Experiments with Ocular Biometric Datasets

A Practitioner's Guideline

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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 on mobile devices. The authors provide a review of ocular databases available in the literature and discuss diversities among these databases, design and parameter consideration issues during acquisition of databases, and selection of appropriate databases for experimentation.

Biometrics is a continuously evolving field that is being widely employed in applications ranging from international border crossings to unlocking smart devices. Among the various biometric characteristics (see Figure 1 and Table 1), ocular biometrics—which refers to recognizing an individual via iris, retina, sclera, periocular, or eye movements (see Figure 2)—is gaining more popularity owing to its ease of use and few user-cooperation requirements.[1]

When developing different systems based on biometric traits, experiments need to be conducted to validate the uniqueness, robustness, and feasibility of a particular trait. There are several public databases containing ocular biometric traits for researchers to experiment with—these are a vital ingredient of ongoing ocular biometrics research as they are needed in system and algorithm development, when creating a platform to be used for comparing the work of different research groups, and when introducing new challenges to the research and industry communities. Choosing the wrong dataset will produce poor results and forge the objective of the experiment, giving a false sense of progress.

To maximize the impact and usability of future ocular biometric systems, in this article we provide some guidelines for researchers and product developers to focus on choosing the proper database and evaluating ocular biometrics algorithms and systems. We also highlight open issues and challenges and discuss future research directions.

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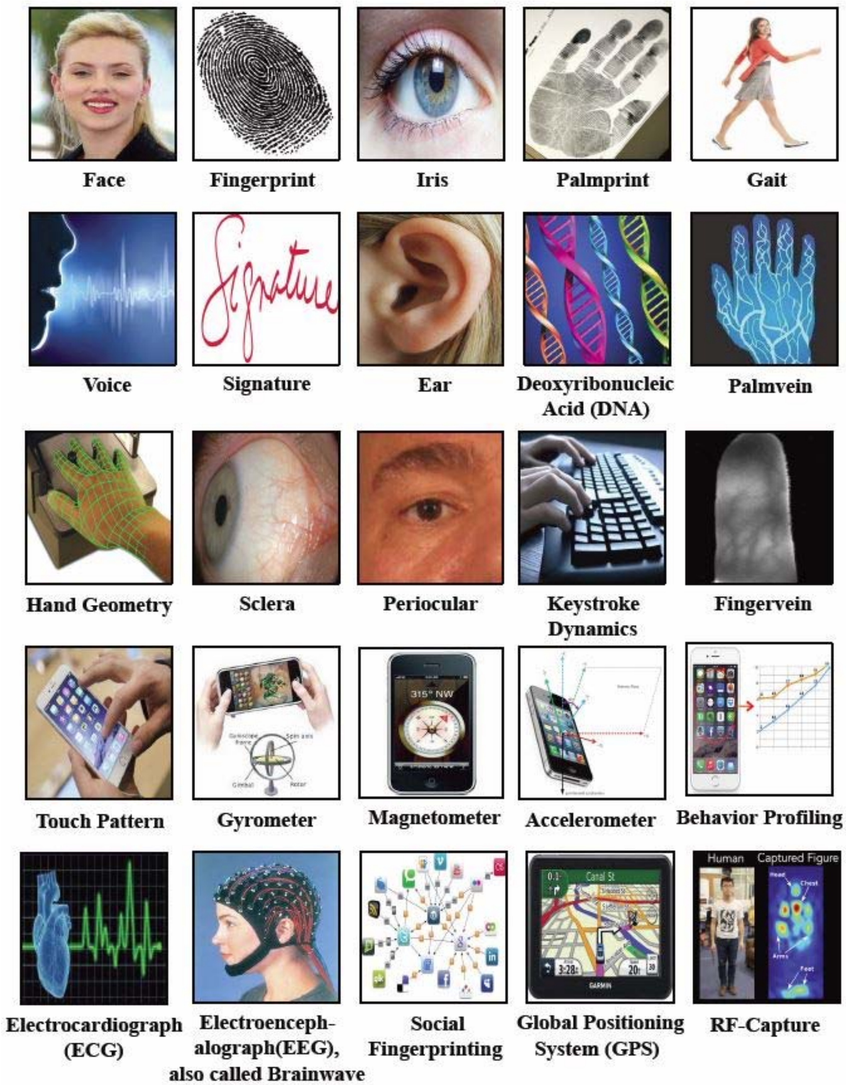

Figure 1. Examples of characteristics that have been proposed and used for person recognition.

