Chapter 1

Contact lens detection in iris images

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Iris texture provides the means for extremely accurate uni-modal person identification. However, the accuracy of iris based biometric systems is sensitive to the presence of contact lenses in acquired sample images. This is especially true in the case of textured (cosmetic) contact lenses that can be effectively used to obscure the original iris texture of a subject and consequently to perform presentation attacks. Since also transparent contact lenses can degrade matching rates, automatic detection and classification of different contact lens types is needed in order to improve the robustness of iris based biometric systems. This chapter introduces the problem of contact lens detection with particular focus on cosmetic contact lenses. The state of the art is analysed thoroughly and a case study on generalised textured contact lens detection is provided. The potential future research directions are also discussed.

1.1 Introduction

Among different biometric traits, iris is considered to be (one of) the most reliable and accurate biometric trait for person identification because iris patterns provide rich texture that is highly discriminative between individuals and stable during ageing of subjects [14]. Iris recognition is being increasingly deployed in large-scale applications requiring identity management, including border and access control, banking, mobile authentication and national identification programs for e.g. voter registration and social benefits. Probably the best example of a large-scale project was initiated by Unique Identification Authority of India[1] (UIDAI) that is implementing the scheme of providing a unique ID (AADHAAR number) for every Indian resident. So far the biometric samples of already over 1 billion citizens of 1.2 billion have been collected in the form of fingerprint, face and iris patterns.

In controlled environments, iris recognition is indeed extremely accurate but recent studies suggest that the iris texture is affected by covariates like pupil dilation [30] and sensor interoperability [3, 11]. Presence of both textured and transparent soft contact lenses is a another issue that may cause severe degradation in iris recognition performance in terms of false non-match rate (FNMR) [4, 5, 35, 56]. The negative effect of contact lenses can be explained with general factors that can ob-

[1] http://uidai.gov.in

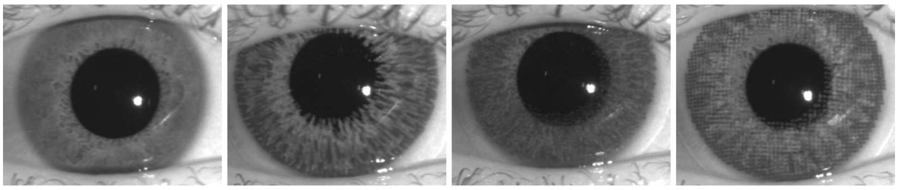

Figure 1.1: Cropped iris images from the Notre Dame Contact Lens Detection 2013 (NDCLD'13) dataset [22] highlighting the variation in texture patterns between one genuine iris and three textured lens manufacturers, Cooper Vision, Johnson & Johnson and Ciba Vision, respectively. Reprinted with permission from [36] © 2014 IEEE.

scure the original iris texture like: (1) change in the optical properties of the eye, (2) presence of deliberate synthetic texture, and (3) small movement of the contact lens on the surface of the eye between different acquisition times, e.g. enrollment and authentication [48].

Commercial iris recognition systems operate on eye images acquired using active near-infrared (NIR) illumination almost without an exception. The iris texture is rather hard to distinguish in conventional colour images, while rich texture can be observed in NIR images. Contact lenses with printed colour texture are designed for reshaping the appearance (color and texture) of the iris tailored to wearer's preferences, e.g. transforming one's apparent eye colour from brown to blue, or from dark to light, thus they are also referred as cosmetic contact lenses. The change in colour and texture of the iris is due to a circular band on the contact lens containing pattern of pigment that is also visible in NIR wavelengths (see Figure 1.1). Typically, the observed iris texture is a mixture of the lens and original iris texture because the synthetic texture band (1) is not fully opaque when the original genuine iris texture is partly visible through it, and (2) might not cover the whole iris region when a separate band of original iris texture is visible (see Figure 1.1) [8]. Still, it has been demonstrated that the presence of textured contact lenses yields to huge increase in FNMR when the gallery iris images of subjects with and without transparent contact lenses are compared with probe images of the same subjects with cosmetic lenses [4, 5, 35, 56].

Textured contact lenses are indeed effective for obfuscating one's true biometric trait in order to avoid positive identification to one's previously enrolled identity because one is on a watchlist. This kind of presentation attack is a serious problem in real-world applications. For instance, iris recognition is utilised for checking if a person is on watch list of people who have been previously expelled from the United Arab Emirates (UAE) [1], thus cosmetic lenses could be potentially used to re-enter the country. In general, it is unlikely that cosmetic lenses would be used for other kinds of presentation attacks like targeted impersonation or creating a fake identity for e.g. extra social benefits. Soft contact lenses tend to move on the surface of the eye and can be put in differently, thus the iris texture of a subject wearing exactly

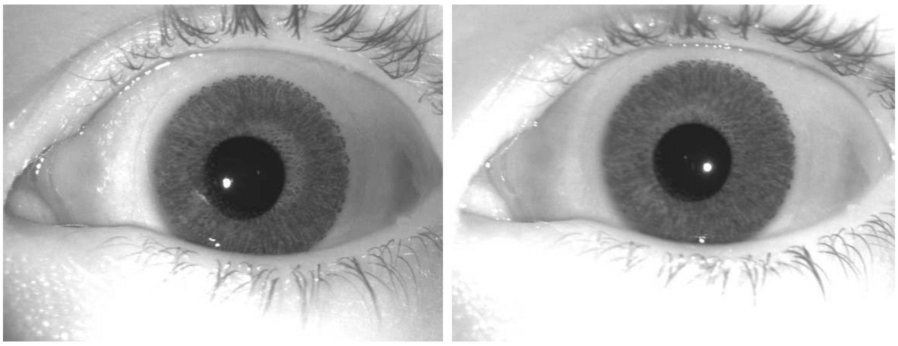

Figure 1.2: Example of images of textured lenses from the NDCLD'13 benchmark dataset [22] illustrating the appearance variation on the same eye at different acquisition times due to small movement of the lens .

the same cosmetic lens cannot be matched between different acquisition times (see Figure 1.2) [4, 5, 35, 56]. However, soft contact lenses can be designed to maintain a specific orientation after eye blinking or any other movement by making it to be heavier at the bottom [5]. In theory, there exist no technical limitations of printing fully opaque cosmetic contact lenses with iris texture of a targeted person and wearing the customized lenses to successfully masquerade as someone else and thereby gaining illegitimate access and advantages [5, 8, 32]. However, there are no known real-world examples of successful presentation attack of this kind [8].

Textured contact lenses should be rejected before enrolment or during verification by labelling them as "failure to process", for instance [56]. The presence of cosmetic contact lenses is quite easy to reveal by manual visual inspection especially if the lens is not properly inserted or if the pure lens and original iris texture are otherwise separately observed [32]. However, detection of well-aligned cosmetic lenses of some printing patterns can be difficult using only the human eye. Furthermore, while manual inspection is feasible to perform e.g. when enrolling a person to national ID system, the same does not hold for practical applications like automated border control. Automatic contact lens detection would be not only faster but potentially also more accurate than manual inspection [32]. The commercial iris recognition systems by IrisGuard are promoted to have a cosmetic contact lens detection feature[2] but no objective security evaluation on their robustness has been conducted [20].

