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Periocular biometrics: A survey

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ABSTRACT

Periocular region is the feature rich region around the eye which may include features like eyelids, eyelashes, eyebrows, tear duct, eye shape, skin texture and many more. Periocular region based authentication system is a good trade-off between face and iris based biometric authentication systems as they need high user cooperation. This paper provides a comprehensive survey of periocular biometrics and a deep insight of various aspects such as utility of periocular region as a stand-alone modality, periocular region and its fusion with iris, application of periocular region in smart phone authentication and the role of periocular region in soft biometric classification etc. The paper also provides an outlook over possible future research in the area of periocular biometrics.

Contents

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1. Introduction

Biometric is an automated process used to recognize humans by measuring their behavioural and physiological characteristics. Biometric systems are generally used either for verification (1:1 matching) or for identification (1: N matching) (Fig. 1).

Based on the literature, among different biometric traits such as fingerprint, ears, sclera, retina, face etc., ocular and face biometrics are the most popular ones. But, both of them have their own drawbacks. Ocular biometrics (using iris) requires lots of user cooperation and good camera stand-off distance for capturing the images while face biometrics generally fails if the captured face images are suffering with A-PIE (Aging, Pose, Illumination, and Expression) challenges. To solve these problems, researchers proposed to use the surrounding area of eye known as periocular region for recognition. Characteristics of Periocular region are shown in Fig. 2.

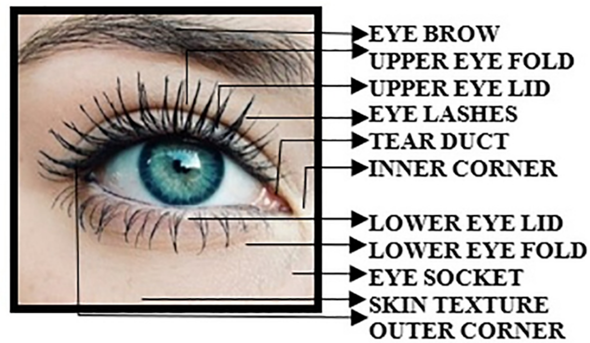

Fig. 2. Periocular region & its features.

Park et al. (2009) were the first researchers who analysed the feasibility of periocular region as a biometric trait. After a year of this study Hollingsworth et al. (2010, 2012) performed an experiment in which they created a GUI to present a pair of eye images to human volunteers and asked them to analyse the periocular features to find out whether the pair of eyes belongs to the same person or not. Based on the response from the volunteers, they ranked the features which were most often used in determining the response. The ranking from the most helpful to the least helpful feature was 1) eye lashes 2) tear duct 3) eye shape 4) eye lids 5) eyebrow 6) outer corner and 7) skin. Whereas, Smereka and Kumar (2013) observed that for NIR spectrum images, eye shape and for Visible spectrum images, shape of the eyebrow are the most discriminating features.

Periocular region also has great importance in soft biometric classification and in matching of medically altered face images (images captured before and after the process of gender transformation, recognition of surgically altered faces and images of human subjects captured pre and post cataract surgery). The strength of this biometric trait is that it requires very low user cooperation which makes periocular region interesting for security, surveillance applications and the scenario where faces are partially occluded as shown in Fig. 3.

This paper provides a state-of-the-art survey of existing literature (from the year 2009 to 2018) on Periocular biometrics. This work can also be considered as an extension of the paper titled "A survey on periocular biometrics research" published by Alonso-Fernandez and Bigun (2016) in Pattern recognition Letters.

2. Periocular biometric system

Periocular biometric system consists of five modules as shown in Fig. 4.

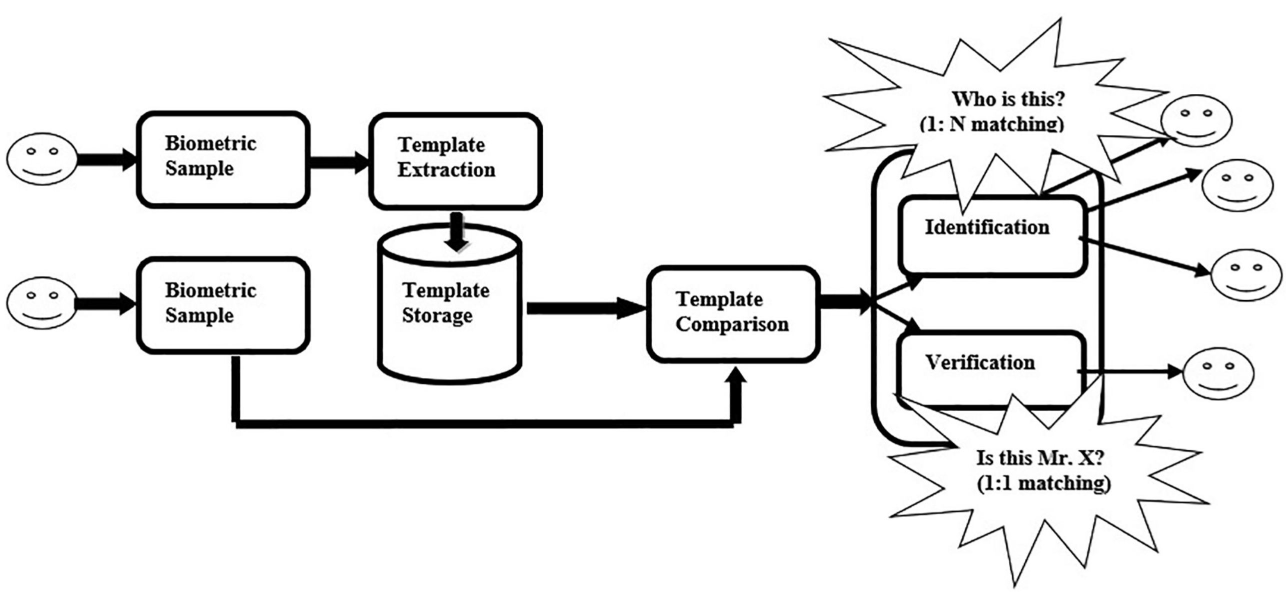

Fig. 1. Biometric system for identification and verification.

