in a single-shot: iris, sclera, eyelashes, eyebrows, hair, skin, and glasses. Deep learning techniques have also been used to detect the periocular region, such as ROI-based object detectors (Reddy et al., 2018b) and supervised semantic mask generators (Zhao and Kumar, 2018). Reddy et al. (2020) proposed spatial transformer network (STN), which is trained in conjunction with the feature extraction model to detect the ROI.

The feature extraction step involves the extraction of discriminative and robust features from the localized periocular region. Alonso-Fernandez and Bigun (2016) categorized feature extraction techniques into global and local approaches. We group deep learning-based approaches separately. Table 1 lists the various feature extraction techniques corresponding to these categories, along with research papers utilizing these techniques. The description of all three approaches are provided below.

1. **Global Feature Approaches:** The global feature extraction approaches consider the entire periocular ROI as a single unit and extract features based on texture, color, or shape. Texture in a digital image refers to the repeated spatial arrangement of the image pixels. Commonly used techniques to capture the textural features from the periocular region are Local Binary Patterns (LBP) and its variants (Park et al., 2009; Adams et al., 2010; Bharadwaj et al., 2010; Juefei-Xu et al., 2010; Miller et al., 2010; Xu et al., 2010; Juefei-Xu and Savvides, 2012; Beom-Seok Oh et al., 2012; Padole and Proena, 2012; Santos and Hoyle, 2012; Uzair et al., 2013; Cao and Schmid, 2014; Mahalingam et al., 2014; Nie et al., 2014; Sharma et al., 2014; Santos et al., 2015; Histogram of Oriented Gradients (HOG) (Park et al., 2009; 2011); Gabor filters (Juefei-Xu et al., 2010; Alonso-Fernandez and Bigun, 2012; Joshi et al., 2014; Cao and Schmid, 2014; Alonso-Fernandez and Bigun, 2015), and Binarized Statistical Image Features (BSIF) (Raghavendra et al., 2013; Raja et al., 2014a). The LBP descriptor computes the binary patterns around each pixel by comparing the pixel value with its neighborhood. The binary patterns are then quantized into histograms, which on concatenation form a feature vector. In the HOG descriptor, gradient orientation and magnitude around each pixel are binned into histograms and histograms are then concatenated to form a feature vector. The Gabor filters extract features by applying textural filters of different frequencies and orientations on an image. The BSIF descriptor convolves the image with a set of filters learned from natural images, and then the responses are binarized. Other texture-based features include Bayesian Graphical Models (BGM) (Boddey et al., 2012), Probabilistic Deformation Models (PDM) (Ross et al., 2012), Discrete Cosine Transform (DCT) (Juefei-Xu et al., 2010), Discrete Wavelet Transform (DWT) (Juefei-Xu et al., 2010; Joshi et al., 2014), Force Field Transform (FFT) (Juefei-Xu et al., 2010), GIST perceptual descriptors (Bharadwaj et al., 2010), Joint Dictionary-based Sparse Representation (JDSR) (Raghavendra et al., 2013; Jillela and Ross, 2014; Moreno et al., 2016), Laws masks (Juefei-Xu et al., 2010), Leung-Mallik filters (LMF) (Tan and Kumar, 2012), Laplacian of Gaussian (LoG) (Juefei-Xu et al., 2010), Correlation-based methods (Boddey et al., 2011; Juefei-Xu and Savvides, 2012; Ross et al., 2012; Jillela and Ross, 2014), Phase Intensive Global Pattern (PIGP) (Smereka and Kumar, 2013; Bakshi et al., 2014), Structured Random Projections (SRP) (Oh et al., 2014), Walsh masks (Juefei-Xu et al., 2010), Higher Order Spectral (HOS) (Alagashaam et al., 2017b), Gaussian Markov random field (Smereka et al., 2015), and Maximum Response (MR) (Raghavendra and Busch, 2016).

The color features of the periocular region correspond to the wavelengths of light reflected from its constituent parts. Woodard et al. (2010b) utilized the color features by applying histogram equalization on the luminance channel and then calculating the color histogram on the spatially salient patches of the image. Lyle et al. (2012) also extracted color features using local color histograms. Moreno et al. (2016) defined color components using linear and nonlinear color spaces such as red-green-blue (RGB), chromaticity-brightness (CB), and hue-saturation-value (HSV) and then applied a re-weighted elastic net (REN) model. The authors in Woodard et al. (2010b) Moreno et al. (2016) utilized both textural and color features from the periocular recognition. Regarding shape features, the work in Dong and Woodard (2011; Le et al., 2014) utilized eyebrow shape-based features, while Proena (2014) extracted eyelid shape features. Ambika et al. (2016) employed LaplaceBeltrami operator to extract periocular shape characteristics. All aforementioned techniques use 2D image data of the periocular region. Chen and Ferryman (2013) combined 3D shape features extracted using the iterative closest point (ICP) method and fused them with 2D LBP textural features at the score-level. One of the major advantages of using global feature approaches is that they generate feature vectors of fixed-length, and matching of fixed-length vectors is computationally effective. However, global feature approaches are more susceptible to image variations, such as occlusions or geometric transformations.

