Experiments with Ocular Biometric Datasets: A Practitioner's Guideline

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***Abstract*—Ocular biometrics is the imaging and use of features extracted from the eyes regions for personal recognition. Ocular biometrics is a promising research field owing to factors such as recognition at a distance and suitability for recognition with regular RGB cameras, especially in visible spectrum on mobile devices. To ensure that ocular biometric academic researches have a positive impact on future technological developments, this paper provides a review of ocular databases available in literature, diversities among these databases, design and parameters consideration issues during acquisition of database and selection of appropriate database for experimentation. Open issues and future research directions are also discussed to identify the path forward.**

I. Introduction

Biometrics is being used in several applications ranging from civilian (e.g., banking) to law enforcement (e.g., passport). There exist various biometric traits (see Figure 1a) and their choice depends upon the application. Face, iris, periocular region, fingerprint, voice, and signature are some of the most adopted biometric traits. Table Ia shows a comparison of biometric traits, advantages and challenges. *Ocular biometrics* (Figure 1d) that refers to recognizing an individual via iris, retina, sclera, periocular or eye movements has become an active research field across the globe due to its high ability of yielding recognition accuracy and it being relatively a bit less-invasive, -constrained, and -need of user-cooperation [19]. While developing different systems based on different biometric traits, experiments needs to be conducted to validate the uniqueness, robustness, and feasibility of a particular trait. There are several databases available publicly that can be experimented upon. These public databases are a vital ingredient of ongoing ocular biometrics based research. They are needed in system/algorithm development, creating a platform to be used for comparing works of different research groups, and introducing new challenges to the research and industry community. A wrongly chosen dataset will produce poor result and forge the objective of experiment leading thus to giving a false sense of progress. To ensure a great impact on future technological developments, this article emphasizes on proper choice of datasets for experimentation on ocular biometrics.

Particularly, we provide some guidelines for the researchers and product developer to focus on proper choice of database and evaluation of ocular biometrics algorithms and systems. We hope that following these guidelines will enhance the likelihood of the results obtained in a laboratory generalizing to the operational scenarios. Further, open issues and challenges are highlighted, and potential future research directions are discussed.

II. What diversity is available in ocular biometric databases

Ocular biometric databases basically contain different images/videos from various subjects in a maintained data structure. The data collected in an ocular biometric database contains following features (usually a subset of these features):

1) **Imaging Technique variation**
   Images in a database can be of three types according to their mode of capturing:
   a) *Direct Capture*: Samples are captured directly through sensor usually in Visual (VS) or Near Infrared (NIR) spectrum and stored in lossless manner. Ocular recognition using different imaging modalities may result in different scores and should be reported accordingly. Tables Ib, IIa and IIb represent some commonly used ocular datasets. Some sample images are shown in Fig 1b.
   b) *Scanned Capture*: Samples are scanned from printed images that have been captured before. It takes advantage of fast data processing by extracting only those part where important information is found [1].
   c) *Latent Capture*: Samples are captured from some impression of the image (reflection of face image on mirror/glass).
2) **Image quality variation** The images may be of different quality, which can be obtained during data collection by changing sensor or computer-aided algorithms after data collection. Three types of variations are:
   a) *Spatial resolution variation:* Spatial resolution is number of pixels in a unitary length, i.e., pixel-per-inch (ppi) that mainly depends on sensor. Higher resolution commonly leads to higher authentication accuracy [16].
   b) *Bit-depth variation through bit-plane slicing:* Bit depth is color information stored in the image. Images with higher bits are expensive in terms of space, thus bit plane slicing method is used. Varying bit-depth leads