Transparent (non-cosmetic) contact lenses can be considered to consist of two main categories based on the used material: rigid gas permeable (RGP) contact lenses and soft contact lenses [23]. The RGP lenses are well-known to degrade iris match quality because the whole lens fits within the iris region and thereby the boundary of the lens causes a severe circular artefact in the iris texture [5]. Daugman's iris recognition algorithm [14] is the basis for many iris based biometric sys-

[2] http://irisguard.com/userfiles/file/Countermeasures.pdf

tems. Assuming that its improved version [17, 18] is indeed able to detect and mask out these boundary artefacts, it seems likely that also many commercial iris recognition algorithms account for the presence of hard contact lenses [5]. In contrast, soft lenses, the most popular type of contacts, are much larger in diameter, thus it has been generally assumed for a long time that they do not substantially degrade the accuracy of iris recognition systems. However, the recent studies [4, 5, 35, 56] have turned out this belief to be false.

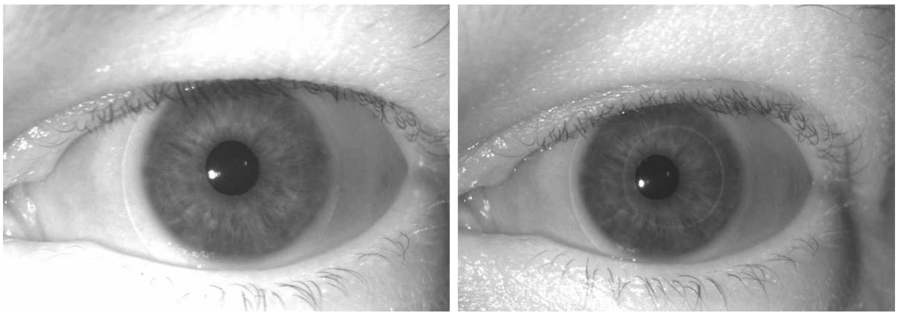

Figure 1.3: Sample images from the NDCLD'13 dataset [22] illustrating typical soft lens artefacts, e.g. circular lens boundary in the sclera region and ring-like outline within the iris region.

Unlike cosmetic lenses, clear soft prescription lenses are not intentionally used for altering the original iris texture. Still, they must have some effect on the observed iris texture because they are designed to change the optical properties of the eye in order to correct eyesight [56]. For instance, the findings presented by Thompson *et al.* [54] imply that differences in iris curvature degrade matching ability of iris recognition systems. Some contact lenses can indeed yield to a ring-like artefact noticeable in the iris region (see Figure 1.3) [5]. As an example, toric lenses have additional curvature for correcting astigmatism in addition to "near-" or "far-sightedness curvature", which causes the circular outlines on the iris texture [5]. Occasionally, the lens boundary might be overlapping with the iris region like in the case of RGP lenses due to misplacement. Similarly to cosmetic lenses, clear lenses may contain also visible markings on them. For instance, toric lenses must maintain a specific orientation and need to be inserted correctly for proper vision correction, thus special visible markings are used to aid the insertion [5]. Some lenses may have even large visible artefacts, like a logo or numbers, on the iris region [5]. Also the alignment of transparent contact lenses can be different on the surface of the eye, thus the nature and location of the potential iris texture artefacts is likely to vary between different acquisition times.

One could try to locate the iris texture artefacts due to e.g. lens boundaries or change in optical properties and mask them appropriately [5] or apply specific image correction techniques for the contact lens artefacts in order to increase the robustness of iris recognition to transparent lenses. The degradation in performance due to clear lenses can be potentially mitigated already without applying any sort of dedicated pre-processing before matching. The results by Baker *et al.* [5] suggest that false reject rates are generally lower for the case in which gallery images consist of subjects without (clear) contact lenses and probe images of subjects with contact lenses (none-soft) than rates for comparing contact lens images to contact lens images (soft-soft). Yadav *et al.* [56] conducted similar experiments but analysed the effect between two different iris sensors as well. Their intra-sensor and inter-sensors evaluations suggest that sensors can react very differently to soft contact lenses as the verification rates for soft-soft comparisons are very high in the intra-sensor scenario but drop dramatically in the inter-sensor case. In contrast, the use of natural iris in gallery images is not that sensitive to unknown sensors also when soft contact lenses are present in the probe images. The findings are somewhat consistent with the ones presented by Baker *et al.*. Therefore, it may be advisable to require enrolment without or, even better, with and without contact lenses to mitigate the effect of contact lenses at the time of verification or recognition regardless if the subject is wearing contact lenses or not [5].

There is indeed a need for a pre-processing stage consisting of robust automated detection and classification of both textured and transparent soft contact lenses in order to improve the robustness and reliability of iris recognition systems. This chapter gives an overview on the state-of-the-art in contact lens detection with particular focus on software-based approaches and the problem of textured lenses. The remainder of the chapter is organized as follows. First, Section 1.2 introduces the prior works on hardware-based and software-based approaches for contact lens detection. A case study on generalised textured contact lens detection is presented in Section 1.3. In Section 1.4, the state-of-the-art in software-based contact lens detection is thoroughly analysed. Finally, the conclusions and possible directions for future research are discussed in Section 1.5.

1.2 Literature review on contact lens detection

This section provides an overview on the prior works in contact lens detection. Since the presence of cosmetic contact lenses has been known to dramatically increase the FNMR of iris recognition systems for a long time and poses a severe security threat, the main research focus in the literature has been on textured contact lenses. Gradually, also the problem of transparent soft lenses has received more attention because the recent studies [4, 5, 35, 56] have pointed out the benefits of detecting these types of lenses as well. Following the historical aspect and evolution of contact lens detection approaches, we introduce first methods developed particularly addressing the issue of cosmetic contact lenses, while transparent lenses are included into to equation in the latter part of this section.

1.2.1 Textured contact lens detection

Iris based biometric systems are prone to presentation attacks (traditionally referred to as spoofing) aiming at false positive or negative identification like solutions using any other biometric traits. Thus, dedicated countermeasures are needed in order to provide secure authentication solutions. Presentation attack detection (PAD) techniques can be broadly categorized into two groups based on the module in the biometric system pipeline in which they are integrated: hardware-based (sensor-level) and software-based (feature-level) methods [24]. Hardware-based methods introduce some custom sensor into the biometric system that is designed particularly for capturing the inherent differences between a valid living biometric trait and others. The measured characteristics can be divided into three groups: 1) intrinsic properties, e.g. reflectance at specific wavelengths [9, 15, 40, 41, 44, 45], 2) involuntary signals, e.g. pupillary unrest [13], or 3) voluntary or involuntary responses to external stimuli (challenge-response), e.g. eye blink [43] or gaze [50], or pupillary light reflex [7, 31, 46, 47]. Feature-level PAD techniques, on the other hand, are exploiting only the same data that is used for the actual biometric purposes, i.e. captured with the "standard" acquisition device. Counterfeit irises can be presented in many forms, including artificial glass and plastic eyes, photographs and videos, and printed textured contact lenses, for instance. In the following, we concentrate only on methods that have been proposed for detecting textured contact lenses. For further details on the advances in the field of iris PAD in general, interested readers are referred to surveys by Sun and Tan [52] and Galbally and Gomez-Barrero [24], for instance.