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Fig. 3. Example images where periocular biometrics is useful.

Fig. 4. Modules of a periocular biometric system.

2.1. Image acquisition

In image acquisition module, images can be captured using camera or some input sensors to create image databases. Researchers can use their own proprietary image database or benchmark databases (created and released by different organizations, online) for their research work. Details of the proprietary databases and benchmark databases used in literature are shown in Tables 1 and 2 respectively.

Table 1
Proprietary Database.

Reference	Capturing Device	# Subject	# Images
Park et al. (2009)	Canon EOS 5D Mark II camera	30	899
Hollingsworth et al. (2010)	LG2200 camera	120	240
Raja et al. (2014a)	Samsung Galaxy S5& Note 10.1 ASUS Nexus 7	32	2880
Hollingsworth et al. (2012)	NIR eye images by LG2200 EOU Camera & VL face images by NIKON D80 CCD Camera	210	420
Raja et al. (2015)	Samsung Galaxy S5 & Samsung Galaxy Note 10.1	78	10,360
Stokkenes et al. (2017)	Samsung Galaxy S5 phone	94	1095
Merkow et al. (2010)	Images are retrieved from Flickr using a web crawler	936	936

*NIR: Near Infrared Spectrum, VL: Visible Light Spectrum.

Table 2
Benchmark Database (Periocular images database).

Database Name	# Subject	# Images	Reference/Link to Download
CSIP (Cross Sensor Iris and Periocular dataset)	50	2004	http://csip.di.ubi.pt
CMPD (Cataract Mobile Periocular Database)	244	2380	Keshari et al. (2016)
FOCS (Face and Ocular Challenge Series)	437	9307	https://www.nist.gov/programs-projects/face-and-ocular-challenge-series-focs
IIITD multispectral database	62	1240	http://www.iabrubric.org/resources/impdatabase.html
SAPID (Surgically Altered Periocular Image Database)	201	402	http://www.nislab.no/biometrics lab/ntnu sapid db
UBIPr (University of Beira Interior)	344	10,252	http://socia-lab.di.ubi.pt/~ubipr/

2.2. Image pre-processing

The primary aim of this module is to enhance the images in order to extract useful features from them. There are various techniques available for pre-processing such as histogram equalization for contrast enhancement (Karahan et al., 2014). This method picked the most frequent intensity value from the image histogram and based on that it adjusts the global contrast of the image. Multiscale retinex (MSR) algorithm (Juefei-Xu and Savvides, 2014) is a subsequent of single scale retinex algorithm which use the combined output of more than one smoothing kernel of different sizes as center-surround image filters for handling different lighting conditions.

2.3. Region of interest (ROI) extraction

There is no standard procedure which can be used to define the optimum size of periocular ROI. Some researchers (Mahalingam et al. 2014; Park et al. 2009; Tan and Kumar, 2012) considered the centre of iris as reference point and calculated the size of ROI as width = 6 $\times$ radius of iris and height = 4 $\times$ radius of iris. Padole and Proenca (2012) proposed to use eye corners as a reference point to calculate ROI as they are least affected by gaze, pose variation and occlusion.

Algashaam et al. (2017) studied that size of periocular window has a greater impact on performance of recognition accuracy and found that while too big window may consider worthless features, too small may not include some useful features. Example of periocular region of interest extracted from face image is shown in Fig. 5.

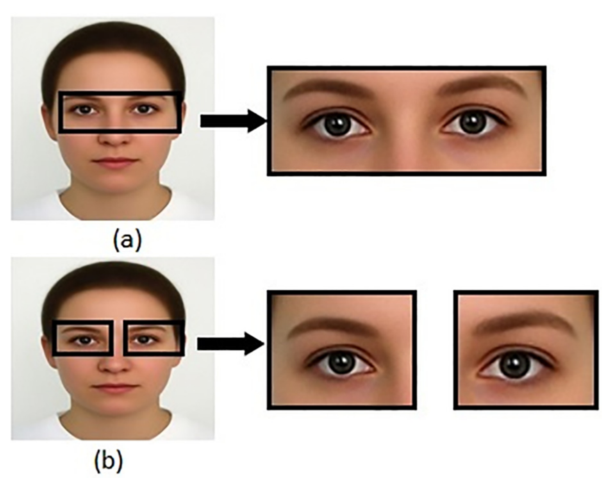

Fig. 5. (a) Periocular region including both left and right eye region (b) Periocular region with separate left and right eye region.

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Bakshi et al. (2013) built a method to extract ROI which was based on standard proportion of different face components in human anthropometry (Ramanathan and Wechsler, 2010). Proportion of the ratio of face components w.r.t width and height of the face is shown in Fig. 6.

Considering iris as reference point, they calculated the size of periocular region with the following formula

$$Width_{Periocular} = Width_{eyebrow} = 0.67 \times \frac{Height_{face}}{2} \quad (1)$$

$$\begin{aligned} Height_{periocular} &= 2 \times \ distance_{(eyebrow,eyecenter)} \\ &= 2 \times \left(0.21 + \tfrac{0.07}{2}\right) \tfrac{Width_{face}}{2} \\ &= 0.49 \times \tfrac{Width_{face}}{2} \end{aligned} \quad (2)$$

2.4. Feature extraction

Features are distinctive properties which can be used to differentiate the categories of input patterns. Feature descriptors can be classified as shown in Fig. 7. After feature extraction, different dimensionality reduction techniques like Principal Component Analysis (Oh et al., 2012) and Linear Discriminant Analysis (Joshi et al., 2014) can be applied for the optimization of feature sets.

2.4.1. Global feature descriptor

Global feature descriptor considers the entire image as a single vector and for feature extraction they often apply same rule for all the pixels of the image.