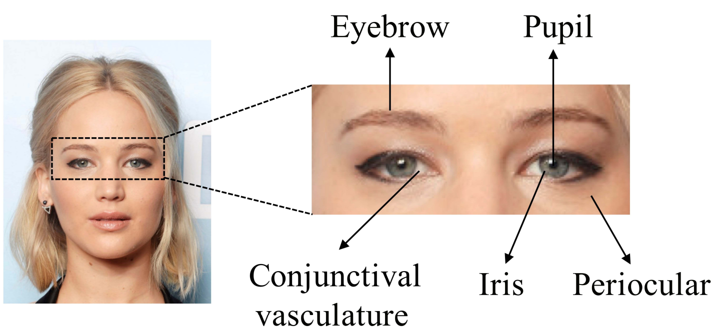

Figure 2. Ocular biometric modalities.

Table 1. Comparison of biometric traits present in the human face.

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 a noninvasive way	Higher accuracy in near-infrared (NIR) images than visual spectrum (VS) images; high cost of NIR acquisition device; low recognition accuracy in unconstrained scenarios; low recognition accuracy for low-resolution images; occlusion due to use of lens; eye might close at the time of capture; does 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 region	Can be captured with face/iris region without extra acquisition cost	Can be occluded by spectacles; fewer features in infants
Lip	Existence of both global and local features	Difficult to acquire; less acceptable socially; shape changes with human expression

DIVERSITY IN OCULAR BIOMETRIC DATABASES

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

Imaging Technique Variation

There are three types of images in an ocular biometric database:

- *Direct capture*. Samples are captured directly through sensors—usually in the visual spectrum (VS) or near infrared (NIR) spectrum—and stored in a lossless manner. Ocular recognition using different imaging modalities might result in different scores and should be reported accordingly. Tables 2, 3, and 4 represent some commonly used ocular datasets. Some sample images are shown in Figure 3.
- *Scanned capture*. Samples are scanned from printed images that have already been captured. This takes advantage of fast data processing by extracting only those parts where important information is found.[2]
- *Latent capture*. Samples are captured from some impression of the image (such as the reflection of a face in a mirror or glass).

Ocular biometric databases contain different images or videos from various subjects in a maintained data structure.

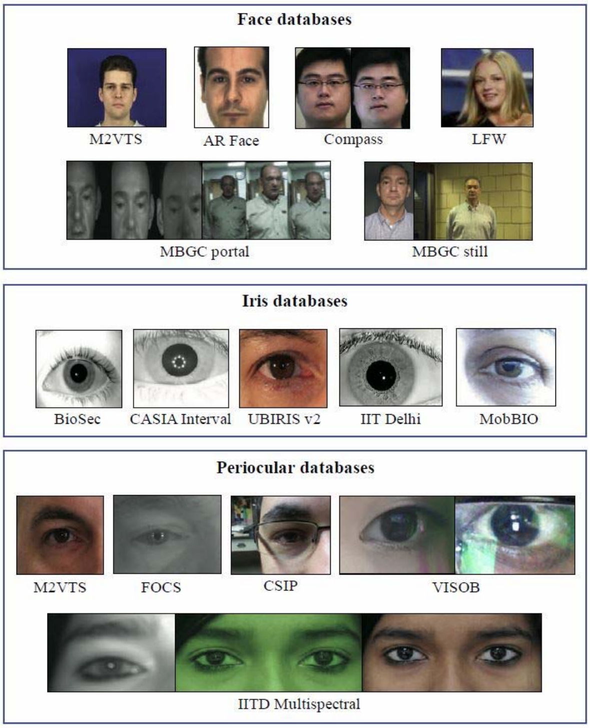

Figure 3. Samples of databases used in ocular biometric research.