Cosmetic contact lenses have received significant attention in the research community in the context of presentation attack detection because they are easy to use in spoofing and are probably the most challenging ones to detect among different iris artefacts. For instance, the results of Iris Liveness Detection Competition 2013 (LivDet-Iris 2013) [57] demonstrate that cosmetic lenses are indeed much more difficult to detect compared to iris paper printouts. One reason for this is that the artefact is visible only within a very small part of the iris image, whereas usually the whole periocular region corresponds to the artefact in the case of a print attack. Furthermore, a cosmetic contact lens might have a transparent region in the vicinity of the pupil boundary (see Figure 1.1 and Figure 1.2), thus the real pupil and its pupillary response, i.e. pupil dilation and contraction due to light stimulus is visible even through the lens. Therefore, PAD methods relying solely on eye blink detection [43], gaze estimation [50], Purkinje images [38, 39], pupillary unrest [13] or pupillary light reflex [7, 31, 46, 47] cannot detect the presence of printed contact lenses.

Few works [31, 46, 47] proposed to solve the failure modes of biological approaches utilising stimulated pupillary light reflex. The printed iris texture is not capable of being dilated and contracted like rubber band model along hippus movement unlike genuine iris patterns. Thus, measurement of iris texture deformation within the vicinity of pupil boundary can be exploited for detecting the presence of textured contact lenses.

Daugman suggested in one of his pioneer works on iris recognition [15] that multi-spectral reflectance analysis of eye region could be used for presentation attack detection. Concequently, multi-spectral measurements at specific wavelengths have been applied in cosmetic contact lens detection by exploiting the light absorption ratio between the iris and the sclera [40, 41] and specific characteristics of conjunctival vessels and iris textures [9]. In addition, a gray-scale image resulted from gradient-based fusion of multiple images acquired at different wavelengths do not present clear iris texture in the case of cosmetic contact lenses, unlike genuine iris images [44, 45].

Natural iris can be considered roughly as a planar surface, whereas a textured contact lens is more curved as it is lying on the eye surface. Two proof-of-concept studies have suggested that 3D shape analysis of the observed iris can be indeed utilised for cosmetic contact lens detection. Connell *et al.* [12] applied structured light projection to measure the curvature of the observed iris, while Hughes and Bowyer [32] used a stereo camera setup for recovering the 3D structure of the iris surface for cosmetic contact lens detection.

While these kinds of hardware-based solutions may provide efficient and generalised means for presentation attack detection, they can be also rather impractical due to unconventional imaging solutions that are not always possible deploy or increased system complexity, or usability issues, e.g. time-consuming data acquisition, additional interaction demands or unpleasant sudden active lighting stimuli. Furthermore, these kinds of techniques have been usually evaluated on limited datasets just to demonstrate a proof of concept, like in [12, 32, 44], or, in the worst case, have not been experimentally validated at all, like in [7, 47].

In the ideal case, textured contact lens detection would be performed entirely in software, i.e. only by further processing the NIR images acquired with "standard" iris sensors. Software-based approaches have been the most popular technique in cosmetic contact lens detection. Unsurprisingly, Daugman has been a pioneer in this field as well. In [16], he demonstrated that Fourier domain can be used well for describing periodic "dot-matrix style" cosmetic lens printing iris patterns (see Figure 1.1). However, defocus blur or the newer lens types with multiple layers of printing smooth the Fourier response when no evident peaks cannot be found.

As seen in Figure 1.1, each printing process leaves its own characteristic signature (or artefacts) that can be detected by analysing the evident textural differences between genuine iris and fake one. In general, genuine iris texture is rather smooth, while the printed texture patterns of contact lenses are somewhat coarse despite the more advanced printing techniques using e.g. multiple layers. Consequently, by far the most common and promising approach has been to apply different local descriptors for cosmetic contact lens detection, including gray level co-occurrence matrix (GLCM) based features [28], a combination of GLCM features and iris-textons [55], multi-resolution local binary patterns (LBP) [21, 29], weighted-LBP [59], scale-invariant feature transform (SIFT) based hierarchical visual codebook [53], and binarized statistical image features (BSIF) [20, 36]. Most of these works are reporting excellent detection rates very close to 100% in controlled scenarios but novel printed lens texture patterns (not seen during training) and sensor interoperability can yield to dramatic decrease in system performance [22, 59]. In-depth analysis on these issues will be provided in Section 1.3 and Section 1.4.

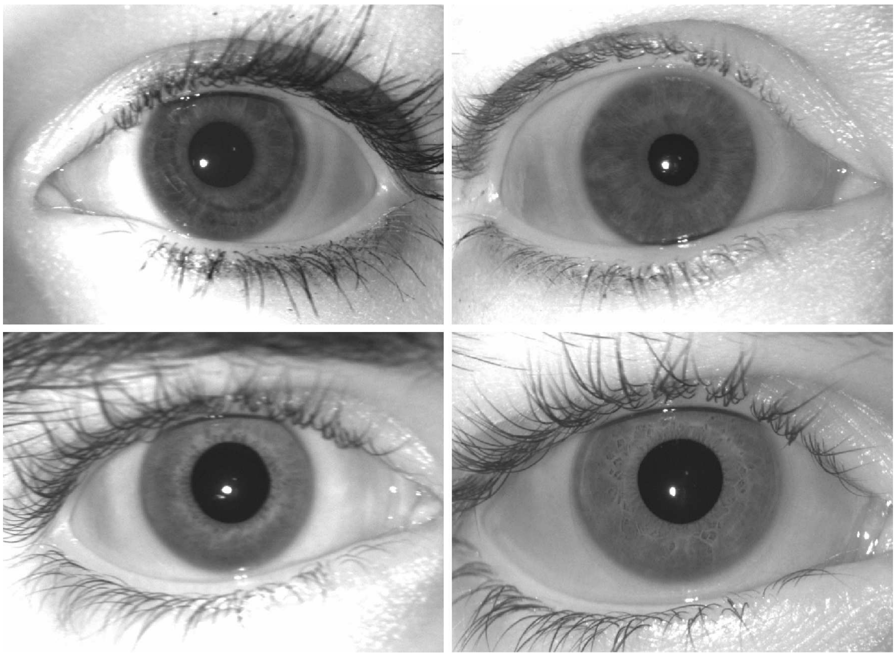

Figure 1.4: Sample images from the NDCLD’13 dataset [22] illustrating the difficulty of lens boundary detection, i.e. thin or virtually invisible boundary outlines in sclera region due to specular reflections or otherwise inconsistent illumination, defocus blur and lens placement.

1.2.2 Classification of contact lens type

The research on the problem of soft contact lenses is just in its infancy because their negative effect on the accuracy of iris based biometric systems has not been discovered until recently. To the best of our knowledge, only one work has proposed a sensor-level approach to the problem. Kywe *et al.* [37] noticed that the variations in temperature on the surface of the eye due to evaporation of water during blinking is different for eyes with and without contact lenses. However, the proposed approach requires a thermal camera and its detection accuracy is highly dependent on environmental conditions like temperature and humidity. Thus, so far even hardware-based methods have not been able to provide generalised solutions for robust detection of transparent contact lenses.