2.4.1.1. Texture-based feature descriptor. Textures are nothing but repeated patterns with regular intervals. Generally, they refer to the appearance of object by density, arrangement and proportion of its elementary parts. A feature descriptor created by textural features of an image is known as texture-based feature descriptor. In the literature, researchers used different texture-based feature descriptors such as Binary Statistical Image Features (BSIF) (Raja et al., 2014b), Local Binary Patterns (LBP) (Mahalingam et al., 2014) and Leung Malik Filters (Tan et al., 2013). BSIF uses independent component analysis to create subspace of images then generates binary code for each pixel by projecting them on same subspace. Local Binary Patterns can be computed by comparing the value of the center pixel of considered window from an image to its neighbouring pixels either in clockwise or anti-clock wise

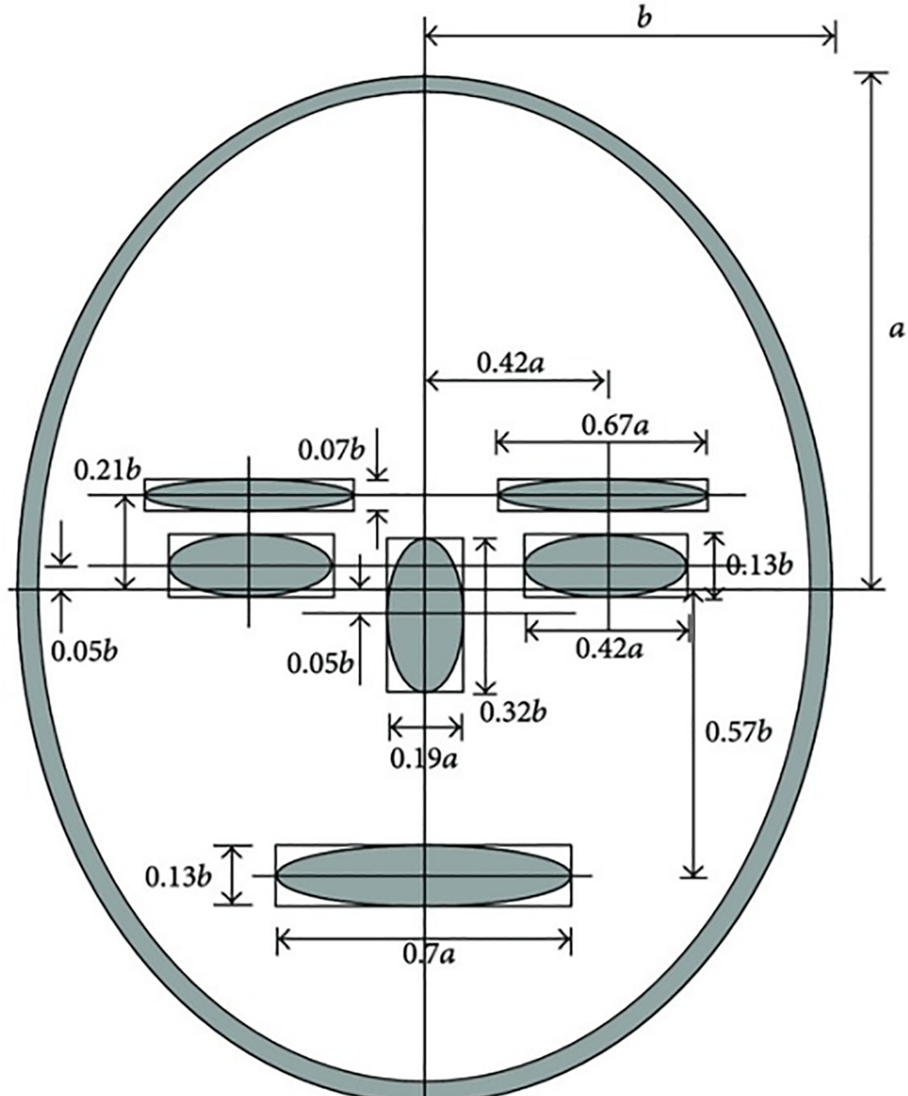

Fig. 6. Proportion of different face components with respect to height and width of face in human anthropometry.

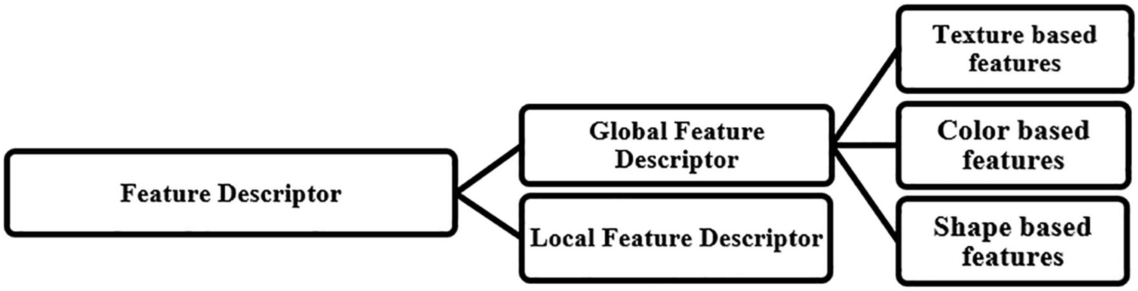

Fig. 7. Classification of feature descriptors.

direction and Leung Malik Filters contains total of 48 filters – 2 Gaussian derivative filters at 6 orientations and 3 scales, 8 Laplacian of Gaussian filters and 4 Gaussian filters. Based on the literature, Local Binary Patterns and its variants are the most popular feature descriptors in the field of periocular biometrics.

2.4.1.2. Colour based feature descriptor. Colour is the attribute of an object that can be visualized because of the light emitted from the object. Woodard et al. (2010a) transformed the RGB images in to different colour space (Hue, Saturation, Value) and compute its histogram to derive colour-based feature descriptor.

2.4.1.3. Shape based feature descriptor. Shape features are generally analysed by external boundary of the object. In periocular region images, features extracted from shape of the eye lid (Proenca et. al., 2014) shape of the eyebrow (Le et al., 2014) are fall in to the category of shape-based feature descriptor.