2. **Local Feature Approaches:** The local feature extraction approaches first detect salient or key points from the ROI and then extract features from their local neighborhood to create a feature descriptor. Commonly used local feature approaches are Scale Invariant Feature Transformation (SIFT) (Xu et al., 2010; Park et al., 2011; Padole and Proena, 2012; Ross et al., 2012; Santos and Hoyle, 2012; Smereka and Kumar, 2013; Alonso-Fernandez and Bigun, 2014) and Speeded-up Robust Features (SURF) (Juefei-Xu et al., 2010; Xu et al., 2010; Raja et al., 2015b). The SIFT feature extractor defines key locations as extrema points on the difference of Gaussians (DoG) images obtained from a series of smoothed and rescaled images. Feature descriptor is then formed by concatenating orientation histograms defined around each key point. On the other hand,
SURF detects key points by utilizing the Hessian blob detector, and the key points are then described using Haar wavelet features. SURF utilizes integral images to speed up the computation. Other local feature descriptors are Binary Robust Invariant Scalable Keypoints (BRISK) (Mikaelyan et al., 2014), Oriented FAST and Rotated BRIEF (ORB) (Mikaelyan et al., 2014), Phase Intensive Local Pattern (PILP) (Bakshi et al., 2015), Symmetry Assessment by Feature Expansion (SAFE) (Mikaelyan et al., 2014; Alonso-Fernandez and Bigun, 2015), and Dense SIFT (Ahuja et al., 2016a). Since the number of detected key points varies among images, the resulting feature vectors also vary in length, making the process computationally expensive in some cases. However, local feature approaches are more robust to occlusions, illumination variations, and geometric transformations compared to global feature approaches.

3. Deep Learning Approaches: With the success of deep learning in computer vision and biometrics, this approach has also been applied to periocular recognition. Earlier work (Nie et al., 2014) based on learning approaches introduced an unsupervised convolutional version of Restricted Boltzman Machines (CRBM) for periocular recognition. Raja et al. (Raja et al., 2016b, 2020) extracted features from Deep Sparse Filters using transfer learning methodology and input them into a dictionary-based approach for classification. On the other hand, Raghavendra and Busch (2016) extracted texture features using Maximum Response (MR) filters and input them into deep coupled autoencoders for classification. Other studies that utilized transfer learning methodologies can be found in (Luz et al., 2018; Silva et al., 2018; Kumari and Seeja, 2020). Proena and Neves (2018) utilized deep CNN to emphasize the importance of the periocular region for recognition by training the network with augmented periocular images having inconsistent iris and sclera regions. The training procedure causes the network to implicitly disregard the iris and sclera region. The authors in (Zhao and Kumar, 2018; Wang and Kumar, 2021) integrated attention model to the deep architecture in order to highlight the significant regions (eyebrow and eye) of the periocular image. Some researchers utilized existing off-the-shelf CNN models to extract deep features at various convolutional levels (Hernandez-Diaz et al., 2018; Kim et al., 2018; Hwang and Lee, 2020; Kumari and Seeja, 2020, 2021a). The authors in (Zhang et al., 2018; Reddy et al., 2018a) proposed compact and custom deep learning models for use in mobile devices. Other deep learning-based methods include PatchCNN (Reddy et al., 2018b), In-Set CNN Iterative Analysis (Proena and Neves, 2019), unsupervised convolutional autoencoders (Reddy et al., 2019), compact Convolutional Neural Network (CNN) (Reddy et al., 2020), VisobNet (Ahuja et al., 2017), semantics assisted CNN (Zhao and Kumar, 2017), heterogeneity aware deep embedding (Garg et al., 2018), and Generalized Label Smoothing Regularization (GLSR)-trained networks (Jung et al., 2020). Deep learning approaches provide state-of-the-art recognition performance, but their approaches are heavily data-driven.

After the feature extraction step, some researchers further processed the feature vector, which generally includes the application of feature selection, subspace projection, or dimensional reduction (Beom-Seok Oh et al., 2012; Joshi et al., 2014) techniques. These techniques aim to transform the feature set into a condensed representative feature set such that it improves the accuracy and reduces the computational complexity. Various post-processing techniques used in periocular recognition are Principal Component Analysis (PCA) (Beom-Seok Oh et al., 2012), Direct Linear Discriminant Analysis (DLDA) (Joshi et al., 2014), and Particle Swarm Optimization (Silva et al., 2018). Finally, the processed features are compared using similarity or dissimilarity metrics such as Bhattacharya distance (Woodard et al., 2010a), Hamming distance (Oh et al., 2014), I-Divergence metric (Cao and Schmid, 2014), Euclidean distance (Ambika et al., 2016), or Mahalanobis distance (Nie et al., 2014).

5. Periocular Recognition in Different Spectra

Different imaging spectra have been described in the literature for capturing the periocular region, including Near-Infrared (NIR), Visible (VIS), Short Wave Infrared (SWIR), Middle Wave Infrared (MWIR), and Long Wave Infrared (LWIR). The most commonly used imaging spectra are NIR and VIS. This is because most research in periocular biometrics is based on face images (VIS) or iris images (NIR). Further, even as a standalone biometric, periocular images are captured using existing face or iris sensors. The NIR spectrum, which operates in the 700-900nm range, predominantly captures the iris pattern, eye shape, outer and inner corner of the eye, eyelashes, eyebrows, and eyelids. Often there is saturation in the area around the eye, skin, and cheek regions. On the other hand, the VIS spectrum (400-700nm) captures textural details of the periocular skin region, conjunctiva vasculature, eye shape, eyelashes, eyebrows, and eyelids. The VIS imaging fails to capture the textural nuances of the iris pattern, especially for dark-colored irides. Examples of periocular recognition techniques in the NIR spectrum are (Monwar et al., 2013; Uzair et al., 2013; Hwang and Lee, 2020; Mikaelyan et al., 2014), and in the VIS spectrum are (Adams et al., 2010; Bharadwaj et al., 2010; Park et al., 2009; Juefei-Xu et al., 2010; Miller et al., 2010; Woodard et al., 2010b; Xu et al., 2010; Park et al., 2011; Beom-Seok Oh et al., 2012; Padole and Proena, 2012; Santos and Hoyle, 2012; Joshi et al., 2014; Nie et al., 2014; Proena and Briceo, 2014; Proena et al., 2014; Bakshi et al., 2015; Santos et al., 2015; Hernandez-Diaz et al., 2018; Luz et al., 2018; Reddy et al., 2019). Rattani and Derakhshani (2017) provided a detailed survey of ocular techniques in the VIS spectrum. The researchers in (Hollingsworth et al., 2010; Smereka and Kumar, 2017) suggested that VIS images provide more discriminative information for periocular recognition compared to NIR images. Hollingsworth et al. (2012) made the same conclusion using human volunteers. The authors in (Alonso-Fernandez and Bigun, 2012; Ross et al., 2012; Alonso-Fernandez and Bigun, 2015; Smereka et al., 2015; Ambika et al., 2016; Zhao and Kumar, 2017) proposed periocular recognition techniques that can be applied to both NIR and VIS images. Other researchers (Alguasha et al., 2017a; Vetrekar et al., 2018; Ipe and Thomas, 2020) fused information obtained from both NIR and VIS images. Table 2 provides a summary (features extraction, datasets,
and performance) of various techniques applied on NIR, VIS, both spectrum, and multi-spectral (fusion of NIR and VIS) images.