Software-based detection of (non-cosmetic) soft contact lenses in NIR iris images in general is far more difficult compared to the case of textured lenses. The appearance differences between no lens and soft lens iris images are very subtle and highly dependent on the input image quality, for instance. Even by the human eye it is generally hard to tell if there is a soft contact lens present on the observed image or

Figure 1.5: No lens vs soft lens images of different eyes from the NDCLD'13 benchmark dataset [22] demonstrating the appearance similarity of no lens and soft lens iris images in the right sclera region.

not unless the lens boundary is visible in the sclera region (see Figure 1.3). Erdogan and Ross [23] proposed a method for detecting non-cosmetic contact lenses in NIR ocular images by checking if the lens boundary can be found in the vicinity of the segmented limbic boundary. They reported moderate overall classification accuracies between 66.8% and 76.0% because inconsistent illumination and defocus blur lead to unsuccessful detections. As illustrated in Figure 1.4, the lens boundary can be indeed hard to describe because its appearance can have significant variations or the outline is virtually invisible due to acquisition conditions, e.g. specular reflections or otherwise inconsistent illumination or defocus blur, or the alignment of the lens. Another issue is that the similar ring-like artefacts can be observed in iris images of a subject without a soft lens as seen in Figure 1.5.

Ideally, contact lens detection could be seen as a three-class problem of categorising acquired iris images as no lens, clear lens or cosmetic lens because the classification of contact lens type is important in addition to detection [21, 22, 35, 56]. Since the pioneer works in automated classification of contact lens type released public benchmarks the Notre Dame Contact Lens Detection 2013 [22, 56] dataset and II-ITD Contact Lens Iris Database [35, 56] consisting of NIR iris images of all the three classes, an increasing trend has been to propose methods for distinguishing cosmetic and transparent soft contact lenses from natural irises [26, 48, 51]. In general, these kinds of approaches are fundamentally the same as the algorithms proposed in the context of presentation attack detection as they are both based on extracting some local feature description from the given iris image. The main differences are that the sclera region is also utilised (lens boundary detection) and three-class classification is performed instead of binary decisions. The state-of-the-art overall accuracy across the three classes varies between 83% and 93% depending on the used iris sensor. While the detection rates for textured lenses are again almost 100%, the rates for no lens and non-cosmetic soft lenses are generally significantly lower and vary from 79% to 96%, and from 76% to 84%, respectively [26]. However, again the overall performances drop in inter-sensor evaluations to 75% due to unsatisfying the classification rates for natural iris and non-cosmetic soft contact lens images [48].

1.3 Case study: generalised software-based textured contact lens detection

As seen in Section 1.2, many software-based approaches for detecting textured contact lenses have been indeed proposed in the literature. Since most of the existing works are reporting astonishing correct classification results of almost 100% on proprietary (e.g. [59]) and publicly available benchmark datasets (e.g. [53]), the cosmetic lens detection appeared to be a solved problem. However, without few exceptions, the effect of two important factors, namely sensor interoperability and previously unseen cosmetic lens patterns, has been overlooked when validating the robustness of the proposed algorithms. Thus, their generalisation capabilities beyond laboratory conditions can be questioned. For instance, Zhang *et al.* [59] reported overall classification rates between 97% and 99% when the training and test sets of iris images were captured with the same sensors, while the performance decreased to between 83% and 88% under cross-sensor evaluation, i.e. training and test sets were captured with different iris sensors. Later, Doyle *et al.* [22] demonstrated that even more dramatic drop in the detection accuracy may be observed if a cosmetic lens with previously unseen printed texture is introduced to a lens detection algorithm.

In practice, biometric systems are installed in open environments, thus the assumption of full prior knowledge of the used sensors and different cosmetic lens patterns, that will be confronted in operation, is far from reasonable. Thus, there is a need for generalised textured lens detection algorithms that can operate under unpredictable conditions. Possible directions towards more robust and generalised software-based solutions include: (1) designing novel feature representations having milder assumptions about the cosmetic contact lens patterns, (2) augmenting training data of counterfeit iris patterns online like databases of anti-virus software [53], (3) using a combination of several (lens-specific) methods, and (4) modelling variability in the mixture of genuine and fake iris feature representations.

One important question is also whether the cosmetic contact lens detection (or PAD in general) should be considered as two-class or one-class problem. While huge amount of genuine iris data is available for training natural iris model, the same does not hold for counterfeit irises because novel brands with previously unseen cosmetic lens patterns will be eventually experienced in operation. Since it is practically impossible to cover every existing printing pattern in training datasets, ideally, the problem can be solved using one-class classifiers for modelling the variations of the only fully known class (genuine). This kind of approach has shown already to be promising direction in speaker verification PAD [2].

In any case, all aforementioned main aspects towards generalised textured lens detection can be considered in both, fundamentally different, principles of one-class and two-class modelling. For instance, in feature design, one needs to figure out how to emphasize and capture the variations characteristic to only genuine iris texture or the differences between genuine iris texture and fake one without exploiting the prior knowledge of known printing signatures too much. Furthermore, where a up-to-date database of known lens printing patterns is useful when upgrading two-class models, it is also necessary for tuning the hyperparameters of the one-class model.

Eventually, the success in real-world applications is mostly dependent on how robust the applied feature representation is. The varying nature of different lens printing techniques makes the problem indeed difficult to solve. First, the market of textured contact lenses is growing, thus the number of texture patterns increases at the same time. Already the three example images seen in Figure 1.1 demonstrate how dissimilar the printing signatures of various suppliers can be. Generalised texture representation of various (unseen) printing techniques itself is a challenging problem but the semi-transparent nature of cosmetic contact lenses makes the problem even less trivial as the natural iris texture may be at least partly observed. In the following, we introduce our work [36] on designing a more generalised (natural) iris texture representation for detecting the presence of cosmetic contact lenses.

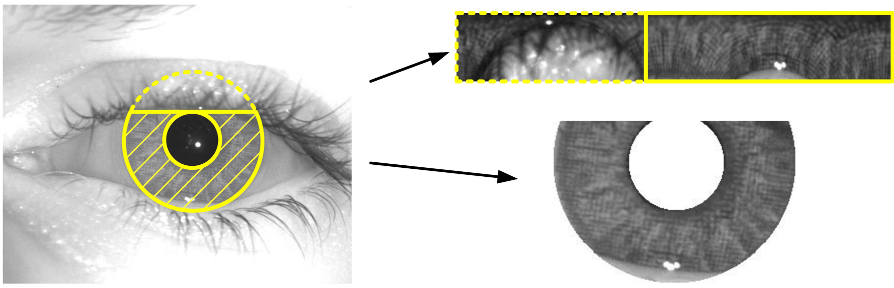

Figure 1.6: Comparison of between traditional polar and the proposed geometric normalization techniques highlighting the distorted texture patterns of Ciba Vision lenses and occlusion in polar domain. The dashed lines represent the omitted area because of possible occlusion due to eyelashes and eyelids. Reprinted with permission from [36] © 2014 IEEE.