2.4.2. Local feature descriptor

Unlike global feature descriptor, Local feature descriptor consider the set of key points in an image and then extract features around these key points to create local descriptors. Some well-known examples of local feature descriptors are Phase Intensive Local Pattern (Bakshi et al., 2015), Symmetry Assessment by Feature Expansion (Alonso-Fernedez et al., 2015) Speeded Up Robust Features (Raja et al., 2015) and Scale Invariant Feature Transform (Ahuja et al., 2016).

2.5. Feature matching

The goal of the feature matching module is to match probe sample with gallery sample to generate matching scores. Few examples of distance measures used for matching are, Bhattacharya Distance (Woodard et al., 2010b), Hamming Distance (Oh et al., 2014), I-Divergence metric (Cao and Schmid, 2014) and Euclidean distance (Ambika et al., 2016).

3. Periocular as a standalone modality

For the very first time Park et al. (2009) analysed the feasibility of periocular region as a stand-alone biometric trait. Later (Park et al., 2011), they evaluated some important facts about periocular region and found that eyebrow is the most discriminating feature and pose variations, face occlusion, template aging, masking of iris and eye regions are some of the performance degradation factors. Oh et al. (2012) also supported the above facts and claimed that the shape of eyebrow is one of the major features in periocular region and masking of iris region (i.e. hiding of iris features) can degrade the performance of periocular biometric system.

Considering the above facts about degradation factors and to improve the recognition accuracy, researchers proposed some novel solutions. Ambika et al. (2017) suggested to fuse texture and shape information extracted by LBPV (Local Binary Pattern Variance) and Zernike moments from images to reduce the effect of pose and expression variation. LBPV extract local contrast information to achieve rotation invariant features whereas, orthogonal property of Zernike moments makes them perfect feature descriptor for shape classification.

Cho et al. (2017) focused on the effect of eye rotation and claimed that, mapping the pixels of input image from cartesian coordinate to polar coordinates before applying any feature descriptor can reduce the effect of eye rotation.

For handling the distortions like occlusion and blur in periocular images, Moreno et al., (2016) described a novel re-weighted elastic net model. This model, first separated the input image data in to its geometrical and colour spatial components and then obtained the sparse representation of images via Bayesian Fusion scheme for classification purpose.

To enhance the recognition accuracy of periocular system a group of researchers implemented the idea of ensemble feature descriptors by combining two or more feature descriptors. Summary of their approaches are shown in Table 3.

Table 3
Summary of periocular as standalone modality with ensembled feature descriptors.

Publication	Feature extraction Techniques	Performance
Woodard et al. (2010a)	LBP to extract skin texture & colour-based feature descriptor	FRGC: 91% (R1) MBGC: 84% (R1)
Xu et al. (2010)	Combination of DWT&LBP	FRGC: 53.2% (R1)
Bhardwaj et al. (2010)	Combination of GIST & Circular LBP	UBIRISv2: 73.65% (R1)
Gangwar and Joshi (2014)	Combination of LPQ & Gabor magnitude descriptor with DLDA for feature optimization	MBGC: 0.20% (EER) G.Tech: 0.25% (EER) PUT: 0.11% (EER) Caltech: 0.14% (EER)
Bakshi et al. (2015)	Combination of PILP & HOG	BATH: 100% (R1) CASIA v3: 100%(R1) UBIRIsv2: 87%(R1) FERET: 85% (R1)
Nie et al. (2014)	Combination of CRBM & DSIFT	UBIPr: 50.1% (R1)
Karahan et al. (2014)	Combination of SIFT & SURF	FERET: 96.8% (R1)

*LBP: Local Binary Pattern, R1: Rank 1 Recognition Rate, DWT: Discrete Wavelet Transform, LPQ: Local Phase Quantization, DLDA: Discrete Linear Discriminant Analysis, EER: Equal Error Rate, PILP: Phase Intensive Local Pattern, HOG: Histogram of Oriented Gradients, CRBM: Convolutional Restricted Boltzman Machine, DSIFT: Dense Scale Invariant Feature Transform, SURF: Speeded Up Robust Features, SIFT: Scale Invariant Feature Transform. Caltech database (Michael Fink, 2019), MBGC database: Multiple Biometric Grand Challenge database (Phillips et al., 2009).

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Juefei-Xu et al. (2014) explored different form of Discrete Transform encoded LBP (DT-LBP) features and observed an interesting fact that if only 40% of the full face is visible, DT-LBP based periocular system is performing better than face biometric authentication system. Bhardwaj et al. (2010) studied the effect of camera standoff distance on the performance of periocular biometrics and found that 6 m to 7 m is an ideal distance for capturing the images of periocular region.

Gangwar and Joshi (2014) employed the combination of Local Phase quantization (LPQ) and Gabor magnitude descriptor for feature extraction to demonstrate the effectiveness of phase descriptors (invariant to blur and uniform illumination) in periocular biometrics. Bakshi et al. (2014) too claimed the usefulness of phase information and proposed a global feature descriptor named as Phase Intensive Global Pattern (PIGP). PIGP depends on variation of intensity of neighbourhood pixels w.r.t different phases. As an extension of their work (Bakshi et al., 2015) invented an idea to create a local descriptor using phase information of key points of images instead of using global descriptor known as Phase Intensive Local Pattern (PILP).

To reduce the dimensionality of feature vectors without affecting the recognition accuracy of periocular based system, Adams et al. (2010) and Dozier et al. (2011) invented a feature optimization technique based on Genetic and Evolutionary computing and called as Genetic & Evolutionary Feature Extraction method (GEFE). They applied GEFE on LBP feature vector for optimization and observed that optimized feature set achieved higher recognition rate as compare to original LBP feature vector on FRGC (Phillips et al., 2005) and FERET (Phillips et al., 1997) database.

Uzair et al. (2013, 2015) formulated periocular biometrics as image set (right eye of a person was mirrored and combined with left eyes) classification problem. They implemented four feature extraction and six state-of-the-art image-set classification techniques. By applying two types of fusion one at feature and other at classifier level they observed the trade-off that image set based method achieved higher recognition rate but very expensive in terms of computation time. To solve this issue, they used PCA and LDA feature optimization algorithm to optimize the features which reduce the computation time. Summary of approaches for periocular as stand-alone modality is shown in Table 4.