A vast amount of research has also focused on cross-spectrum matching, where enrolled images are in one spectrum, while probe images are in another spectrum. The cross-spectrum evaluation scenario implicitly encapsulates the cross-sensor scenario (enrolled and probes images are from different sensors) as well. Examples of papers discussing the cross-spectrum scenario are (Cao and Schmid, 2014; Sharma et al., 2014; Ramaiah and Kumar, 2016; Behera et al., 2017; Raja et al., 2017; Hernandez-Diaz et al., 2019; Alonso-Fernandez et al., 2020; Behera et al., 2020; Hernandez-Diaz et al., 2020; Zanoloresi et al., 2020; Vyas, 2022; Behera et al., 2019) provided a detailed survey on cross-spectrum periorcular recognition. A more difficult evaluation scenario is when testing is performed on different datasets (cross-dataset) as it has to account for the variations due to different sensors, data acquisition environments, and subject population. Examples of cross-dataset evaluation can be found in (Reddy et al., 2019, 2020). Table 5 summarizes various cross-spectrum and cross-dataset techniques. The cross-sensor techniques are mainly evaluated on different mobile devices, so we provide these details in Section 7 (Periorcular Recognition on Mobile Devices).

6. Periorcular Fusion with Other Modalities

Simultaneous acquisition of periorcular with the iris modality, and its complementary nature with respect to iris, has motivated researchers to fuse periorcular with iris to improve the overall recognition performance. The authors in (Woodard et al., 2010a; Ross et al., 2012) proposed the fusion of periorcular with iris to improve the performance when acquired iris images are of low quality due to partial occlusions, specular reflections, off-axis gaze, motion and spatial blur, non-linear deformations, contrast variations, and illumination artifacts. The fusion is also helpful when iris images are captured from a distance as the periorcular region is relatively stable even at a distance (Tan and Kumar, 2012). It is also advantageous when iris images are acquired in the visible spectrum (Santos and Hoyle, 2012; Tan and Kumar, 2013; Proena, 2014; Jain et al., 2015; Santos et al., 2015; Verma et al., 2016), or using mobile devices (Santos et al., 2015; Ahuja et al., 2016b). The iris texture is better discernible in NIR illumination, whereas periorcular features become more perceptible in VIS illumination (Alonso-Fernandez and Bigham, 2015). The overall performance obtained on the fusion of iris and periorcular traits is generally better than using the iris only as shown in (Komgortsev et al., 2012; Raghavendra et al., 2013; Raja et al., 2014a; Ahmed et al., 2017; Verma et al., 2016). The fusion of iris and periorcular is mainly performed at the score-level (Woodard et al., 2010a; Tan et al., 2012; Tan and Kumar, 2013; Proena, 2014; Alonso-Fernandez et al., 2015; Jain et al., 2015; Santos et al., 2015; Verma et al., 2016; Ahuja et al., 2016b; Alghaam et al., 2021), though there is some work on feature-level (Jain et al., 2015; Stokkenes et al., 2017; Silva et al., 2018) and decision-level (Santos and Hoyle, 2012) fusion also. Ogawa and Kameyama (2021) proposed Multi Modal Selector that adaptively selects a iris and periocular...
Table 2. A chronological overview (description, datasets, and performance) of periocular techniques utilizing NIR, VIS, or multispectral images. Here, RR is Recognition Rate, EER is Equal Error Rate, TMR is True Match Rate, FRR is False Rejection Rate, and FAR is False Acceptance Rate. The acronyms used in the ‘Description’ column are defined in the text or in the referenced papers.