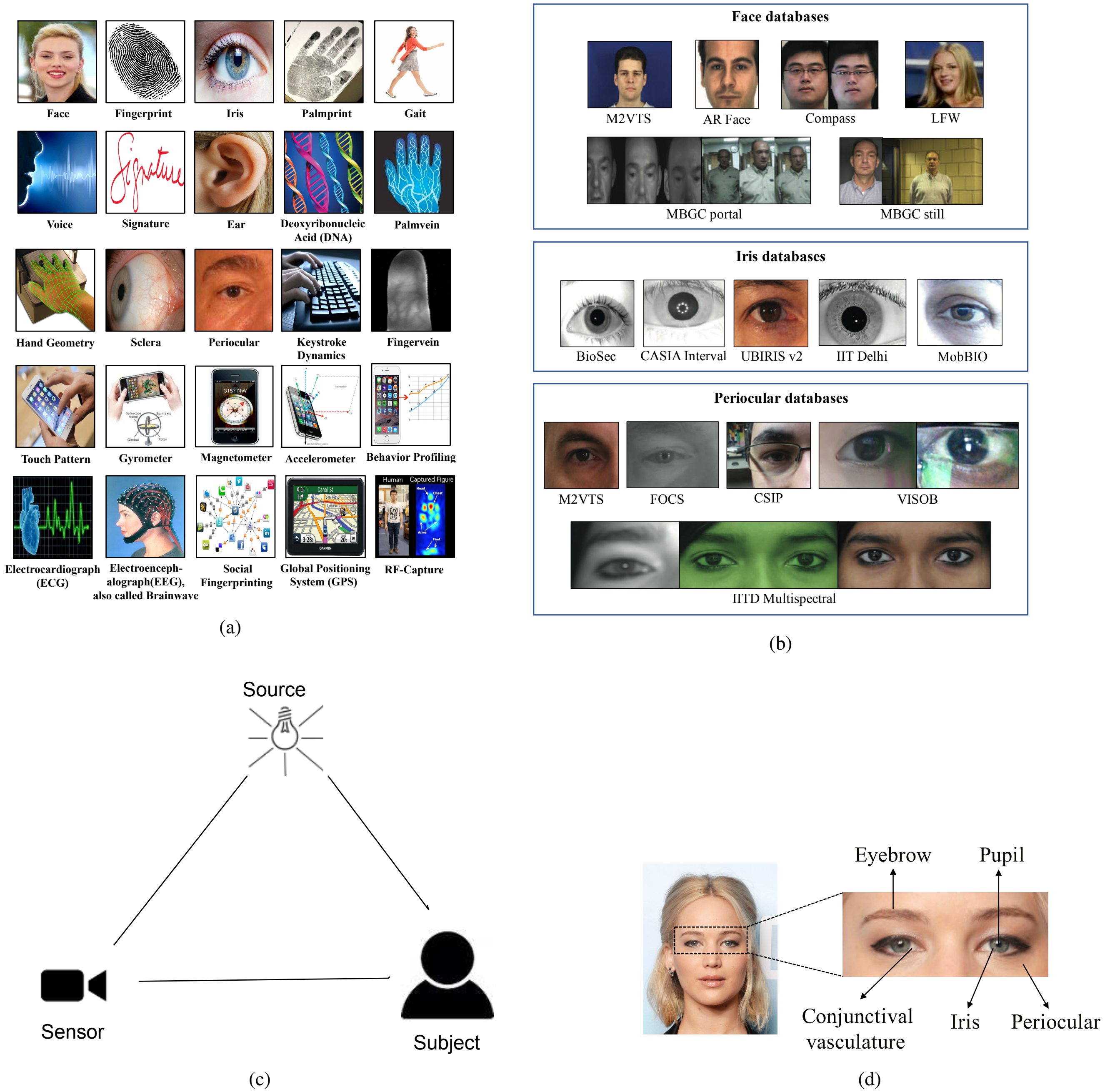

Fig. 1: (a) Examples of characteristics that have been proposed and used for person recognition. (b) Samples of databases used in ocular biometric research. (c) Image acquisition setup. (d) Ocular biometric modalities.

to variations in informative features of the image and accuracy.

c) *Focus variation to obtain focused and blurred images of different degrees:* Change in focus produces images of varying quality such as samples with out-of-focus blur. Both hardware and software can be used obtaining samples with varying focus properties. Techniques and standards are available for assessing focus/quality of biometric images [2].