Smereka et al. (2016) applied an unsupervised patch selection approach on images to find out the best discriminating region. For this, first divide the image in to grids and find out initial patch similarity (using correlation filter) then flag the region with poor match score and combine those patches with their neighbourhood to obtain new patches to improve performance of 1:1 image matching accuracy.

Zhao et al. (2017) developed a semantic assisted convolutional neural network. The concept was to add some additional CNN branch (trained with the semantic information like gender and ethnicity) to already existing CNN.

In biometrics, matching of images captured in different spectrums itself is a challenging task. Periocular region based biometric systems provide remarkable result for cross spectral matching of images as Summarized in Table 5.

Best accuracy obtained by Periocular region based system on different databases is shown in Table 6.

Table 4
Summary of approaches for periocular biometrics as standalone modality.

Publication	Feature extraction Techniques	Performance
Park et al. (2009)	Combination of SIFT, HOG & LBP	Proprietary: 77%(R1)
Park et al. (2011)	Combination of SIFT, HOG & LBP	FRGC:87.32% (R1)
Miller et al. (2010a)	LBP to extract skin texture	FRGC: 89.76% (R1) FERET: 74.07% (R1)
Ambika et. al. (2017)	Combination of LBPV & Zernike Moments	UBIPr: 97.8% (R1) UBIrisv2: 85% (R1) CMU AMP: 99.1 (R1) cross eyed: 87.8% (R1)
Cho et al. (2017)	LBP	CASIA-Irisv4:10.0172 (EER)
Adams et al. (2010)	LBP for feature extraction and GEFE for feature optimization	FRGC: 89.76% (R1) FERET: 85.06% (R1)
Juefei-Xu and Savvides (2012)	Walsh Hadamard LBP	FRGC: 60.7% (VR)
Bakshi et al. (2014)	PIGP	FERET:82.86%
Zhao et al. (2017)	SCNN	FRGC: 91.13% (R1) FOCS: 96.93% (R1) UBIPr: 82.43% (R1) CASIAv4: 98.9%(R1)
Le. et al. (2014)	Shape of the eyebrow via Fast Graph cut eyebrow segmentation technique	MBGC: 76% (IR) AR: 85% (IR)
Joshi et al. (2014)	Gabor filter for feature extraction, DLDA for feature optimization and Parzan Probabilistic Neural Network for matching	MBGC: 75.8% (R1) GTECH: 89.2% (R1) IITK: 67.6% (R1) PUT: 89.7% (R1)
Ambika et al. (2016)	Laplace-Beltrami operator to extract geometric information	CASIA 3D-FV1: 97% (R1)
Mikaelyan et al. (2014)	SAFE	BioSec: 2.16% (EER) MobBio: 11.11% (EER)
Smereka et al. (2016)	Correlation filter	FOCS: 57.90% (L) :57.95% (R) UBIPr: 84.14% (L) : 78.59%(R) FRGC: 97.01% (L) :97.36% (R) BDCP:59.76% (L) :53.16% (R)

* SIFT: Scale Invariant Feature Transform, HOG: Histogram of Oriented Gradients, LBP: Local Binary Pattern, R1: Rank 1 Recognition Rate, LBPV: Local Binary Pattern Variance, EER: Equal Error Rate, GEFE: Genetic Evaluation and Feature Extraction, VR: Verification Rate, PIGP: Phase Intensive Global Pattern, SCNN: Semantic assisted Convolutional Neural Network, IR: Identification Rate, DLDA: Discrete Linear Discriminant Analysis, SAFE: Symmetry Assessment by Feature Expansion, L: left eye, R: Right eye. GTECH face database (Ara V. Nefian, 1999), AR face database (Martinez, A. R., Benavente, R., 2019).

4. Periocular biometrics and its fusion with iris biometrics

Since periocular region images automatically consists of iris and sclera images, researchers found that the fusion of both the iris and periocular can dramatically increase the recognition accuracy.

Table 5
Periocular biometrics in cross spectral matching.

Publication	Feature extraction Technique	Performance
Sharma et al. (2014)	Pyramid HOG	Visible to Night Vision: 71.93% (VR) Night Vision to NIR: 48.21% (VR) Visible to NIR: 47.08%(VR)
Cao and Schmid (2014)	Combination of Gabor LBP & Gabor Weber	SWIR to Visible spectrum:0.75% (GAR) NIR to Visible spectrum: 0.44% (GAR) MWIR to Visible spectrum0.35% (GAR)
Cao and Schmid (2014)	Combination of Gabor LBP, WLD & HOG	SWIR to Visible: 93.88% (GAR) NIR to Visible: 98.05% (GAR) MWIR to Visible 42.39% (GAR) LWIR to Visible: 5.78% (GAR)

* HOG: Histogram of Oriented Gradients, VR: Verification Rate, NIR: Near Infrared Spectrum, LBP: local Binary Pattern, SWIR: Short Wave Infrared Spectrum, MWIR: Medium Wave Infrared Spectrum, GAR: Genuine Acceptance Rate, LWIR: Long-Wave Infrared Spectrum, WLD: Weber Local Descriptor.

Summary of approaches for periocular biometrics and its fusion with iris is shown in Table 7.

Instead of fusing iris with Periocular, Oh et al. (2014) suggested an idea to fuse sclera with periocular. For this purpose, they first implemented Multi resolution LBP and 2D structured random projection method for feature extraction from sclera and periocular region respectively and then applied score level fusion via extreme learning machine on images captured from UBIris v1 (Proenca et al.,2010) database and obtained 3.25% EER. They also observed that horizontal features of sclera gives better performance as compare to vertical features for recognition.

To achieve better ROI, Proenca (2014) proposed an image labelling algorithm (based on Markov Random field) to segment and label the components of periocular region such as eye lashes, iris, sclera. They further extended their work and considered iris (strong expert) and feature of the periocular region (weak expert) as an independent component. For iris feature extraction, multilobe differential filters (MLDF) and for periocular they used LBP and Gabor filters. By fusing both at the score level they obtained better accuracy as compare to other state of the art techniques and proved that considering two different modalities as an independent component can also improve the recognition accuracy.