| Paper | Description | Datasets and Performance |
|-------|-------------|-------------------------|
| **NIR Spectrum** | | |
| Uzair et al., 2013 | Formulate as an image set classification problem, where each image set corresponds to single subject | MBGC: RR is 97.70% |
| Monwar et al., 2013 | PDM, modified SIFT, GOH features Fusion: Highest rank, borda count, plurality voting, markov chain rule at rank-level | FOCS: RR is 99.2% |
| Mikaelyan et al., 2014 | Symmetry patterns | BioSec: EER is 10.75% |
| Hwang and Lee, 2020 | Mid-level CNN features (plain CNN, ResNet, deep plane CNN, and deep ResNet) + Features selection | Proprietary: EER is 11.51% CASIA-Iris-Lamp: EER is 0.64% |
| **Visible Spectrum** | | |
| Park et al., 2009 | HOG, LBP, SIFT | FRGC: RR is 79.49%(SIFT) |
| Xu et al., 2010 | Comparison of different features and their fusion | FRGC: TMR of 61.2% 0.1% FMR |
| Adams et al., 2010 | GEFE+LBP | FRGC: RR is 92.16% FERET: RR is 85.06% |
| Juefei-Xu et al., 2010 | LBP, WLBP, SIFT, DCT, Gabor filters, Walsh masks, DWT, SURF, Law Masks, Force Fields, LoG | FRGC: RR is 53.2%(LBP+DWT) FG-Net: RR is 53.1%(LBP+DCT) |
| Park et al., 2013 | Fusion of HOF, LBP and SIFT | FRGC: RR is 87.32% |
| Padole and Proena, 2012 | HOG, LBP, SIFT | UBIPr: EER is ~20%(HOG + LBP + SIFT) |
| Santos and Hoyic, 2012 | LBP, SIFT | UBIPr: EER is 6.4% and RR is 50.1% |
| Joshi et al., 2014 | Gabor-PPNN, DWT, LBP, HOG | MBGC: EER is 64.3%, GTDB: EER is 5.9%, IITK: EER is 15.5%, PUT: EER is 4.8% |
| Nee et al., 2014 | PCA to: CRBM, SIFT, LBP, HOG | UBIPr: EER is 6.4% and RR is 50.1% |
| Proena and Briceo, 2014 | OC-EGM to: LBP + HOG + SIFT | FaceExpressUBI: EER is 16% |
| Hernandez-Diaz et al., 2018 | Fusion of off-the-shelf CNN (AlexNet, GoogLeNet, ResNet, and VGG) features and traditional features | UBIPr: EER of 5.1% and FRR is 11.3% at 1% FAR |
| Jung et al., 2020 | Generalized label smoothing regularization-trained networks | ETHNIC: PUBFig, Facescrub, and IMDb |
| Woodard et al., 2010 b | Tessellated image + Histograms of texture and color | FRGC (VIS): RR is 91%, MBGC (NIR): RR is 87% |
| Ross et al., 2012 | Fusion of GOH, PDM, SIFT features at the score-level | FOCS (NIR): RR is 18.8%, FRGC (VIS): EER is 1.59% |
| Alonso-Fernandez and Bigun, 2015 | Gabor features | 4 NIR datasets: Accuracy is 97% 2 VIS datasets: Accuracy is 27% |
| Bakshi et al., 2015 | Raw pixels, LBP, PCA, LBP + PCA | MBGC: NIR-RR is 99.8%, VIS-RR is 98.3% CMU: Hyperpectral: RR is 97.2%, UBIPr: RR is 99.5% |
| Ambika et al., 2016 | LaplaceBeltrami based shape features | CASIA FV1: accuracy is 95%, Basel 3D: Accuracy is 97% 3D periorocular: Accuracy is 97.8% |
| Smereka et al., 2015 | Periocular probabilistic deformation models | 2 NIR and 3 VIS images datasets |
| Zhao and Kumar, 2017 | Semantics-assisted convolutional neural networks | UBIRIS V2: RR is 82.43%, FRGC: RR is 91.13%, FOCS: RR is 96.93%, CASIA v4-distance: RR is 98.90% |
| **Multi-spectrum** | | |
| Algashaam et al., 2017 a | Multimodal compact multi-linear pooling feature fusion | IMP: Accuracy is 91.8% |
| Neto et al., 2016 | HOG, GIST, Log-Gabor transform and BSIF + CRC | Proprietary: RR is 96.92% |
| Ipe and Thomas, 2020 | Fusion of the off-the-shelf CNN feature | IMP: Accuracy is 97.14% |
The fusion of periocular with the face modality is also a viable option as periocular is a part of the face, and no additional acquisition is required. Though the periocular region is already accounted in face recognition as a part of the face, isolating the periocular and performing region-specific feature extraction provides an overall improvement in recognition performance. The fusion of face with periocular is also beneficial when face images are occluded, having large pose variations, or captured at a very close distance (e.g., a selfie). The work of periocular fusion with face in the context of plastic surgery (Jillela and Ross, 2012), gender transformation (Mahalingam et al., 2014) and mobile devices (Raja et al., 2015a; Pereira and Marcel, 2015) shows improved recognition accuracy. Table 4 summarizes various techniques that fuse periocular with iris and face modalities. In another research work, Oh et al. (2014) fused periocular features (structured random projections) with binary sclera features at the score-level for identity verification. Nigam et al. (2015) provided a detailed survey on the fusion of various ocular biometrics.