3) **Human involvement variation :**
a. Constrained involvement: Different impressions of same subject can be captured by involvement of human variation in biometric system. Under constrained condition, e.g., subject follows mentioned expression, for data collection.
b. Pseudo-unconstrained scenario: Database images in such scenario are acquired under uncontrolled or less constrained environment.

4) **Session:** Time separation between two successive data acquisition round is known as session. M2VTS [3] is an example of session based face database consists of audio recordings and video sequences of 37 subjects uttering digits 0 through 9 in five sessions spaced apart by at least one week.

5) **Gender specification:** Gender is an important demographic attribute, which can also be used for separate

Trait	Advantages	Possible challenges
Iris	High dimensional feature can be extracted; Difficult to spoof; Permanence of iris; Secured within eye folds; Can be captured in non-invasive way	Higher accuracy in NIR images than VS images; High cost of NIR acquisition device; Low recognition accuracy in unconstrained scenarios; Low recognition accuracy for low resolution; Occlusion due to use of lens; Eye may close at the time of capture; Do not work for keratoconus and keratitis patients
Face	Easy to acquire; Yields accuracy in VS images; Most available in criminal investigations	Not socially acceptable for some religions; Full face template makes database large; Variation with expression and age
Periocular	Can be captured with face/iris region without extra acquisition cost	Can be occluded by spectacle; Less features in case of infants
Lip	Existence of both global and local features	Difficult to acquire; Less acceptable socially; Shape changes with human expression
Ear	Easy segmentation due to presence of contrast in the vicinity	Difficult to acquire; Can be partially occluded by hair

(a)

Database	Research Lab	Version	Acquisition Device	Images	Subjects	Resolution	Color Model
UBIRIS	Soft Computing and Image Analysis (SOCIA) Group, Department of Computer Science, University of Beira Interior, Portugal	v1 [6]	Nikon E5700	1,877	241	800×600	RGB
		v2 [5]	Canon EOS 5D	11,102	261	400×300	sRGB
CASIA	Iis Recognition Research Group, Center for Biometrics and Security Research, National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences Beijing, China	TestV1	IrisGuard AD100	10,000	1,000	640×480	Grayscale
		IRISv1	Self-developed	756	108	320×280	Grayscale
		IRISv2	OKI IRISPASS-h	1,200	60	640×480	Grayscale
			CASIA-IrisCamV2	1,200	60	640×480	Grayscale
		IRISv3-Interval	Close-up iris camera	2,639	249	320×280	Grayscale
		IRISv3-Lamp	OKI IRISPASS-h	16,212	411	640×480	Grayscale
		IRISv3-Twins	OKI IRISPASS-h	3,183	200	640×480	Grayscale
		IRISv4-Interval	Close-up iris camera	2,639	249	320×280	Grayscale
		IRISv4-Lamp	OKI IRISPASS-h	16,212	411	640×480	Grayscale
		IRISv4-Twins	OKI IRISPASS-h	3,183	200	640×480	Grayscale
		IRISv4-Distance	Long range iris camera	2,567	142	2352×1728	Grayscale
		IRISv4-Thousand	Irisking IKEMB-100	20,000	1,000	640×480	Grayscale
		IRISv4-Syn	By image synthesis	10,000	1,000	640×480	Grayscale
ND-IRIS	Department of Computer Science & Engineering, University of Norte Dame, USA	-	Iridian LG EOU2200	64,980	356	640×480	Grayscale
MMU	Multimedia University Malayasia	v1	LG IrisAccess2200	450	100	320×280	Grayscale
		v2	Panasonic BM - ET100US Authenticam	995	100	320×280	Grayscale
BATH	University of Bath Bath United Kingdom	Iris DB 400	IrisGuard AD-100 Dual-Eye Autofocus Camera	8,000	200	1280×960	Grayscale
		Iris DB 800		16,000	400	1280×960	Grayscale
		Iris DB 1600		32,000	800	1280×960	Grayscale
UPOL [8]	Department of Computer Science, Palacky University Olomouc, Czech Republic	-	SONY DXC-950P 3CCD	384	64	576×768	RGB
BioSec	Biometric Recognition Group ATVS	-	LG IrisAccess EOU3000	3,200	200	640×480	Grayscale
IITD [10]	Biometrics Research Laboratory IIT Delhi	v1.0	JIRIS, JPC1000, digital CMOS	1120	224	320×240	Bitmap
MICHE	Biometric and Image Processing Lab	v1	iPhone5	1600	50	1536×2048	RGB
			Galaxy Samsung IV	1600	50	2322×4128	RGB
			Galaxy Tablet II	1600	50	640×480	RGB
MobBIO	Visual Computing and Machine Intelligence (VCMI) INESC Porto	-	TF300T-000128	384	105	300×200	RGB