Boddeti et al. (2011) compared the recognition accuracy of iris and ocular biometrics. First they detected the iris centre to extract ROI and then calculated binary code for iris and patch-based fusion correlation filter for ocular which were used as feature descriptors. With Bayesian graphical model as matcher they observed that ocular biometrics obtained better EER than iris for FOCS dataset.

For cross spectrum matching of images, Jillela and Ross (2014) matched periocular images captured in visible spectrum to iris images captured in NIR spectrum. Iris features were extracted by VERIEYE software and periocular features were created by LBP, Normalized Gradient Correlation, and Joint Dictionary-based Sparse Representation. After fusion of all those features they obtained nearby 50% matching accuracy which shows the requirement of further work in this area. Alonso-Fernandez et al. (2015) also compared iris and periocular modality for different spectrum and observed that iris matcher was better for NIR spectrum images whereas periocular matcher was good for visible light spectrum

Table 7
Summary of approaches for periocular biometrics and its fusion with Iris.

Publication	Feature extraction techniques	Performance
Woodard et al. (2010b)	2D Gabor filter for iris & LBP for periocular	MBGC dataset Left eye: 96.5% (R1) Right eye: 92.4% (R1)
Santos and Hoyle (2012)	Wavelet for iris, combination of LBP&SIFT for periocular region	UBIRIS v2 dataset EER: 18.48% Cumulative acc.: 74.3%
Tan et al. (2012)	Log Gabor filter for iris & combination of Leung-Mallik filter & SIFT for periocular region	CASIA v4 dataset 84.5% (R1)
Joshi et al. (2012)	DWT for iris and LBP for periocular then DLDA for feature optimization	UBIRISv2 and CASIA Iris dataset 96% (IDR)
Raghavendra et al. (2013)	LBP& SRC for both iris and periocular	Proprietary: 81% (EER)
Alonsoi-Fernendez et al. (2015)	1D Log Gabor filter, DCT & SIFT for iris and Gabor features, SAFE & SIFT for periocular	BioSec: 0.75% (EER) CASIA: 0.51% (EER) IITD: 0.38% (EER) MobBIO: 6.75% (EER) UBIris: 15.17% (EER)
Ahmed et. al. (2017)	1D Log-Gabor filter for iris and Multi-Block Transitional LBP for periocular	MICHE II: 1.22% (EER)

* R1: Rank 1 Recognition Rate, EER: Equal Error Rate, LBP: Local Binary Pattern, SIFT: Scale Invariant Feature Transform, DLDA: Dimensional Linear Discriminant Analysis, SRC: Sparse Representation Classifier, NGC: Normalized Gradient Correlation, JDSR: Joint Dictionary-based Sparse Representation, DCT: Discrete Cosine Transformation, DWT: Discrete Wavelet Transform, IDR: Identification Rate, SAFE: Symmetry Assessment by Feature Expansion. MICHE II database (Castrillion-Santana et al., 2016a).

Table 6
Best accuracy obtained till date on different databases.

Database Name	Best Database performance		Database Name	Best Database Performance	
	Feature extraction Technique	Rank 1 Recognition Accuracy		Feature extraction Technique	Rank 1 Recognition Accuracy
CASIA v3	LBPV + Zernike moments	100%	CSIP	SIFT, LBP + HOG	93.3
CMU	PILP	100%	PUT	DLDA + PPNN	89.7
MBGC	LBP + PCA	99.8%	GTDB	LPQ + DLDA	89.2
UBIPr	LBP + PCA	99.7%	AR	Eyebrow ASM	76
FRGC	LBP	98.3	IITD	PHOG + NN	71.93
FERET	SIFT + SURF	96.8	IITK	DLDA + PPNN	67.6
UBIRISv2	LBP + DLDA	94			

*LBVP: Local Binary Pattern variance, PILP: Phase Intensive Local Pattern, LBP: Local Binary Pattern, PCA: Principal Component Analysis, SIFT: Scale Invariant Feature Transform, SURF: Speeded up Robust Feature, DLDA: Dimensional Linear Discriminant Analysis, HOG: Histogram of Oriented Gradients, PPNN: Parzen Probabilistic Neural Network, LPQ: Local Phase Quantization, ASM: Active Shape Model, PHOG: Pyramid Histogram of Oriented Gradients, NN: Neural Network. CMU (FIA) : CMU face in action database (Goh et al., 2005).

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images. They also observed that the fusion of both the modalities always lead to performance improvement.

5. Periocular biometrics in smart phone authentication

Periocular biometrics also played a major role in smart phone authentication as summarized in Table 8.

Ahuja et al. (2016) suggested a two-step machine learning algorithm for user authentication on smartphone. In the first phase of the algorithm they trained a multinomial naïve-bayes classifier using SURF features extracted from local eye region and obtained an accuracy of 64.96%. While in the second phase, they created a pyramid of top k% features from the first phase and implemented Dense SIFT algorithm for nearest neighbour matching. They obtained 79.49% accuracy, highest as compare to other state of the art techniques. They also explored the impact of deep learning on Smartphone authentication (Ahuja et al., 2017) in periocular biometrics. With the same setup as in Ahuja et al. (2016) they put forward a combination of supervised and unsupervised convolution-based model with ROOT sift for identification and obtained an accuracy of 99.5%, which shows the potential of the above method in real life scenario.

Bakshi et al. (2018) demonstrated the effectiveness of Phase Intensive Local Pattern (PILP) in smartphone biometrics using Reduced-PILP. For reducing the feature set they arranged all phase intensive local patterns (Bakshi et. al., (2015)) in a sequence from most significant to least significant and prune least significant features. In this experiment they observed that maximum 20% of the reduction in features provides same accuracy as whole feature set but speeded up the matching time by the factor of 1.56.

Table 8
Summary of approaches for periocular biometrics in smart phone authentication.