7. Periocular Recognition on Mobile Devices

The extensive usage of mobile devices motivates the need for human authentication on mobile devices for various purposes, such as access control, digital payments, or mobile banking. Several mobile devices are now emerging with integrated biometric sensors – iPhone 12 has a Touch ID fingerprint sensor and Face ID cameras, and the Samsung Galaxy S20 series has an in-display fingerprint sensor and an iris scanner. Periocular images are generally acquired using the front or rear camera of mobile devices in the visible spectrum. The challenges in mobile biometrics are low-quality input images and relatively limited computational power. The low-quality images are due to hardware limitations and less constrained capturing environments. Raja et al. (2014b) explored periocular recognition on smart devices using well known feature extraction techniques (SIFT, SURF, and BSIF) and achieved a Genuine Match Rate (GMR) of 89.38% at 0.01% False Match Rate (FMR). There is some work on NIR images captured from mobile devices (Bakshi et al., 2018; Zhang et al., 2018). Bakshi et al. (2018) utilized a reduced version of Phase Intensive Local Pattern (PILP) features, whereas Zhang et al. (2018) fused compact CNN features of iris and periocular through a weighted concatenation. Majority of the periocular-based mobile biometrics are performed on VIS images (Pereira and Marcel, 2015; Raja et al., 2015b; Ahuja et al., 2016a; Keshari et al., 2016; Raja et al., 2016b; Raghavendra and Busch, 2016; Ahmed et al., 2017; Ahuja et al., 2017; Rattani and Derakhshani, 2017; Stokkenes et al., 2017; Boutros et al., 2020; Krishnan et al., 2020; Raja et al., 2020). Keshari et al. (2016) investigated periocular recognition on pre- and post-cataract surgery mobile images. Krishnan et al. (2020) investigated the fairness of mobile ocular biometrics methods across gender. The work in Pereira and Marcel, 2015; Raja et al., 2015b; Ahmed et al., 2017; Zhang et al., 2018 used fusion of different modalities for mobile biometrics – Raja et al. (2015b) fused iris, face and periocular modalities, Pereira and Marcel, 2015 combined face and periocular, whereas Santos et al., 2015; Ahmed et al., 2017; Zhang et al., 2018 combined iris and periocular. Recent work on mobile biometrics used deep learning features (Raja et al., 2016b; Raghavendra and Busch, 2016; Ahuja et al., 2017; Rattani and Derakhshani, 2017; Raja et al., 2020; Boutros et al., 2020) verified an individual wearing Head Mounted Display (HMD) using four handcrafted feature extraction methods and two deep-learning strategies. Generalizability across different mobile sensors (cross-sensor) are also evaluated in Santos et al., 2015; Raja et al., 2016a; Garg et al., 2018; Reddy et al., 2018b.
Table 4. A chronological overview (description, datasets, and performance) of periocular techniques focusing on the fusion of periocular with iris and face modalities. Here, AUC is Area Under the Curve. The acronyms used in the ‘Description’ column are defined in the text or in the referenced papers.

| Paper | Description | Datasets and Performance |
|-------|-------------|--------------------------|
| Woodard et al., 2010a | Iris: Gabor features, Periocular: LBP Fusion: Weighted sum at score-level | MBGC: EER is 0.18, RR is 96.5% |
| Santos and Hoyle, 2012 | Iris: Wavelets, Periocular: LBP, SIFT Fusion: Logistic regression at decision-level | NICE.II: EER is 18.48, AUC is 0.90, RR is 74.3% |
| Tan et al., 2012 | Iris: Ordinal measures and color analysis Periocular: Textron representation and semantic information Fusion: Weighted sum rule at score-level | USIRISv2: d is 2.57, EER is 12% |
| Tan and Kumar, 2012 | Iris: Log-Gabor features Periocular: SIFT, Leung-Malik filters, LBP Fusion: Weighted sum rule at score-level | CASIA-IrisV4-distance: RR is 84.5% |
| Tan and Kumar, 2013 | Iris: Log-Gabor features Periocular: DSIFT, GIST, LBP, HOG, LMF Fusion: Weighted sum rule at score-level | UBIIRIS V2: RR is 39.6% |
| Raghavendra et al., 2013 | Iris, Periocular: LBP, SRC Fusion: Weighted sum at score-level | Proprietary: EER is 0.81% |
| Proena, 2014 | Iris: Multi-lobe differential filters Eyelids, Eyelashes, Skin: shape and LBP features Fusion: ANN at score-level | UBIRISv2: d is 2.97 and AUC is 0.96 |
| Santos et al., 2015 | Iris: Gabor features, Periocular: SIFT, GIST, LBP, HOG, ULBP Fusion: ANN at score-level | CSIP: d’ is 2.501, AUC is 0.943, EER is 0.131 |
| Jain et al., 2015 | Iris, Periocular: LBP, SIFT, GIST Fusion: Feature-level (context-switching), score-level (sum) | UBIRISv2: RR-10 is 76.16 % |
| Alonso-Fernandez et al., 2015 | Iris: Log-Gabor filters, DCT, SIFT Periocular: Symmetry patterns, gabor features, SIFT Fusion: Logistic regression at score-level | (EER) BioSec: 0.75%, MobBIO: 6.75% CASIA-Iris Inverval v3: 0.51% IIT Delhi v1.0: 0.38%, UBIIRIS v2: 15.17% |
| Verma et al., 2016 | Iris: Gabor features, Periocular: PHOG, GIST Fusion: Random decision forest at score-level | CASIA-IrisV4-distance: GMR is 61% at 0.1% FMR FOCIS: GMR is 21% at 0.1% FMR |
| Ahuja et al., 2016b | Iris: RootSIFT, Periocular: Deep features Fusion: Mean rule and linear regression at score-level | MICHE II: AUC is 0.985 and EER is 0.057 |
| Ahmed et al., 2017 | Iris: Gabor features, Periocular: Multi-Block Transitional LBP Fusion: Weighted sum rule at score-level | MICHE II: EER is 1.22%, FRR is 2.56% at FAR RR is 100% |
| Zhang et al., 2018 | Iris, Periocular: CNNs with max out units Fusion: Weighted concatenation at the feature-level | CASIA-Iris-MobileV1.0: EER is 0.60%, FNMR is 2.32% at 0.001% FMR |
| Silva et al., 2018 | Iris, Periocular: Deep features Fusion: Particle swarm optimization at feature-level | UBIRISv2: d’ is 3.45 and EER is 5.55% |

Fusion of Periocular and Face

| Paper | Description | Datasets and Performance |
|-------|-------------|--------------------------|
| Jillela and Ross, 2012 | Face: Verilook and PittPatt Scores, Ocular: SIFT, LBP Fusion: Mean rule at score-level fusion | Plastic surgery database: RR is 87.4% |
| Pereira and Marcel, 2015 | Periocular: Tessellated images + DCT + GMM Face: Inter-session variability modeling + GMM Fusion: Linear logistic regression at score-level fusion | MOBIO: HTER is 6.58% CPqD Biometric: HTER is 3.87% |
| Raja et al., 2015b | Iris: Gabor features, Periocular, Face: SIFT, SURF, BSIF Fusion: Min, max, product, weighted sum at score-level | Proprietary: EER of 0.68% |
| Stokkenes et al., 2017 | Face, Periocular: BSIF + Bloom filters Fusion: XOR operation, concatenation at feature-level | Proprietary: GMR is 88.54% at 0.01% FMR EER is 2.05% |
8. Specific Applications