1.3.1 Pre-processing

Iris image pre-processing, including localisation, geometric normalization and occlusion handling due to eyelashes and eyelids, is as important part of a counterfeit iris detection pipeline as the actual texture feature extraction. Traditionally iris images are normalized into polar coordinate system also when detecting counterfeit irises [21, 28, 29, 56, 53, 55]. However, the geometric transformation causes severe distortion on the regular lens texture patterns. In addition, valuable details are probably lost due to interpolation when mapping the ring-shaped iris region into rectangular image. As seen in Figure 1.6, the printing signatures are far less evident in the resulting polar coordinate image as opposed to the original Cartesian domain, hence probably also harder to describe. While the polar coordinate system is convenient for finding distinctive features across different individuals and matching purposes, it might be unsuitable for creating generalised feature representation for cosmetic contact lens detection.

In order to preserve the regularity of the lens patterns, we compute the iris texture description in the original image space by normalizing the square bounding box of the limbic boundary into N×N pixels. We omit all pixels belonging to the pupil and sclera region using the pupillary boundary and the limbic boundary to avoiding the effect of irrelevant information that is not part of iris texture (see Figure 1.6). Furthermore, we take the possible occlusion due to eyelashes and eyelids into account and further refine our region of interest (ROI) to focus on the lower part of the iris, i.e. the upper limit of the pupillary boundary acts also as the upper limit for the ROI.

1.3.2 Texture description

For describing the inherent textural differences between natural and synthetic iris texture, we adopted binarized statistical image features (BSIF) [34] because they have shown potential tolerance to image degradations appearing in practice, e.g. rotation and blur. More importantly, the BSIF filters are derived from statistics of natural images, thus they are probably suitable for emphasising the textural properties of those characteristic to natural iris images and not synthetic ones.

Many local descriptors, such as LBP [42], compute the statistics of labels for pixels in local neighbourhoods by first convolving the image with a set of linear filters and then quantizing the filter responses. The bits in the resulting code string correspond to binarized responses of different filters. Kannala & Rahtu [34] proposed to learn the filters by utilising statistics of natural images instead of using manually predefined heuristic code constructions.

Given an image patch X of size $l \times l$ pixels and a linear filter W_i of the same size, the filter response s_i is obtained by:

$$s_i = \sum_{u,v} W_i(u,v)X(u,v) = w_i^T x, \tag{1.1}$$

where vector notation is introduced in the latter stage, i.e. the vectors w and x contain the pixels of W_i and X. The binarized b_i feature is then obtained by setting $b_i = 1$ if $s_i > 0$ and $b_i = 0$ otherwise. Given n linear filters the bit strings for all image patches of size $l \times l$, surrounding each pixel of an image, can be computed conveniently by n convolutions. Like in the case of LBP, the properties of the iris texture are represented using histograms of BSIF values extracted over normalized and masked iris image.

The filters W_i are obtained using independent component analysis (ICA) by maximising the statistical independence of s_i. In general, this approach has shown to produce good features for image processing [33]. Furthermore, the independence of s_i provides justification for the independent quantization of the elements of the response vector s [34]. Thus, costly vector quantization, used e.g. in [53], is not needed in this case for obtaining a discrete texton vocabulary.

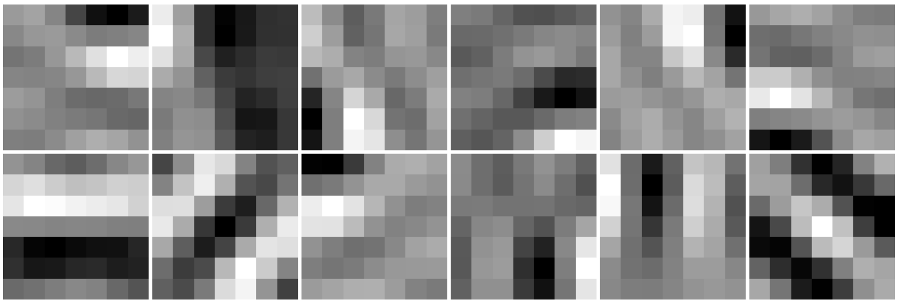

Figure 1.7: BSIF filters size of 7 × 7 learned from natural images. Reprinted with permission from [36] © 2014 IEEE.

BSIF descriptor has two parameters: the filter size l and the length n of the bit string (i.e. number of learned filters). We used the set of filters[3] provided by the authors of [34]. The filters W_i with different choices of parameter values were learned using 50000 patches that were randomly sampled from a set of 13 natural images provided in [33]. The BSIF filters used in the proposed iris description can be seen in Figure 1.7.

1.3.3 Experimental analysis

Next, we conduct extensive set of experiments in order to compare the performance of different feature representations for textured contact lens detection, including iris image pre-processing and texture features. The main purpose of our experimental analysis is to evaluate the generalisation capability of the different algorithms under two varying conditions, cosmetic lenses with previously unseen texture patterns and unknown iris sensors. For performance evaluation, we considered the extended version of the Notre Dame Contact Lens Detection 2013 (NDCLD'13) benchmark dataset [22] as it provides the means for evaluating the effect of both of these variables separately, unlike many other databases.

1.3.3.1 Experimental setup

The NDCLD'13 database consists of iris images of subjects without contact lenses, with soft and textured contact lenses, acquired under near-infrared illumination. The database can be used for evaluating methods that try to solve a three-class problem of categorising iris images as no lens, clear lens or cosmetic lens [21]. In the following, we focus on two-class problem considering iris images without contact lenses and with clear lenses as genuine samples, whereas the iris images with cosmetic lenses are regarded as artefact samples.

[3] http://www.ee.oulu.fi/∼jkannala/bsif/bsif.html

	Train		Test	
Subset	Genuine	Fake	Genuine	Fake
ND I	2000	1000	800	400
ND II	400	200	200	100
Cooper	2160	2160	667	667
J & J	1955	1955	872	872
Ciba	1539	1539	1288	1288

Table 1.1: Composition of the different subsets of the NDCLD'13 database. Reprinted with permission from [36] © 2014 IEEE.

The updated NDCLD'13 database contains three subsets of iris images. The first subset (ND I) consists of a training set of 3000 samples and a test set of 1200 samples acquired using an LG 4000 iris camera. Second subset (ND II) contains 600 for training images and 300 images for testing acquired with an IrisGuard AD100 iris sensor. Both datasets are balanced across the three different categories of iris images. Moreover, the iris images are divided into ten subject-disjoint and class-balanced folds for training and tuning the algorithms. Although the number of iris images in training and test sets between ND I and ND II is a bit unbalanced, the consistent composition enables fair cross-sensor experiments.

The third subset (ND III) is an extended set of ND I because it contains constant set of no lens and soft lens images from ND I but, more importantly, 1427 additional iris images with cosmetic lenses acquired with the LG4000 camera. ND III can be used for testing how well a textured contact lens detection algorithm is able to perform when an unseen cosmetic texture pattern is shown because it provides leave-one-out protocol across the three types of cosmetic contact lenses by Cooper Vision[4], Johnson & Johnson[5] and Ciba Vision[6] (667, 872 and 1288 counterfeit iris images, respectively). Table 1.1 summarizes the composition of different subsets in the NDCLD'13 database.