Publication	Feature extraction Techniques	Performance
Santos et. al. (2015)	Combination of LBP, HOG & SIFT	CSIP: 0.145% (EER)
Raja et al. (2014b)	BSIF for feature extraction and SRC for classification	Proprietary: 0.61% (EER)
Raja et al. (2014a)	SIFT, SURF & BSIF independently	Proprietary: 89.38% (GMR) @ 0.01% FMR using BSIF
Raja et al. (2015)	SIFT, SURF, BSIF independently then weighted score level fusion	VISOB: 89.96% (GMR) @ 0.01% FMR
Raja et al. (2016a)	Deep sparse filter	VISOB 97.56% (GMR) @0.001 FMR.
Ahuja et al. (2016)	SURF and Dense SIFT algorithm	VISOB dataset Samsung L: 64.18% R: 68.22% (R1) Apple L: 71.05% R: 70.13% (R1) Oppo L: 78.51% R: 79.49%(R1)
Ahuja et al. (2017)	Convolution based deep Learning approach	MICHEII: 0.053% (EER) VISOB: 99.5% (TPR)
Stokkenes et al. (2017)	BSIF	Proprietary 1.3444% (EER)
Bakshi et. al. (2018)	Reduced phase intensive local pattern	BATH: 100% (R1) CASIA: 100% (R1) UBIRIS: 86.43% (R1) FERET: 85.64% (R1)

*R1: Rank 1 Recognition Rate, EER: Equal Error Rate, GMR: Genuine Match Rate, FMR: False Match Rate, LBP: Local Binary Pattern, HOG: Histogram of Oriented Gradients, SIFT: Scale Invariant Feature Transform, BSIF: Binary Statistical Image Feature, SRC: Sparse Reconstruction Classifier, SURF: Speeded Up Robust Feature, LPQ: Local Phase Quantization, CSIP: Cross Sensor Iris & Periocular dataset, TPR: True Positive Rate, VISOB: Visible light mobile Ocular Biometric Dataset.

6. Periocular biometrics in soft biometric classification

Soft biometrics consists of number of biometric traits like gender, race, ethnicity, age, height and weight which cannot be unique for a person but may support other biometric traits for identification and verification and can improve the recognition accuracy of any biometric system. In literature, periocular biometry is primarily used for gender, ethnicity and race classification and SVM as a classifier is consider as a good choice for soft biometric classification. Table 9 outline the performance of periocular biometrics in soft biometric classification.

Chen et al. (2017) carried out an experiment for Race classification using periocular region images. They focused to classify East Asian from Caucasian (vice versa) and used five local features 1) texture of tear duct region 2) texture of the region between upper eyelid and eyebrow 3) color of iris 4) intensity in upper region of inner eye corner and 5) distance between upper eyelid and eyebrow. To extract the local features first they used STASM method for automatic landmark detection, then LBP for textural feature extraction and obtained 97.45% race classification accuracy with KNN classifier. They also obtained recognition rate of 98.15% for same gender images and 93.4% when subject are wearing glasses.

7. Periocular biometrics in special scenario

7.1. Age invariant face recognition

Juefei-Xu et al. (2011) carried out an experiment to analyse the feasibility of periocular region in age invariant face recognition. They used FG-NET (Yanwei, 2019) dataset which contain images of age range from 0 to 69. For pose correction and illumination

Table 9
Summary of approaches for periocular biometrics in soft biometric classification.

Publication	Feature extraction Techniques	Performance
Lyle et al. (2010)	LBP, LIBSVM software	FRGC dataset Gender: 93% (R1) Ethnicity: 91% (R1)
Merkow et al. (2010)	LBP for feature extraction and LDA using PCA for dimensionality reduction	Proprietary dataset Gender: 85% (R1)
Dong and Woodard (2011)	eyebrow shape-based features and SVM for classification	Gender MBGC: 96% (R1) FRGC: 97% (R1)
Kumari et al. (2012)	Convolution Neural Network techniques: BPNN and RBFNN	FERET dataset Gender RBFN & BPNN: 90% (R1)
Castrillion-Santana et al. (2016b)	Combination of FHOG, FLBP & HSHOG for feature extraction and SVM with RBF kernel for classification	GROUPS dataset Gender: 92.46% (R1)
Chen et al. (2017)	LBP for feature extraction, STASM for landmark detection, KNN classifier	Composed OFD-FERET dataset RACE: 97.45% (R1)
Rattani et al. (2017)	HOG & Multi-Layer Perceptron	VISOB dataset Gender Samsung: 89.10% (R1) Oppo: 90.10% (R1) Iphone: 90.20% (R1)

* R1: Rank 1 Recognition Rate, LBP: Local Binary Pattern, LDA: Linear Discriminant Analysis, PCA: Principal Component Analysis, BPNN: Back propagation neural network, RBFNN: Radial Basis Function Neural Network, FHOG: Histogram of Oriented Gradients with facial Pattern, HSHOG: Histogram of Oriented Gradients with Head and Shoulder patterns, HOG: Histogram of Oriented Gradients, SVM: Support Vector Machine, RBF: Radial Basis Function, STASM: Statistical Active Shape Model, KNN: K Nearest Neighbour.

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normalization they applied pre-existing active appearance model and anisotropic diffusion model respectively. With Walsh-Hadamard transform encoded LBP as feature descriptor and Unsupervised Discriminant Projection (UDP) for subspace modelling they obtained 100% rank-1 identification rate and 98% verification rate at 0.1% false acceptance rate.

7.2. Medically altered images

7.2.1. Face images obtained before and after plastic surgery

Jillela and Ross (2012) developed a method to match images captured before and after plastic surgery of face. Face features were extracted using Verilook and PitPatt software and SIFT, LBP feature descriptors were used for ocular region. After fusing the score obtained by both the modalities (face and ocular) they obtained rank1 recognition accuracy of 87.4% which is highest compared to other reported works in existing literature for plastic surgery database.

7.2.2. Periocular images obtained before and after plastic surgery

Raja et al. (2016b) examine the performance of periocular biometrics for the images obtained before and after plastic surgery of near-by region of eyes. They created a database SAPID database (details are mentioned in Table 2), applied several shape and texture feature descriptors and obtained rank 1 identification rate of 53.73%. Based on the lower identification accuracy they concluded that surgical changes degrade the performance of periocular biometrics and this area needs further research.