1. Soft-biometrics from Periocular Region: Soft-biometrics refer to attributes used to classify individuals in broad categories such as gender, ethnicity, race, age, height, weight, or hair color. The periocular region has also been used for automatically estimating age, gender, ethnicity, and facial expression information. An exploration of gender information contained in the periocular region is performed in (Merkow et al., 2010; Lyle et al., 2012; Bobeldyk and Ross, 2016; Castrillón-Santana et al., 2016; Tapia and Arellano, 2019). Tapia and Arellano (2019) synthesized NIR periocular images using a conditional GAN based on gender information, and then identify gender using the synthesized periocular images. The work in Lyle et al., 2012 [Woodard et al., 2017] extracted race information from the periocular region, while the work in (Rattani et al., 2017) determined an individual’s age from the periocular region. Alonso-Fernandez et al. (2018) investigated the feasibility of using the periocular region for facial expression recognition.

2. Long Distance Recognition: Bharadwaj et al. (2010) showed the degradation of iris recognition performance with an increase in standoff distance and suggested the use of the periocular region on long-distance images. The authors in Tan and Kumar (2012) proposed fusion approaches (iris and periocular) for human recognition at a distance (NIR images). Kim et al. (2018) explored the effectiveness of periocular region in verifying kinship using a Block-based Neighborhood Repulsed Metric Learning framework. Juefei-Xu et al. (2011) presented a framework of utilizing the periocular region for age invariant face recognition. The authors applied Walsh-Hadamard transform encoded Local Binary Patterns (WLBP) and Unsupervised Discriminant Projection (UDP), and achieved 100% rank-1 identification rate on a dataset of 82 subjects. The authors in Jillela and Ross (2012) Raja et al., 2016a utilized the periocular region to identify individuals after they undergo facial plastic surgery. Mahalingam et al. (2014) introduced a medically altered gender transformation face dataset and proposed the fusion of periocular (patched-based LBP) with face, which outperformed standalone commercial-off-the-shelf face matchers. Keshari et al., 2016 investigated periocular recognition on pre- and post-cataract surgery images.

3. Face Generation from Periocular Region: Juefei-Xu et al. (2014), Juefei-Xu and Savvides (2016) recreated the entire face from the periocular region alone using dictionary learning algorithms, while Ud Din et al. (2020) proposed a GAN-based method to regenerate the masked part of the face. Li et al. (2020) utilized de-occlusion distillation framework to recover face content under the mask.

4. Cross-modal Recognition (Face and Iris): Jillela and Ross (2014) presented the challenging problem of matching face in VIS spectrum against iris images in NIR spectrum (cross-modal) using periocular information. They utilized LBP, Normalized Gradient Correlation (NGC), and Joint Dictionary-based Sparse Representation (JDSP) methods to accomplish cross-modality matching.

5. Periocular Forensics: The authors in Marra et al., 2018; Banerjee and Ross, 2018 deduced sensor information from the periocular images. In another work, Banerjee and Ross (2019) suppressed the sensor-specific information (sensor anonymization) and also incorporated the sensor pattern of a different device (sensor spoofing) in periocular images.

6. Other Applications: Du et al. (2016) utilized the periocular region to correct mislabeled left and right iris images in a diverse set of iris datasets. The work in Alonso-Fernandez and Bigun (2014) Hoffmann et al., 2019 suggested the use of periocular information for iris spoof detection. Alonso-Fernandez and Bigun (2014) Hoffman et al. (2019) detected iris spoofs using VIS periocular images, whereas Hoffmann et al., 2019 utilized NIR periocular images. Patel et al. (2017) explored the effectiveness of periocular region in verifying kinship using a Block-based Neighborhood Repulsed Metric Learning framework. Juefei-Xu et al. (2011) presented a framework of utilizing the periocular region for age invariant face recognition. The authors applied Walsh-Hadamard transform encoded Local Binary Patterns (WLBP) and Unsupervised Discriminant Projection (UDP), and achieved 100% rank-1 identification rate on a dataset of 82 subjects. In Jillela and Ross, 2012 Raja et al., 2016a utilised the periocular region to identify individuals after they undergo facial plastic surgery. Mahalingam et al. (2014) introduced a medically altered gender transformation face dataset and proposed the fusion of periocular (patched-based LBP) with face, which outperformed standalone commercial-off-the-shelf face matchers. Keshari et al., 2016 investigated periocular recognition on pre- and post-cataract surgery images.