(b)

TABLE I: (a) Comparison of biometric traits present in human face. (b) Review of Existing Iris Databases (Clicking on the database name opens its official website).

recognizers to improve accuracy. Most ocular databases provide a detailed annotation of age and gender [14].

6) **Age specification in session databases:** Session databases record the changes due to ageing in features of subject over time, which can be used to improve recognition accuracy [14].
7) **Variation of environment :** Most databases acquired under controlled environment facilitate the study of specific parameters on biometric recognition. However, real time data is unconstrained in nature were a practitioner has no control over parameters. Environmental variations largely affect the quality of acquired image in visible spectrum [4]. Image acquisition location such as outdoor (cloudy/sunny day) or indoor (improper illumination) may constitute a problematic factor due to variation in illumination. BioID [7] is an example of face database acquired in indoor environment consist of 1521 images of 23 different subjects .
8) **Static or On-the-go Capture :** Databases, e.g., UBIRIS v2 [5], have distance variability, where subject is static and standing at several stand-off distances with respect to acquisition device/sensor. Recognition using these databases require cooperative users which is not often real. A few number of databases (e.g., MBGC [20]) consist on-the-go acquisition images were subject walk through an acquisition portal.
9) **Special Cases :** Despite recent advances, there are several special challenges still need to be solved, e.g., individual with spectacles or identical twins. Various methods have been proposed to distinguish twins, but still require improvement for higher accuracy. Also, some diseases affect iris and cornea that may have a negative impact on the features [1].

III. How to choose an ocular biometric database for experimentation

Various ocular databases are publicly available for research. Databases under constraint environments lack diversity, thereby leading to low generalization capability of systems devised using them. Databases acquired under unconstrained environments with non-cooperative users (e.g., operations such as recognition at a distance) contain glasses, contact lens, thus facilitate the capability developing real-world robust algorithms. Databases acquired in different spectrum produce different outcomes. A researcher/practitioner should consider their research criteria and above issues before choosing ocular dataset(s). Database selection is application dependent, e.g., for face/ocular based uni-/multi-modal recognition of moving users, one should choose video database such as M2VTS [3] and CMU-H, whereas BioID [7] is suitable for indoor applications. For large-scale and unconstrained evaluation, Labeled Face in Wild (LFW) [16] can be useful. It is very common practice by research community to use face and iris databases also for ocular recognition systems, thus Table IIa lists face databases collected in NIR and VS ranges, while Table Ib refers iris databases. Number of test samples is another criterion that needs to be considered while selecting database, e.g., M2VTS [3] (1180 recording of 295 subjects acquired over a period of four months) attracted many researchers which facilitate evaluation of many algorithms in a set-up very close to real-world settings. Few databases, e.g., VISOB (Visible Light Mobile Ocular Biometric) [18], for periocular region is specially imagined are available in public domain, as described in Table IIb. As, iris databases contain eye and its immediate vicinity including eyelashes, eyelids, nearby skin area and eyebrows, which can be used as periocular features. In turn, face databases may be cropped in a rectangular template using eye areas to be latter utilized as periocular datasets. Bakshi et al. [19] has proposed how to select optimally a rectangular template around periocular region.