Since the focus of our experiments is on exploring the generalisation capabilities of textured lens detection algorithms, we utilise the segmentation information included in the NDCLD'13 dataset that provides center and radius for circles defining the pupillary boundary and the limbic boundary. The average radius of the limbic boundary in the provided segmentation data is bit over 130 pixels, thus the bounding box of the proposed Cartesian iris image normalization is set to 255×255 pixels. For training and tuning the classifiers, we follow the predefined folds in the ND I and ND II. However, due to the lack of fixed folds in the ND III, cross-validation is applied during the leave-one-out lens test.

LBP texture feature based algorithms have shown to be effective in cosmetic contact lens detection [21, 29, 59], thus we adopted multi-resolution LBP [21, 29] using uniform patterns (denoted by LBP^{u2}) [42] as a baseline descriptor for comparing the

[4] Expressions Colors: http://coopervision.com/contact-lenses/expressions-color-contacts
[5] ACUVUE2 Colours: http://www.acuvue.com/products-acuvue-2-colours
[6] FreshLook Colorblends: http://www.freshlookcontacts.com

	LBP		BSIF	
Pre-processing	CCR	EER	CCR	EER
Polar	87.16	6.30	93.23	2.05
Polar with ROI [55]	91.55	4.95	94.40	1.11
Proposed	**94.01**	**3.11**	**98.42**	**0.33**

Table 1.2: Mean CCR and EER (in %) across different lens types using different geometric normalization approaches, i.e. polar and Cartesian coordinate systems and ROI processing. Reprinted with permission from [36] © 2014 IEEE.

benefits of the proposed pre-processing approach and the BSIF based iris texture description. In our experiments, the multi-resolution representation was extracted by applying $\mathrm{LBP}^{u2}_{P,R}$ operator with eight sampling points ($P = 8$) at multiple scales (radii R) and concatenating the resulting LBP histograms into a single feature vector. For fair comparison, the best-performing combination of different $\mathrm{LBP}^{u2}_{8,R}$ operators and best-performing BSIF descriptor are selected when comparing the different features in general.

1.3.3.2 Leave-one-out lens validation

Since the algorithms are likely to fail in detecting cosmetic lenses with textured patterns not present in training material, we begin our experiments with the leave-one-out protocol of the ND III. Following the protocol used in [22], the models are trained on images of two of the three lens manufacturers while third one is left out for evaluating the generalisation capability.

First, we want to find out the actual benefit that we gain by extracting the features in the original image domain with the proposed pre-processing method instead of applying traditional normalization into polar coordinate transform. For the sake of simplicity, a linear support vector machine (SVM) is utilised for classifying both feature representations. The mean correct classification rate (CCR) and equal error rate (EER) across different lens folds are shown in Table 1.2. Since the eyelids and eyelashes often cause severe occlusion over the iris texture, it is not surprising that the use of ROI already in polar domain leads to increase in performance for both features. More importantly, the results support our hypotheses as even more significant performance enhancement is obtained when the proposed pre-processing approach is used. Thus, we utilise it in the following experiments.

In Table 1.3, we can see the mean performance across different lens folds when different SVM classification schemes are applied. The use of nonlinear SVM leads to best results for every feature representation, especially for multi-resolution LBP as it is able to reach the same performance level as with BSIF descriptors. However, it is also important to note that the BSIF features perform extremely well even with linear classifier and the performance does not gain too much when utilising nonlinear SVM, which shows that the BSIF based iris texture description is indeed suitable for detecting cosmetic contact lenses.

	Linear		RBF		One-class	
Feature	CCR	EER	CCR	EER	CCR	EER
BSIF 6b 5×5	98.23	0.95	**98.31**	**0.90**	92.88	5.52
BSIF 9b 5×5	**97.65**	0.61	**97.65**	**0.37**	94.86	4.18
BSIF 12b 7×7	98.42	0.33	**98.47**	**0.11**	95.28	2.09
$\mathrm{LBP}_{8,[1-3]}^{u2}$	94.01	3.11	**97.67**	**0.69**	94.00	5.18

Table 1.3: Mean CCR and EER (in %) across different lens types using different SVM classifiers. Reprinted with permission from [36] © 2014 IEEE.

We also included one-class SVM for comparison and tried to approach the problem by modelling only the genuine iris texture inspired by the work by Alegre *et al.* [2]. The use of one-class SVM lead to satisfactory results but both of the two-class SVMs performed better because the false rejection rate of one-class SVM was much higher. Although better generalisation capability was achieved with proper feature design in our experiments, one-class approach should not be forgotten in future studies because of the limited number of different textured printing signatures and (genuine) training samples in the leave-one-out lens validation.

	Cooper		J & J		Ciba		Mean
Feature	CCR	EER	CCR	EER	CCR	EER	CCR
BSIF 6b 5×5	99.55	0.60	96.73	1.49	98.64	0.62	98.31
BSIF 9b 5×5	98.28	0.30	94.67	0.80	**100.00**	**0.00**	97.65
BSIF 12b 7×7	**99.78**	**0.00**	95.76	**0.34**	99.88	**0.00**	**98.47**
$\mathrm{LBP}_{8,[1-3]}^{u2}$	99.33	0.60	**97.25**	0.46	96.43	1.01	97.67

Table 1.4: Lens specific CCR and EER (in %) of the leave-one-out lens test. Reprinted with permission from [36] © 2014 IEEE.

The final results of the leave-one-out lens validation and lens specific breakdown for the best features and nonlinear SVM can be seen in Table 1.4. Like in [22], we found out that the Cooper Vision lens appears to be the easiest one to detect probably because its printing texture is somewhere in between Ciba Vision and Johnson & Johnson. The results suggest that certain lens types can be more useful in training and tuning generalised models, like Johnson & Johnson seems to be in the case of the BSIF based description. It is also worth mentioning that the CCR and EER do not always go hand in hand due to the cross-validation used during training and tuning the lens detection models. A proper pre-defined validation set could be probably used for tuning the operating point in order to avoid this kind of overfitting.

1.3.3.3 Device independent validation

Another important property in practical applications is device independent performance. Next, we perform intra-sensor and inter-sensor experiments using ND I and

	Trained on LG4000				Trained on AD100			
	Intra-sensor		Inter-sensor		Intra-sensor		Inter-sensor	
Feature	CCR	EER	CCR	EER	CCR	EER	CCR	EER
BSIF 6b	98.75	1.25	89.00	5.00	97.67	2.00	97.67	2.50
BSIF 9b	99.33	0.50	**93.00**	3.00	98.67	**1.00**	98.67	1.50
BSIF 12b	**99.42**	**0.00**	92.33	**1.00**	**99.00**	**1.00**	**99.33**	**0.75**
$\text{LBP}^{u2}_{8,[1-3]}$	98.67	1.25	85.33	16.00	96.33	4.00	90.75	9.25

Table 1.5: CCR and EER (in %) of the cross-sensor validation. Reprinted with permission from [36] © 2014 IEEE.