9. Datasets and Competitions

In early literature, periocular recognition was performed using face and iris as there were limited datasets available that contained the periocular region only. Commonly used face datasets to perform periocular recognition research on VIS images are FRGC, FERET, FG-NET, MobBIO, and on NIR images are IIT Delhi v1.0, CASIA Interval, BioSec. The iris datasets used for periocular recognition research are UBIRIS v2 (VIS), MBGC (NIR), and PolyU cross-spectral datasets. Table 6 describes the datasets specifically collected for periocular recognition. Figures 4, 5, and 6 show a few images from these periocular datasets. The datasets used to perform periocular recognition research under variable stand-off distance are FRGC, UBIRIS v2, and UBIPr. Examples of datasets providing video data of subjects for periocular biometrics research are MBGC, FOCs, and VSSIRIS. Other datasets provide special evaluation scenarios such as aging (MORPH, FG-NET), plastic surgery (Raja et al., 2016a), gender transformation (Mahalingam et al., 2014), expression changes (FaceExpressUBI), face occlusion (AR, Compass), cross-spectral matching (CMU-H, IMP, CROSS-EYED 2016, CROSS-EYED 2017), or mobile authentication (CASIA-Iris-Mobile-V1.0, CSIP, MICHE I and II, VSSIRIS, VISOB 1.0 and 2.0, CMPD). Various competitions focusing on periocular recognition can be found in (Rattani et al., 2016; Sequeira et al., 2016; De Marsico et al., 2017; Sequeira et al., 2017). The competitions in (Rattani et al., 2016; De Marsico et al., 2017) are on mobile periocular images, while the competitions in (Sequeira et al., 2016; Sequeira et al., 2017) evaluated the cross-spectrum (matching of VIS and NIR images) scenario. Table 7 summarizes details about these competitions. Zanlorensi et al., 2021 surveyed various ocular datasets
### Table 5. A chronological overview (description, datasets, and performance) of periocular techniques utilizing images acquired using the sensors and cameras in a mobile device such as a smartphone. Here, HTER is Half Total Error Rate. The acronyms used in the ‘Description’ column are defined in the text or in the referenced papers.

| Paper | Description | Datasets and Performance |
|-------|-------------|--------------------------|
| Juefei-Xu and Savvides 2012 | Walsh-Hadamard transform encoded LBP + Kernel class-dependence feature analysis | Compass: GAR is 60.7% at 0.1% FAR |
| Raja et al. 2014b | SIFT, SURF and BSIF + Nearest Neighbors (SIFT and SURF), Bhattacharyya distance(BSIF) | Proprietary: GAR is 89.38% at 0.01% FAR |
| Ahuja et al. 2016a | SURF + Multinomial Naive Bayes learning + Pyramid-up topology using Dense SIFT + RANSAC | VISOB: RR is 48.76%-79.49% |
| Keshari et al. 2016 | Dense SIFT, Gabor, Scattering Network features + PCA + LDA + Cosine similarity weighted sum | IMP: RR-10 is 69% |
| Raghavendra and Busch, 2016 | Maximum Response filters + Deeply coupled autoencoders | VISOB: GMR of 93.98% at 0.001 FMR |
| Raja et al. 2016c | Laplacian decomposition + GLCM + STFT + Histogram features of freq. response + SRC | MICHE I: Cross-camera EER is 7.53% |
| Ahuja et al. 2017 | Hybrid CNN model + Mean fusion at the score-level | VISOB: GMR is 99.5% at 0.001% FAR |
| Rattani and Derakhshani, 2017 | Fine-tuned VGG-16, VGG-19, InceptionNet, ResNet | MICHE II: AUC of 98.6% |
| Garg et al. 2018 | Heterogeneity aware loss function in deep network | (RR) CSIP (cross-sensor): 89.53%, IMP: 61.20%, VISOB (cross-spectrum): 99.41% |
| Reddy et al. 2018b | Patch-based OcularNet | (EER) VISOB: 1.17%, UBIRIS-I: 9.86%, UBIRIS-II: 9.77%, CROSS-EYED2016: 14.95% |
| Raja et al. 2020 | Deep Sparse Features, Deep Sparse Time Frequency Features + CRC classification | (GMR at 0.01% FMR) VISPI: 99.80%, MICHE: 100%, VISOB: 98.78% |
| Boutros et al. 2020 | Periocular, Iris: Hand-crafted and deep features + Synthesize identity-Preserved periocular images | OpenEDS: EER (iris) is 6.35%, EER (periocular) is 5.86% |

and discussed popular ocular recognition competitions. The authors described 36 iris, 4 iris/periocular, 4 periocular, and 10 multimodal datasets.

### 10. Challenges and Future Directions

1. **Definition and Standardization:** The definition of the periocular region is not standardized. What is the actual boundary around the eye? Should we consider a single eye or both eyes to be in the periocular region? These questions about the scope of the periocular region is yet to be answered. Apart from these definitional concerns, issues around standardization has to be resolved for ground-truth segmentation, and the minimum resolution needed for recognition.

2. **Generalizability:** Periocular biometric solutions should be generalizable, which refers to the matching of periocular images under cross-sensor (images from different sensors), cross-spectrum (images from different spectra), cross-dataset (images from different datasets), cross-resolution (images at multiple distances), and cross-modal (images from different modalities) scenarios.

3. **Non-ideal Conditions:** Researchers need to focus on periocular matching under non-ideal conditions, i.e., pose variations [Park et al., 2011, Karakaya, 2021], expression, non-uniform illumination, low-resolution, occlusions (eyeglasses, eye-blinking, different types of masks, scarfs or helmets or eye makeup), or large stand-off distance.

4. **Effects of Aging:** With age, wrinkles and folds around the eye could change the overall appearance of the periocular region. The effects of aging on periocular recognition are yet to be comprehensively studied [Ma et al., 2019].

5. **Anti-spoofing Measures:** While periocular region has been utilized to detect iris spoof attacks [Alonso-Fernandez and Bigun, 2014, Hoffman et al., 2019], we should also be vigilant about spoof attacks directed at the periocular region.

6. **Explainability and Interpretability:** Increasing use of deep learning-based techniques in periocular biometrics opens another direction which involves explainability of these deep learning models [Brito and Proena, 2021].