For choosing a proper database for experimentation, a practitioner needs to know under which acquisition environment the database was captured. The following will discuss a typical acquisition set up and the key components in it. Understanding how to set up a biometric acquisition platform and what variations can be there in acquisition parameters, can help a practitioner choosing the right database for his/her experimentation.

A. Image acquisition setup and issues

Setting up imaging environment is a critical first step to any imaging application. Figure 1c shows the image acquisition setup and parameters need to setup before acquisition of images. Before acquiring images, following elements and parameters need to be considered:

Setting up imaging environment is a critical first step to any application. Figure 1c shows the image acquisition setup and parameters need to set before acquisition. Before acquiring images, following elements need to be considered:

1) **Acquisition Device Parameters:**
   a) *Imaging resolution:* Quality of acquired image is greatly affected by resolution. Though high-resolution digitized images contain a wealth of features, they require more storage space and vice-versa.
   b) *Imaging modalities:* Since visual spectrum (VS) samples suffers from illumination [11], infrared (IR) imaging sensors are gaining much interest. The short-wave infrared (SWIR) (0.9–2.4μm) and near-infrared (NIR) (0.7–0.9μm) spectra are reflective and eliminate indirect illumination, usually providing good image quality for recognition. SWIR and NIR spectrum databases are useful in testing the cases where the application is to be done in very much controlled environment with cooperation of the subject.
   c) *Static or motion state*: Contrary to static, moving acquisition sensors usually produce blur images and later require some enhancement for feature extraction. Sometimes there is requirement to test the performance of some method on motion blurred images. In those cases databases with moving camera of object can be considered for experimentation.
   d) *Focus Parameter:* Setting proper focus parameter is vital, as wrong parameters may result blurring of acquired image.

Database	Research Lab	Version	Images	Subjects	Resolution	Color Model
FERET	National Institute of Standards and Technology (NIST)	v4	14,126	1,191	768×512 384×256 192×128	RGB
PIE [11]	Carnegie Mellon University	-	41,368	68	3072×2048	RGB
Multi-PIE	Carnegie Mellon University	-	7,50,000	337	3072×2048	RGB
SCface	Video Communications Laboratory, Faculty of Electrical Engineering and Computing, University of Zagreb, Croatia	-	4,160	130	100×75 144×108 224×168 and 1600×1200	Grayscale and RGB
Yale [12]	Yale University, US	-	165	15	640×480	Grayscale
Yale B	Yale University, US	-	5,850	10	640×480	Grayscale
ORL	AT & T Laboratories Cambridge	-	400	40	112×92	Grayscale
UMIS	University of Manchester, Institute of Science and Technology	-	564	20	112×92	Grayscale
M2VTS [3]	ACTS European Language Resource Agency	v1.0	185	37	286×350	RGB
AR [13]	The Ohio State University	-	3276	126	576×768	Color Image
GTDB	Georgia Institute of Technology	-	750	50	640×480	JPEG
Caltech	Computational Vision Group	-	450	27	896×592	JPEG
CMU-PIE	Vision and Autonomous Systems CMU	-	750,000	337	3072×2048	PNG
FRGC	University of Notre Dame	-	50,000	4,003	1704×2272	RGB, 3D channels
MORPH	University of North Carolina Wilmington	-	55,000	13,000	400×500	PGM
PUT	Poznan University of Technology Poland	-	10000	100	2048×1536	JPEG
Plastic Surgery	IIIT Delhi	-	1800	900	200×200	RGB
ND-Twins	University of Notre Dame	-	24,050	435	480×640	RGB
FaceExpressUBI [15]	University of Beira Interior	-	90, 160	184	2056×2452	Tiff
FG-NET	Face and Gesture Recognition Working group	-	1,002	82	400×500	Gray Scale
CMU-H	Carnegie Mellon University	-	764	54	640×480	videos
Compass	CyLab Biometrics Center Carnegie Mellon University	-	3,200	40	128×128	RGB
MBGC [20]	National Institute of Standards and Technology	v2 still	3,482	437	$variable$	RGB, Range
		v2 portal	628	114	2048×2048	video
LFW [16]	Coumputer vision lab University of Massachusetts, Amherst	-	13,233	5749	250×250	JPEG