7.2.3. Periocular images obtained before and after cataract surgery

Keshari et al. (2016) implemented the concept of periocular biometrics for matching the images captured before and after cataract surgery of human eyes. They created scat net feature descriptor and obtained nearby 30% recognition accuracy. The output shows the requirement of further exploration in this field.

7.2.4. Face images obtained before and after gender transformation

Mahalingam et al. (2014) collected more than 1.2 million face images from you tube videos of 38 subjects (who were undergoing gender transformation). They processed those videos over a period of several month to three years and created HRT-Transgender dataset (Mahalingam and Ricanek 2017). They analyse and compare the matching accuracy of face and periocular region based biometric authentication in such a non-ideal scenario and revealed the fact that periocular region with simple texture-based feature descriptor (LBP, HOG and patch baseed local binary patterns) achieved higher recognition rate of 57.79% as compare to full face authentication system which was only achieved 46.39% recognition accuracy in the same scenario.

7.3. Hallucinating of full face using only periocular features

Juefei-Xu et al. (2014) claimed that periocular region is a very feature rich region on the face and to prove this claim they proposed an approach to reconstruct whole face using only periocular region features. They developed a Dictionary learning approach known as Dimensionality weighted K-Singular Value Decomposition (DWKSVD) method; They first obtained the sparse representation of the periocular image using OMP (Orthogonal Matching Persuit) and then reconstructed the whole face using the face components of the DW-KSVD dictionary. For analysing the performance of their reconstructed face and it's matching with original face they re-implemented the method described by Juefei-Xu et al. (2010) and obtained a verification accuracy of 82.6%, which shows that periocular region can be considered as a good option to hallucinate full face via DWKSVD without losing much verification accuracy. Considering the drawback of dictionary learning approach (it required a huge amount of training sample and a large kernel size) they provide a modification (Juefei-Xu et al., 2016) in which they implemented fast food transform method to achieve kernel expansion explicitly for dictionary learning and obtained 95.1% verification accuracy. One more advantage of this method is that, it can de-kernelize the image back to image space from feature space which is very useful in cross-domain reconstruction, and missing data recovery.

8. What's new in 2018?

Recognition accuracy of any periocular system is highly dependent on type of handcrafted features (LBP, SIFT and SURF etc) and how to extract them. To reduce the dependency and to improve the recognition accuracy researchers are slowly moving from handcrafted to non-handcrafted features extracted via deep learning approaches.

Proença and Neves (2018) claimed that discarding of ocular components like sclera and iris from periocular region of interest can optimize the recognition accuracy of the system. To justify their claim, they created a large set of multiclass samples by interchanging the periocular and ocular parts of different subjects' images captured from UBIRIS.V2 and FRGC datasets. They pass those images as an input to Alexnet CNN model for training and testing and obtained 88% and 92% rank 1 recognition accuracy for UBIRIS.V2 and FRGC respectively.

Tapia and Aravena (2018) proposed a method to classify gender by using periocular images captured in NIR spectrum (ND-GFI database created by Bobeldyk and Ross 2016). They created two individual CNN models one for left and one for right eye and then fused these two models to create a new CNN model. This new CNN model obtained 87.26% rank 1 recognition accuracy which was comparable with other state of the art techniques.

Zhao and Kumar (2018) analysed that some components of periocular region such as eye and eyebrow are critical to extract features and need more attention for feature learning. They developed a new deep learning architecture which was a combination of ROI detection network (to detect predefined critical components: eye and eyebrow) and attention module to make an explicit attention on critical components during feature learning and matching. They examined the performance of the model on 6 different databases UBIPr, FRGC, FOCS, CASIA iris (Tieniu and Zhenan, 2019), UBIPRIS v2 and VISOB (Rattani et al., 2016) and obtained 2.26%, 8.59%, 7.68%, 4.90%, 0.14% and 1.47% EER respectively. They also found that the model was comparable with other CNN models already existing in literature.

9. Future scope

Even after nine years of exhaustive research in the field of periocular biometrics, further research options are possible as given below:

1. Study and use of combination of handcrafted and non-handcrafted features for periocular recognition is an area which needs further exploration.
2. Concept of attention mechanism; Explicit focus on critical components (shape of eyelid, density of eyebrow, shape of eyebrow etc.) of an image needs to be explored for further improvement in recognition accuracy of periocular based biometrics authentication system.
3. Defining the size of optimal ROI (Region of Interest) is still a topic of research in the field of periocular biometrics.

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4. Integration of semantic information (eg: gender information) with basic features (edge, corners, key points etc.) in a single learning model.
5. Most of the pretrained CNN models which are trained on very large 'ImageNet' dataset (contained thousands of image classes) encountered the problem of overfitting when trained with small size databases. This issue also need to be explored further to use these pretrained models for small size databases without overfitting.
6. Developing methods for matching heterogeneous periocular region images captured in different spectrum using deep learning concepts.
7. Improving the recognition accuracy of medically altered images.

10. Conclusion

The primary objective of this paper is to provide an explanatory view of periocular biometrics literature and about what features, feature extraction methods and matching schemes are already explored and what issues are remaining to be unexplored in this field. With the fast-growing technological world, it is necessary that the system used for identification and verification of the persons must ask for less user cooperation and periocular biometrics is a very good solution for this problem. Periocular region can be considered as a very promising trait both as a single modality and as a support for face and iris biometric. Periocular region achieved better result in many cases where face biometric suffers from different constraints like pose, illumination variation, occlusion and aging effect. Fusion of iris and periocular region also achieved better results as compared to iris as a stand-alone modality. More over iris biometrics requires high user cooperation and it needs images captured in NIR Spectrum. In contrast to this, periocular biometric does not require very high user cooperation and work well with the images captured in visible spectrum and in wild. This paper also demonstrates the importance of periocular biometry in some special scenarios like soft biometric classification (classification of Gender, Race and ethnicity) and recognition of medically altered faces (Transgender, cataract surgery) and proved that periocular region is one of the promising traits for biometric authentication systems.

Declaration of Competing Interest

None.

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Further reading

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