### 11. Summary

This article provided a survey on periocular biometrics in the wake of its importance due to the increased use of face masks. Firstly, we reported recent face and periocular recognition techniques specifically designed to recognize humans wearing a face mask. Subsequently, we provided details on various aspects of periocular biometrics, viz., anatomical cues in the periocular region used for recognition, various feature extraction and matching techniques, cross-spectral recognition, its fusion with other biometrics modalities (face or iris), authentication in mobile devices, usefulness of this biometric in other applications, periocular datasets, and competitions. Finally, we discussed the various challenges and future directions to work on. The applicability of the periocular biometrics is likely to extend to other scenarios where only the ocular region of the face may be visible. This could be due to cultural etiquette (e.g., women covering their face) or safety precautions (e.g., surgeons or construction workers covering their nose and mouth).
Table 6. Description of periocular datasets (NIR, VIS, and multi-spectrum), along with representative research papers utilizing these datasets.

| Datasets          | Description                                                                 | Papers                                                                 |
|-------------------|-----------------------------------------------------------------------------|------------------------------------------------------------------------|
| NIR Spectrum      |                                                                             |                                                                        |
| NIST- Face and ocular challenge series | 9,588 total images, 136 subjects, 750x600 resolution, monocular images | Boddeti et al., 2011; Ross et al., 2012; Muninar et al., 2013; Smereka and Kumar, 2013; Smereka et al., 2015 |
| MIR 2016          | 16,300 total images, 550 subjects, 1988x2014 resolution, biocular images    | Zhang et al., 2016                                                     |
| CASIA-Iris-Mobile V1 | 11,000 total images, 8,100 subjects, biocular images, CASIA NIR mobile camera | Zhang et al., 2018                                                     |
| CASIA-IrisV4-Distance | 2,567 total images, 142 subjects, 2352x1728 resolution, biocular images, CASIA long-range iris camera | Tan and Kumar, 2012; Verma et al., 2016 |
| Visible Spectrum  |                                                                             |                                                                        |
| UBIP  | 10,950 total images, 261 subjects, Canon EOS 5D, biocular images | Padole and Proena, 2012; Nie et al., 2014; Hernandez-Diaz et al., 2018; Santos et al., 2015; Ahmed et al., 2017; Keshari et al., 2016 |
| CSIP  | 2,004 total images, 50 subjects, monocular images | Santos et al., 2015; Garg et al., 2018; De Marsico et al., 2015; Boddeti et al., 2011 |
| MICHE-I        | 3,712 total images, 92 subjects, monocular images | De Marsico et al., 2015; Raja et al., 2016; Reddy et al., 2019; Raja et al., 2020 |
| VISIBIR         | 560 total images, 28 subjects, monocular images | Raja et al., 2015; Alonso-Fernandez et al., 2020 |
| VISOB v1.0      | 158,136 total images, 550 subjects, monocular images | Amma et al., 2015; Sequeira et al., 2016; Amma et al., 2017; Sequeira et al., 2017 |
| CMPD           | 2,567 total images, 56 subjects, monocular images | Keshari et al., 2016; Keshari et al., 2017; Ahmed et al., 2017 |
| MICHE-II       | 3,120 total images, 75 subjects, monocular images | Amma et al., 2016; Ahmed et al., 2017; Ahmed et al., 2017 |
| UFPR-Ferriarum  | 33,660 total images, 1,122 subjects, both monocular and biocular images      | Zanlorensi et al., 2020                                               |
| VISOB 2.0       | 75,428 total images, 250 subjects, monocular images | Krishnan et al., 2020 |
| Multi-spectrum  |                                                                             |                                                                        |
| IMP              | 1,240 total images, 62 subjects, monocular and biocular images | Keshari et al., 2015; Ramadoti and Kumar, 2015; Algashaam et al., 2017a; Behera et al., 2017; Behera et al., 2020 |
| CROSS-EYED 2016 | 3,840 total images, 120 subjects, 900x800 resolution, monocular images | Raja et al., 2017; Reddy et al., 2018; Ahuja et al., 2017; Sequeira et al., 2017 |
| CROSS-EYED 2017 | 5,600 total images, 175 subjects, 900x800 resolution, monocular images | Sequeira et al., 2017; Sequeira et al., 2017; Sequeira et al., 2017 |
| QUT Multispectral | 212 total images, 53 subjects, 800x600 resolution, biocular images | Algashaam et al., 2017a |

Table 7. A summary (datasets and performance achieved) of various competitions on periocular recognition. Here, GFRR is Generalized False Rejection Rate, and GFAR is Generalized False Acceptance Rate.

| Competition          | Dataset                                                                 | Performance                                                                 |
|----------------------|-------------------------------------------------------------------------|----------------------------------------------------------------------------|
| MICHE-II (De Marsico et al., 2017) | MICHE-I and MICHE-II                                                   | EER is 2.74% and FRR is 9.13% @ 0.1% FAR (Ahmed et al., 2015) |
| ICIP (Raja et al., 2015) | VISOB                                                                  | EER is 0.06% ~ 0.20% and GMR is 92% @ 0.1% FMR (Kehagia and Basu, 2016) |
| CROSS-EYED 2016 (Sequeira et al., 2016) | CROSS-EYED 2016                                                        | GFRR is 0.0% @ 1% GFAR and EER is 0.29% (HH1) (Sequeira et al., 2016) |
| CROSS-EYED 2017 (Sequeira et al., 2017) | CROSS-EYED 2016 and 2017                                               | GFRR is 0.74% @ 1% GFAR and EER is 0.82% (HH1) (Sequeira et al., 2017) |
Fig. 4. Examples of periocular images from NIR datasets: (a) FOCUS Dataset, (b) MIR 2016 Dataset, (c) CASIA-Iris-Mobile-V1.0 Dataset (Zhang et al. 2018).

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Fig. 6. Examples of periocular images from Multi-spectral datasets: (a) IIITD Multispectral Periocular (IMP) (Sharma et al., 2014), (b) QUT Multispectral (Algasham et al., 2017a), and (c) Cross-Eyed 2016 (Sequeira et al., 2016).
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