Image Quality Variation

Images in the database might be of different quality, which can be obtained during data collection by changing sensor or computer-aided algorithms after data collection.

Three types of image quality variations are:

- *Spatial resolution variation*. This is the number of pixels in a unitary length—such as pixels per inch (ppi)—that mainly depends on the sensor. Higher resolution commonly leads to higher authentication accuracy.[3]
- *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 the bit-plane slicing method is used. Varying bit depth leads to variations in informative features of the image and accuracy.
- *Focus variation*. Change in focus produces images of varying quality such as blurred samples. Hardware and software can be used to obtain samples with varying focus properties. Techniques and standards are available for assessing the focus and quality of biometric images.[4]

Human Involvement Variation

Two types of human involvement variations are:

- *Constrained involvement*. Different impressions of the same subject can be captured by involvement of human variation in the biometric system. For example, under constrained conditions, the subject follows a mentioned expression for data collection.
- *Pseudo-unconstrained scenario*. Database images in such a scenario are acquired under uncontrolled or less-constrained environments.

Session

The time separation between two successive data-acquisition rounds is known as a session. M2VTS[5] is an example of a session-based face database. It consists of audio recordings and video sequences of 37 subjects uttering digits 0 through 9 in five sessions separated by at least one week.

Gender Specification

Gender is an important demographic attribute, which can also be used for separate recognizers to improve accuracy. Most ocular databases provide a detailed annotation of age and gender.[6]

Age Specification in Session Databases

Session databases record changes due to aging in the features of a subject over time, which can be used to improve recognition accuracy.[6]

Variation of Environment

Most databases acquired under a controlled environment facilitate the study of specific parameters on biometric recognition. However, real-time data is unconstrained in nature, where a practitioner has no control over parameters. Environmental variations largely affect the quality of acquired VS images.[7] Image acquisition location such as outdoor (cloudy/sunny day) or indoor (improper illumination) might constitute a problematic factor due to variation in illumination. BioID[8] is an example of a face database acquired in an indoor environment. It consists of 1,521 images of 23 different subjects.

Static or On-the-go Capture

Databases like UBIRIS v2[9] have distance variability, where the subject is static and standing at several distances with respect to the acquisition device/sensor. Recognition using these databases requires cooperative users, which is not often realistic. A few databases (such as MBGC)[10] consist of on-the-go acquisition images, where subjects walk through an acquisition portal.

Special Cases

Despite recent advances, there are several special challenges that still need to be solved, including identifying individuals with spectacles and identical twins. Various methods have been proposed to distinguish twins, but they require improvement for higher accuracy. Also, some diseases that affect the iris and cornea might have a negative impact on the features.[2]

CHOOSING A BIOMETRIC DATABASE FOR EXPERIMENTATION

Various ocular databases are publicly available for researchers to use for experimentation. Databases under constrained environments lack diversity, leading to low-generalization capability of systems devised using them. Databases acquired in unconstrained environments with uncooperative users (for example, operations such as recognition at a distance) contain spectacles and contact lenses, thus facilitating the capability of developing real-world robust algorithms. Databases acquired in different spectrums produce different outcomes. A researcher or practitioner should consider their research criteria and the issues mentioned here before choosing an ocular dataset. Database selection is dependent on the application—for example, for face/ocular-based uni-/multimodal recognition of moving users, one should choose a video database such as M2VTS[5] or CMU-H, whereas BioID[8] is suitable for indoor applications. For large-scale and unconstrained evaluation, Labeled Face in the Wild (LFW)[3] can be useful.

It is a very common practice by the research community to use face and iris databases for ocular recognition systems. Table 2 lists existing iris databases and Table 3 lists face databases collected in NIR and VS ranges.

Table 2. Review of existing iris databases.