(a)

Database	Research Lab	Version	Images	Subjects	Illumination	Resolution	Color Model
UBIPr [1]	University of Beira Interior, Portugal	-	10950	261	VW	Variable	RGB
UBIPosePr [17]	University of Beira Interior, Portugal	-	2400	100	VW	Variable	RGB
FOCS	National Institute of Standards and Technology Department of Commerce,U.S.	-	9581	136	NIR	750×600	Grayscale
IMP [4]	Image Analysis and Biometrics Lab IIIT Delhi	-	620	62	NIR	640×480	Grayscale
			310		VW	600×300	Grayscale
			310		Night vision	540×260	Grayscale
CSIP [2]	Soft Computing and Image Analysis Lab University of Beira Interior	-	2004	50	VW	Variable	RGB
VISOB [18]	University of Missouri	-	5010381	550	VW	240×160	RGB

(b)

TABLE II: (a) Review of Existing Face Databases (Clicking on the database name opens its official website). (b) Review of Existing Periocular Databases (Clicking on the database name opens its official website).

e) *Standoff distance:* Distance between camera front lens to user under inspection is called standoff distance, which should be set according to acquisition area of interest, and required degree of detail of the region of interest.

2) **Lighting Setup:**

a) *Source:* Obtaining samples with clearly visible objects, lighting conditions during image acquisition must be considered carefully. LED, and laser are good source of light, if arranged properly can reduce some illumination problems.

b) *Characteristics of the Light Source:*

i) Point light: It emanates concentric light and almost parallel light when placed near and far away from object, respectively.

ii) Diffuse light: It scatters light rays, so that an object is lighted from several directions.

iii) Directed light: Directed light is described by rays of light following a defined direction.

c) *Imaging environment:* Ambient light affects visual appearance of objects/users, therefore issues like outdoor and indoor image acquisition, smoke, etc. are need to be considered during image acquisition.

3) **Object:**
   a) *Movement Considerations:* Recognition under motion, when either camera or user mobile, remains a difficult task due to blurring.
   b) *Constrained or unconstrained environment:* Though accuracy is higher under constrained environments, real-world applications are unconstrained where one has no control over parameters. e.g., pose.
   c) *Cooperative or non-cooperative user:* Iris trait has uniqueness and stability throughout life. But, it requires very cooperative user and usually fails when samples are captured at a distance with low quality. Therefore, periocular recognition is getting so much momentum an alternative.

IV. Open Issues and Future Research Directions

Despite recent progress, several exigent problems have yet to be addressed to unleash ocular biometrics' full potential. To further advance the state-of-the-art in ocular biometrics, following some open issues and general future directions are discussed:

A. Heterogeneous ocular biometric recognition

Cross-dataset, cross-sensor, and cross-spectral settings (in which training and testing sets are from different datasets, sensors (cameras), and spectra respectively) are a method to assess interoperability and generalization capability of systems. Few preliminary studies reported that ocular biometric algorithms' performance degrade remarkably under these settings. There is still a room to address interoperability of systems under cross-settings, since it is a research direction that holds significant practical value for real-world systems.