ND II in the NDCLD'13 database. In other words, we train the algorithms on the training set of ND I and evaluate the models on the test sets of ND I and ND II, and vice versa. The results in Table 1.5 depict that all texture descriptions using the proposed pre-processing perform extremely well in the intra-sensor test. However, BSIF outperforms multi-resolution LBP in the inter-sensor validation, especially in terms of EER when even 6 bit version of BSIF performs reasonably well. The better performance of BSIF might be due to its potential tolerance to image degradations, e.g. blur [34].

1.4 Discussion

The experimental results from Section 1.3 show that it is indeed possible to perform more generalised textured contact lens detection across unknown iris sensor data and novel lens printing texture patterns with carefully designed iris texture representation. Further works by other researchers have been reporting similar findings highlighting the importance of proper pre-processing and feature spaces in the context of generalised textured contact lens detection [20] and the three-class problem of categorising iris images as no lens, clear lens or cosmetic lens [26, 48, 51].

1.4.1 Further work on generalised textured contact lens detection

Doyle and Bowyer [20] extended their prior work [22] and released the Notre Dame Contact Lens Detection 2015 (NDCLD'15) dataset that introduces additional sensor and two additional lens brands (printing patterns), Clearlab[7] and United Contact Lens[8], that were not included in the extended version of the NDCLD'13 database [22]. Their experiments on the more comprehensive dataset provided additional evidence verifying our preliminary results on the robustness of BSIF based iris description extracted from the original Cartesian image domain. First, the CCR drops only from 100% in the intra-sensor case to just over 95% in the inter-sensor case, while the CCR regains back to almost 100% when the data of the different sensors

[7]Eyedia Clear Color Elements: http://www.clearlabusa.com/eyedia-clear-color.php
[8]Cool Eyes Opaque: http://www.unitedcontactlens.com/contacts/opaque-lenses.html

is included into the training set. Second, the average CCR across all leave-n-out novel lens experiments, where $n = \{1,2,3,4\}$ and models are trained $5-n$ and evaluated on n lens types, were 97.65%, 95.97%, 92.59% and 85.69%, respectively. It is also worth mentioning that BSIF outperformed LBP in all of their experiments and generalised better in every test protocol.

These results suggest that: (1) reasonably good interoperability between different iris sensors can be achieved in textured contact lens detection but additional models are (probably) required for novel iris sensors in order achieve extremely high detection rates, and (2) cosmetic lens detection algorithms can be robust to a previously unseen printed lens texture patterns and the more lens brands are introduced to the training set, the better generalisation capabilities can be obtained. When the detection algorithms are trained with iris images of the target sensor and no previously unseen lens type is confronted in operation, textured contact lens detection seems to be a solved problem. In less restricted conditions, sensor-specific factors, e.g. how their different NIR wavelengths interact with the pigments used in the textured lenses [20], and the different printing signatures types may degrade the detection rates but still reasonable generalisation capability may be achieved if substantial number of known lens types are used in training.

1.4.2 The role of pre-processing in contact lens detection

Pre-processing, e.g. iris image segmentation and normalization, is an important factor in contact lens detection. The contact lens detection algorithm pipelines, i.e. pre-processing, feature extraction and classification, have been usually evaluated as a whole and compared with other approaches having significant differences especially in the used pre-processing techniques and feature descriptors. Therefore, based on the literature, it is very hard to tell what is the actual effect of different pre-processing strategies.

Intuitively, textured contact lenses are the more challenging to detect than other types of presentation attacks because the artefact is visible only within a very small part of the iris image. Thus, while periocular region might be useful in e.g. printed iris image detection, it can be considered to be irrelevant for detecting cosmetic lens or even distracting. However, recent studies [20, 26] demonstrated that accurate segmentation and geometric normalization of iris region might not be required for robust and generalised textured contact lens detection when operating in the original Cartesian image domain.

Doyle and Bowyer [20] experimented with three different pre-processing strategies for extracting the BSIF description using: (1) the entire given iris image (whole image), (2) average iris location for the dataset to guess the ROI (best guess), and (3) accurate automatic segmentation for the given iris image (known segmentation). In the last two cases, radius of the estimated or segmented ROI is increased by 30 pixels to include sclera region where the contact lens boundary might be present. The pixels not belonging to the ROI were masked out and no geometric normalization, e.g. resizing, was applied on the used iris region. Interestingly, the CCR was only slightly decreased when best guess estimate of ROI was utilised instead of exact segmentation in inter-sensor validation, while the performance of all three strategies was roughly the same in intra-sensor evaluation. Gragnaniello *et al.* [26] used three different ROIs, whole iris image, segmented iris region and segmented region containing both iris and sclera for computing dense scale-invariant local descriptors (SID) and bag-of-features (BoF) paradigm based iris representation. Also their experiments showed that cosmetic contact lenses can be detected with high accuracy using all three pre-processing techniques.

While accurate segmentation and geometric normalization might not be important for robust textured lens detection, the same does not hold for the three-class problem because the differences between no lens and soft lens iris images are not that evident (as seen in Figure 1.5) compared with textured lenses (at least in the case of familiar printing patterns). Gragnaniello *et al.* [26] found out that the specifically segmented sclera region plays a key role in accurate contact lens detection especially for no lens and soft lens classes, while the whole image and iris region based feature representations fail to capture crucial fine details. Therefore, they approached the three-class problem by utilising accurate sclera and iris segmentation and avoiding any kind of geometric normalization on the iris images that might distort the subtle texture variations in sclera and iris regions due to the presence of a contact lens. The proposed method extracting SID and BoF encoding from the combined sclera and iris regions obtained the state-of-the-art overall CCR of 88,04% across the three classes in intra-sensor tests. Unfortunately, the generalisation capabilities of the proposed pre-processing across different sensors remain unexplored because no inter-sensor results were reported.

Silva *et al.* [51] conducted a preliminary study on the effectiveness of deep convolutional neural networks (CNN) in contact lens detection. Based on their experiments, even CNNs require approximation of ROI containing iris and possible visible contact lens boundary in order to reach comparable performance with the state of the art as overall CCRs of 82,165% and 70,57% across the three classes in intra-sensor tests and 76,67% and 42,30% in inter-sensor tests were obtained by processing localized iris region and entire given iris images, respectively. However, these preliminary experiments cannot be regarded as the final word on the effectiveness of deep neural networks in contact lens detection. Further attention is likely required in order to find out their full potential.

The idea of using minimal pre-processing, e.g. operating on "raw iris images" or approximate iris region, or avoiding any geometric normalization in order to preserve all valuable fine details, is reasonable when operating on "classic-still" iris images captured in controlled and cooperative conditions. For instance, the iris cameras, like LG4000 and IrisGuard AD100, aim at placing the iris (or the pupil) in the center of the acquired iris image and acquire an image only when the built-in proximity sensor tells that there is a subject within a certain distance from the camera. Therefore, the variation in the position and the size of the iris in the captured images is not that significant. However, this kind of approaches are not likely to be suitable for operating e.g. on iris images taken at a distance using an iris on the move (IOM) system that captures NIR face video of subjects while they are walking through a portal at a distance three meters away from the camera.