Database, color model	Research lab	Version	Acquisition device	Images	Subjects	Resolution
UBIRIS (v1 RGB, v2 sRGB)	Soft Computing and Image Analysis (SOCIA) Group, Dept. of Computer Science, Univ. of Beira Interior	v1[11]	Nikon E5700	1877	241	800×600
		v2[9]	Canon EOS 5D	11102	261	400×300
CASIA (gray-scale)	Iris Recognition Research Group, Center for Biometrics and Security Research, National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences	TestV1	IrisGuard AD100	10000	1000	640×480
		IRISv1	Self-developed	756	108	320×480
		IRISv2	OKI IRISPASS-h	1200	60	640×480
			CASIA-IrisCamV2	1200	60	640×480
		IRISv3-Interval	Close-up iris camera	2639	249	320x280
		IRISv3-Lamp	OKI IRISPASS-h	16212	411	640×480
		IRISv3-Twins	OKI IRISPASS-h	3183	200	640×480
		IRISv4-Interval	Close-up iris camera	2639	249	320×280
		IRISv4-Lamp	OKI IRISPASS-h	16212	411	640×480
		IRISv4-Twins	OKI IRISPASS-h	3183	200	640×480
		IRISv4-Distance	Long range iris camera	2567	142	2352×1728

		IRISv4-Thousand	Irisking IKEMB-100	20000	1000	640×480
		IRISv4-Syn	By image synthesis	10000	1000	640×480
ND-IRIS (grayscale)	Dept. of Computer Science & Engineering, Univ. of Notre Dame	-	Iridian LG EOU2200	64980	356	640×480
MMU (grayscale)	Multimedia Univ.	v1	LG IrisAccess2200	450	100	320×280
		v2	Panasonic, BM - ET100US, Authenticam	995	100	320×280
BATH (grayscale)	Univ. of Bath	Iris DB 400	IrisGuard, AD-100 Dual-Eye, Autofocus Camera	8000	200	1280×960
		Iris DB 800		16000	400	1280×960
		Iris DB 1600		32000	800	1280×960
UPOL[12] (RGB)	Dept. of Computer Science, Palacky Univ. Olomouc	-	SONY DXC-950P 3CCD	384	64	576×768
BioSec (grayscale)	Biometric Recognition Group, ATVS	-	LG IrisAccess EOU3000	3200	200	640×480
IITD[13] (Bitmap)	Biometrics Research Laboratory IIT Delhi	v1.0	JIRIS, JPC1000, digital CMOS	1120	224	320×240

MICHE (RGB)	Biometric and Image Processing Lab	v1	iPhone5, Galaxy Samsung IV, Galaxy Tablet II	1600	50	1536×2048
				1600	50	2322×4128
				1600	50	640×480
MobBIO (RGB)	Visual Computing and Machine Intelligence (VCMI), INESC TEC	-	TF300T-000128	384	105	300×200

Table 3. Review of existing face databases.

Database, color model	Research lab	Version	Images	Subjects	Resolution
FERET (RGB)	NIST	v4	14126	1191	768×512 384×256 192×128
PIE[14] (RGB)	Carnegie Mellon Univ. (CMU)	-	41368	68	3072×2048
Multi-PIE (RGB)	CMU	-	750000	337	3072×2048
SCface (grayscale and RGB)	Video Communications Laboratory, Faculty of Electrical Engineering and Computing, Univ. of Zagreb	-	4160	130	100×75 144×108 224×168 1600×1200
Yale[15] (grayscale)	Yale Univ.	-	165	15	640×480
Yale B (grayscale)	Yale Univ.	-	5850	10	640×480
ORL (grayscale)	AT&T Laboratories Cambridge	-	400	40	112×92
UMIS (grayscale)	Univ. of Manchester, Institute of Science and Technology	-	564	20	112×92
M2VTS[5] (RGB)	ACTS European Language Resource Agency	v1.0	185	37	286×350
AR[16] (RGB)	The Ohio State Univ.	-	3276	126	576×768
GTDB (JPEG)	Georgia Institute of Technology	-	750	50	640×480
Caltech (JPEG)	Computational Vision Group	-	450	27	896×592