B. Automatic segmentation

Though automatic segmentation of ocular parts can aid to avoid those that are not beneficial (e.g., hair or glasses) and deteriorate performance of systems, automatic segmentation of ocular/periocular regions is an understudied field. Reported results of automatic segmentation methods for ocular biometrics are far from the accuracy required in real-world applications, thus more efforts based on advanced image processing and machine learning should be put in this direction.

C. Multibiometrics

It is well-documented that multimodal biometrics lead to better accuracy results than unimodal approach. But, most studies on ocular biometrics are based on single modality. Thus, devising novel fusion schemes using ocular and other modalities needs to be explored. Further, use of image and feature quality as well as device information may be incorporated in fusion algorithms for enhanced performance. Dynamic selection based fusion scheme may also help to curb problems that arise in ocular recognition under unconstrained environments.

D. Webscale ocular biometrics

Phenomenal growth of facial/ocular videos and images on the Web, in social networks and surveillance is attracting much attention toward webscale/large-scale/open-universe biometrics. With billions of videos/images to consider, Web-scale ocular biometrics is a difficult task that demands speed, accuracy, and scalability. Also, there exist no large scale evaluation of ocular recognition schemes, which may establish statistical significance for published methods. Better performances might be achieved by combining meta-information associated with ocular samples. Another research track that may be pursued is formulating data-independent feature extraction and classification learning via deep neural networks.

E. Soft Biometrics

Soft biometrics typically refers to attributes (e.g., gender, age, and race) that don't explicitly identify the person but complement identity information that primary biometrics provide. Despite soft biometrics' applications in recognition, indexing, and sample retrieval, state-of-the-art in ocular soft biometrics is nascent, specially in unconstrained conditions. Automatic soft biometrics estimation from ocular modalities remains a challenge as demographic attributes are affected by internal as well as external factors, such as place of residence and worldwide culture/racial mixing.

F. Ocular biometric spoofing and anti-spoofing

Regardless of recent progress, ocular recognition systems are vulnerable to spoof attack, which consists in submitting to system an artefact ocular modality, e.g., replayed video of eyes. Quintessential anti-spoofing mechanism is anti-spoofing techniques. None of existing ocular anti-spoofing methods exhibit low enough error rates. One of the factors on which acceptability of ocular biometric traits depend for real-world applications is its resilience to spoofing attacks. Therefore, biometric community should focus on devising novel measures to minimize spoofing of the trait. Lack of public databases containing ocular/periocular spoofing attacks has further stymied research on this topic.

G. Unconstrained periocular recognition at a distance

Among all ocular biometric traits, periocular modality requires least constrained acquisition process. Moreover, periocular modality can be captured at large stand-off distances (e.g., in surveillance applications) and efficiently used for personal recognition. Nonetheless, compared to other areas, periocular recognition at a distance is less analyzed.

H. Mobile ocular/periocular recognition

Ubiquity of mobile devices with cameras has opened nearly limitless applications for ocular recognition technology. Nonetheless, mobile processing power is limited, and even commercial mobile ocular/periocular systems are either vulnerable to spoofing or produce a high level of false positives on a large dataset. Moreover, existing methods in literature are unsuited for mobile applications because of the complex features they analyze or high computational cost. So, to make such applications more practical, researchers must address the issue of ocular/periocular recognition on mobile devices.

V. Conclusions

Biometrics is a continuously evolving field that is widely being employed in applications ranging from international border crossings to unlocking smart devices. Among the biometric characteristics, ocular traits are getting more popularity owing to ease in use and less user co-operation requirements. Over the recent years, number of ocular biometric traits' datasets are made available to public by different research groups. But, there is a gap between the requirements postulated by intended biometric application and solutions offered in many publications using these datasets. In order to maximize the future ocular biometric systems' impact and usability, it is important to identify application domain(s) and proper datasets with benchmark protocols. To this aim, in this paper we offered some suggestion to researchers with regards to choice of problem and selection of ocular datasets. Furthermore, there are still various issues remaining to be addressed to attain increased performance in ocular biometrics. Thus, the paper also discussed some of open issues, and future research directions.

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