Robustness and generalisation of software-based contact lens detection in less controlled conditions can be probably improved by combining different (complementary) pre-processing strategies. Instead of operating on a single Cartesian image, Raghavendra *et al.* [48] proposed to combine the iris representations computed over three different images: (1) whole eye image resized into 120×120 pixels, (2) 300×50 strip image cropped from the original iris image starting from the pupil center, i.e. roughly representing the iris, pupil and sclera regions, and (3) "traditional" unrolled iris image resized into 512×64. While the ensemble of BSIF descriptions extracted at multiple scales was not able beat the state of the art [26] on three-class problem in intra-sensor evaluation (overall CCR of 81,46% vs 88,04), very promising state-of-the-art performance of 74,73% was obtained in inter-sensor tests. Again, BSIF based iris image description obtained very high accuracy in textured contact lens detection in both intra-sensor and inter-sensor tests.

In general, the textured contact lenses can be detected quite well while there seems to be confusion between natural irises and non-cosmetic soft contact lenses. This suggests that alternatively the three-class iris image classification problem could be simplified into a cascade of two binary classification tasks: (1) considering iris images with and without clear contact lenses as genuine samples and the one with cosmetic lenses as counterfeit samples, and then (2) discriminating images with transparent lenses from natural images. In this manner, the algorithms could be tuned to distinguish the fine differences between the two more difficult classes.

1.4.3 On the evaluation of contact lens detection algorithms

The current publicly available benchmark databases have been a very important kick-off for finding out best practices for contact lens detection. The existing databases have been and are still useful for developing and evaluating contact lens detection algorithms, especially for transparent soft lenses. However, the almost perfect CCRs for textured contact lens detection in "homogeneous" training and test conditions indicate that even more challenging configurations are needed. On the other hand, LivDet-Iris 2013 competition [57] showed that already these kinds of experimental setups can be made challenging if the actual test data is kept inaccessible during algorithm development and third-party evaluation is deployed in order to simulate real-world operating conditions. The resulting performances were far from satisfactory even for the winning method, which suggest that the laboratory results reported in scientific papers might be indeed overly optimistic estimate on the true generalisation capabilities of the existing textured contact lens detection methods. It is worth highlighting that any later comparison to these competition results should be treated with caution because it is impossible to reproduce the "blind" evaluation conditions any more and, consequently, to achieve a fair comparison.

Another issue in textured contact lens detection is that while the training and test folds are subject-disjoint, the individual folds contain usually different genuine and fake subjects, e.g. in [6, 55, 59]. Intuitively, the arrangement of not including subjects with and without (cosmetic) lenses can be justified in the training phase as it would prevent methods from learning the subject features instead of lens properties [56]. However, this kind of configuration in the test set might lead to biased results because presentation attack detection methods are well-known for their subject-dependent performance [10, 58]. Furthermore, on this type of database it is impossible to conduct user-specific studies, e.g. to analyse the impact of contact lens detection algorithms and according follow-up procedures on the recognition accuracy. When subjects for the different classes are not the same, the acquisition conditions, e.g. used iris sensor [7, 53], may be different [25]. This potential flaw can be prevented by following exactly the same data collection protocol for all classes, like conducted e.g. in [20, 22, 56]. It is worth mentioning that the different benchmark datasets, like [20, 56], enable different kinds of contact lens detection studies but the effect of important factors, e.g. users and novel lenses, cannot be isolated and analysed together.

The general evaluation protocols and performance metrics could be also improved. The benchmark datasets contain usually separate folds only for training and testing which may cause bias due to "data peeking". While independent (third-party) evaluations are impossible to arrange without collective evaluations, like LivDet-Iris 2013 [57], the use of pre-defined training, development and test sets would mitigate the effect of tuning the methods on the test data. Unambiguous evaluation protocols would also allow fairer and direct comparison between different studies. The specific validation set would also help to improve and standardize performance metrics that have been not been corresponding to real-world operating scenarios e.g. with specific operating points, or otherwise very informative. For instance, the detection accuracy for each class in the three-class problem is not that meaningful if the confusion between the different classes [21, 22], especially in the case of no lens and transparent lens, is not analysed, e.g. in [26, 48, 51, 56]. As the generalisation capabilities of contact lens detection algorithms in unknown conditions, e.g. novel sensors and lenses, have shown to be a real issue, the inter-test protocols should be followed when provided in a dataset.

1.5 Conclusions

The presence of a contact lens in the acquired iris image degrades the performance of iris recognition systems. This is particularly true for textured contact lenses that are designed to alter the original iris texture of the wearer but also for clear soft lenses due to the change in optical properties of the eye and varying alignment. Automatic detection of both types of contact lenses would be beneficial for detecting iris presentation attacks (cosmetic lenses) and engaging adaptation algorithms, e.g. distortion correction or masking, that could increase the accuracy of iris recognition systems against transparent lenses.

Since the effect of clear soft prescription lenses on recognition accuracy has been understated until recently, the research focus has been on textured contact lens detection and many hardware and software based approaches (and combination of both) have been proposed in the literature. While hardware-based solutions provide efficient and generalised means for presentation attack detection, they can be also rather impractical due to additional interaction or unconventional imaging requirements, and unpleasant active lighting. Furthermore, these kinds of techniques have been usually evaluated just to demonstrate a proof of concept or, in the worst case, have not been experimentally validated at all.

Software-based approaches exploiting only the data captured with "standard" iris sensors would be an inexpensive and attractive solution for contact lens detection. In known operating conditions, cosmetic contact lens detection can be considered as a solved problem but sensor interoperability and previously unseen printed lens texture patterns can cause dramatic degradation in detection accuracy. The recent studies on generalised contact lens detection have demonstrated, however, that with careful feature design and comprehensive training sets containing target sensors and multiple contact lens types/brands reasonable, or even rather high, performance can be maintained in challenging operating conditions. The issues with generalised contact lens detection have been recognized but there is still room for future work. Since there are virtually no technical limitations to fabricate cosmetic contact lenses suitable for targeted impersonation, it would be interesting to see if new approaches are needed for discriminating original natural iris texture from replica of it.

The research on the problem of soft prescription lenses, on the other hand, is just in its infancy and only a few approaches have been introduced. Detection of clear soft contact lenses is far more difficult compared to the problem of textured lenses because the appearance differences between no lens and soft lens iris images are very subtle and highly dependent on the input image quality, for instance. The reported results have not been satisfactory so far and even hardware-based methods have not been able to provide generalised solutions yet. Thus, robust soft contact lens detection is still an open research topic.

Compared with "classic-still" NIR iris images, distant iris acquisition would be more practical e.g. in watchlist applications but there are no studies that perform contact lens detection from images captured with iris on the move (IOM) systems. While NIR iris sensors are emerging in mobile devices, already the standard high-quality cameras embedded in smartphones facilitate iris recognition [19]. Detection of print [27] and video [49] based presentation attacks from conventional RGB iris images has received already some attention but textured contact lenses have not been included in these preliminary works. Even though there are still unresolved issues when operating on "classic-still" NIR iris images, contact lens detection in iris images captured in less restricted acquisition conditions and application scenarios would be an interesting and important research topic.

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