CMU-PIE (PNG)	Vision and Autonomous Systems CMU	-	750000	337	3072×2048
FRGC (RGB, 3D channels)	Univ. of Notre Dame	-	50000	4003	1704×2272
MORPH (PGM)	Univ. of North Carolina Wilmington	-	55000	13000	400×500
PUT (JPEG)	Poznan Univ. of Technology	-	10000	100	2048×1536
Plastic Surgery (RGB)	IIIT Delhi	-	1800	900	200×200
ND-Twins (RGB)	Univ. of Notre Dame	-	24050	435	480×640
FaceExpress UBI[17] (TIFF)	Univ. of Beira Interior	-	90160	184	2056×2452
FG-NET (grayscale)	Face and Gesture Recognition Working Group	-	1002	82	400×500
CMU-H (video)	CMU	-	764	54	640×480
Compass (RGB)	CyLab Biometrics Center CMU	-	3200	40	128×128
MBGC[10] (v2 still RGB, range; v2 portal video)	NIST	v2 still	3482	437	Variable
		v2 portal	628	114	2048×2048
LFW[3] (JPEG)	Univ. of Massachusetts, Amherst	-	13233	5749	250×250

Table 4. Review of existing periocular databases.

Database, color model	**Research lab**	**Images**	**Subjects**	**Illumination**	**Resolution**
UBIPr[2] (RGB)	Univ. of Beira Interior	10950	261	VW	Variable
UBIPose Pr[18] (RGB)	Univ. of Beira Interior	2400	100	VW	Variable
FOCS (grayscale)	NIST Dept. of Commerce	9581	136	NIR	750×600

IMP[7] (grayscale)	Image Analysis and Biometrics Lab IIIT Delhi	620	62	NIR	640×480
		310		VW	600×300
		310		Night vision	540×260
CSIP[4] (RGB)	Soft Computing and Image Analysis Lab Univ. of Beira Interior	2004	50	VW	Variable
VISOB[19] (RGB)	Univ. of Missouri	5010381	550	VW	240×160

The number of test samples is another criterion that needs to be considered when selecting a database. For example, M2VTS[5] (which has 1,180 recordings of 295 subjects acquired over a period of four months) attracted many researchers, facilitating evaluation of many algorithms in a setup very close to real-world settings. Few databases for the periocular region such as VISOB (Visible Light Mobile Ocular Biometric)[19] are available in the public domain, as described in Table 4. As iris databases contain the eye and its immediate vicinity including eyelashes, eyelids, and nearby skin area and eyebrows, these can be used as periocular features. In turn, face databases might be cropped in a rectangular template using eye areas to be utilized as periocular datasets. Bakshi et al.[1] proposed how to optimally select a rectangular template around the periocular region.

When choosing a proper database for experimentation, a practitioner needs to know under which acquisition environment the database was captured. Next, we will discuss a typical acquisition setup and its key components. Understanding how to set up a biometric acquisition platform and what variations there are in the acquisition parameters can help a practitioner choose the right database for experimentation.

Image Acquisition Setup and Issues

Setting up an imaging environment is a critical first step to any imaging application. Figure 4 shows the image acquisition setup and parameters needed before image acquisition. Before acquiring images, the following elements and parameters need to be considered.

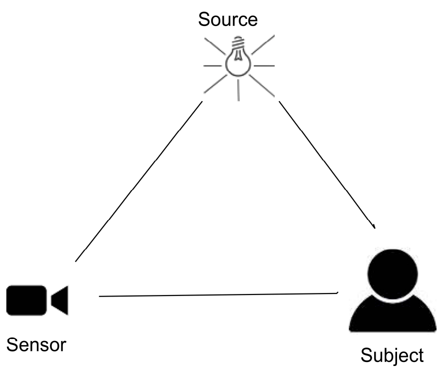

Figure 4. Image acquisition setup.

Acquisition Device Parameters

- *Imaging resolution*. The quality of an acquired image is greatly affected by resolution. High-resolution digitized images contain a wealth of features, but they require more storage space.
- *Imaging modalities*. Because VS samples suffer from illumination,[14] infrared (IR) imaging sensors are gaining much interest. The short-wave infrared (SWIR; 0.9−2.4μm) and 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 cases where the application is to be done in a very controlled environment with cooperation of the subject.
- *Static or motion state*. Moving acquisition sensors usually produce blurred images and require some enhancement for feature extraction. Sometimes there is a requirement to test the performance of some method on motion-blurred images. In those cases, databases with moving cameras or objects can be considered for experimentation.
- *Focus parameter*. Setting the proper focus parameter is vital, as the wrong parameters could result in blurring of acquired image.
- *Standoff distance*. The distance between the front lens of the camera to the user under inspection is called standoff distance, which should be set according to the acquisition area of interest and the required degree of detail of the region of interest.

Lighting Setup

- *Source*. When obtaining samples with clearly visible objects, lighting conditions during image acquisition must be considered carefully. LED and lasers are good sources of light, and can reduce some illumination problems if arranged properly.
- *Characteristics of the light source*. Point light emanates concentric light and almost parallel light when placed near and far from the object, respectively. Diffuse light scatters light rays so that an object is lit from several directions. Direct light is described by rays of light following a defined direction.
- *Imaging environment*. Ambient light affects the visual appearance of objects/users, therefore the environment needs to be considered during image acquisition.

Object

- *Movement considerations*. Recognition under motion, when either the camera or the user is mobile, remains a difficult task due to blurring.
- *Constrained or unconstrained environment*. Though accuracy is higher under constrained environments, real-world applications are unconstrained, where one has no control over parameters (for example, pose).
- *Cooperative or uncooperative user*. The iris trait requires a very cooperative user and usually fails when samples are captured at a distance with low quality. Therefore, periocular recognition is gaining momentum as an alternative.

OPEN ISSUES AND FUTURE RESEARCH DIRECTIONS

Despite recent progress, several exigent problems have yet to be addressed to unleash ocular biometrics' full potential.

Heterogeneous Ocular Biometric Recognition

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

Automatic Segmentation

Although automatic segmentation of ocular parts can help avoid those that are not beneficial (such as hair or spectacles), 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 attention should be placed on advanced image processing and machine learning.

Multibiometrics

It is well-documented that multimodal biometrics lead to better accuracy than the unimodal approach. However, most studies on ocular biometrics are based on a 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 might be incorporated in fusion algorithms for enhanced performance. A dynamic selection-based fusion scheme might also help curb problems that arise in ocular recognition in unconstrained environments.

Webscale Ocular Biometrics

The phenomenal growth of facial and 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 and images to consider, webscale ocular biometrics is a difficult task that demands speed, accuracy, and scalability. Also, there is currently no large-scale evaluation of ocular recognition schemes to establish statistical significance for published methods. Better performance might be achieved by combining meta-information associated with ocular samples. Another research track that might be pursued is formulating data-independent feature extraction and classification learning via deep neural networks.

Soft Biometrics

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

Ocular Biometric Spoofing and Antispoofing

Regardless of recent progress, ocular recognition systems are vulnerable to spoof attacks, which consist of submitting an artifact ocular modality, such as a replayed video of eyes, to a system. None of the existing ocular antispoofing methods exhibit low-enough error rates. One of the factors on which acceptability of ocular biometric traits depends for real-world applications is its resilience to spoofing attacks. Therefore, the biometric community should focus on devising novel measures to minimize spoofing of biometric traits. Lack of public databases containing ocular/periocular spoofing attacks has further stymied research on this topic.

Unconstrained Periocular Recognition at a Distance

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

Mobile Ocular/Periocular Recognition

The ubiquity of mobile devices with cameras has led to 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 the literature are unsuited for mobile applications because of the complex features they analyze or high computational cost. To make such applications more practical, researchers must address the issue of ocular/periocular recognition on mobile devices.

CONCLUSION

In recent years, a number of ocular biometric trait datasets have been made available to the public by different research groups. However, there is a gap between the requirements postulated by the intended biometric applications and solutions offered in many publications using these datasets. In this article, we provided guidelines for researchers and product developers to focus on choosing the right database and evaluating ocular biometrics algorithms and systems. We hope that following these guidelines will enhance the likelihood of the results obtained in a laboratory being generalized to operational scenarios.

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