Iris Recognition in Visible Wavelength: Impact and automated Detection of Glasses

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***Abstract*—The prevalence of visual impairment around the world is rapidly increasing, causing large numbers of people to wear glasses. Glasses are generally considered an important noise source in iris recognition; under objective metrics, they have recently been shown to deteriorate the sample quality of near-infrared (NIR) ocular images (consequently impairing the segmentation accuracy and biometric performance). Automatically and robustly detecting glasses in ocular images is therefore one of the prerequisites for the acquisition of high quality iris samples. While this issue has recently been addressed for NIR ocular images, it remains an open issue in the visible wavelength (VW) spectrum. As the popularity of VW iris recognition increases (due to e.g. deployment of iris recognition in consumer grade mobile devices and general improvements in VW recognition algorithms), it becomes a matter of interest to quantitatively evaluate the impact of glasses on such systems, as well as develop methods for automatic detection of glasses in VW ocular images.**

In this paper, the impact of glasses on VW iris segmentation performance is investigated using the UBIRISv2 and MobBIO iris databases. It is shown that the presence of glasses significantly degrades the accuracy of iris segmentation. In addition, a state-of-the-art iris segmentation method which can perform a semantic segmentation of ocular images (including the segmentation of glasses) is employed for the purpose of glasses detection. On the used databases, correct classification rates (CCRs) of 98.57% and 83.62% are obtained, respectively.

***Index Terms*—biometrics, iris recognition, iris segmentation, glasses detection**

I. Introduction

In the past years, biometric recognition has become ubiquitous in various applications ranging from automated border control to forensic investigations. While some technologies, e.g. face or fingerprint recognition, are already commercially deployed in numerous application scenarios, the potential of others still needs to be explored. In particular, non-cooperative iris recognition based on images captured at VW represents a challenging task [1]. In contrast to iris images captured under NIR light, the iris tends to exhibit less textural information when acquired at VW, depending on the eye colour of a data subject. Furthermore, within VW iris images possible artefacts, such as specular reflections or shadows, are more pronounced. Those issues generally lead to an increased intra-class variation, which can cause a severe drop in the biometric performance. Accurate segmentation of the iris region in VW images represents one of the most critical tasks [2] in the processing pipeline and has also been the topic of several competitions (e.g. MICHE [3], [4] and NICE [5], which concentrated on mobile devices and noisy images, respectively) aimed at improving the accuracy of the contemporary algorithms. The segmentation of the iris involves a detection of inner and outer iris boundaries, a detection of eyelids, an exclusion of eyelashes and contact lense rings, as well as scrubbing of specular reflections [6]. More recently, methods based on deep learning, e.g. [7]–[10], revealed encouraging results for the task of iris segmentation.

Visual impairment is becoming an increasingly common affliction around the world. By some recent estimates (e.g. [11], [12]), over 50% of adults in the developed world are glass-wearers. In Eastern Asia, the prevalence of short-sightedness (myopia) has been rapidly increasing to unprecedented levels [13]. Several researchers mention glasses as a significant noise factor for iris recognition systems (e.g. [14]–[16]). However, very little related work on this subject is available in the contemporary scientific literature. In [17], the impact of glasses on the pre-processing pipeline of NIR iris images was evaluated in a small-scale study. Recently, a more thorough investigation on the impact of glasses for NIR iris images was done in [18]. In both works the drastic impact of glasses on NIR iris image pre-processing and recognition is demonstrated. Furthermore, in ISO/IEC 29794-6 biometric sample quality standard [19], it is recommended to exercise increased care during image acquisition from data subjects wearing glasses, or to outright instruct them to remove their glasses. Due to the non-trivial negative impact of glasses on the biometric performance of iris recognition systems, as well as the aforementioned pervasiveness of vision impairment (and, consequently, of glasses in the world population), automatic detection of glasses is an important matter in iris recognition. This is particularly the case for automatic sample acquisition systems, where higher sample quality could be facilitated through interactive sample acquisition with a glasses detection module.

In [18] methods based on texture descriptors, deep learning, edge/reflection detection, and a fusion thereof have been shown to achieve near-optimal results for glasses detection in

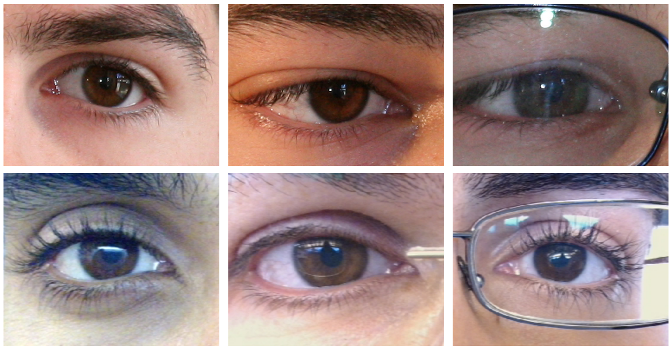

Fig. 1. Example images of the UBIRISv2 (top) and the MobBIO (bottom) VW iris image databases.

TABLE I
OVERVIEW OF EMPLOYED VW IRIS DATABASES.

Database	UBIRISv2	MobBIO
Total	2,250	800
Without glasses	1,931	656
With glasses	319	144
Resolution (pixels)	400×300	250×200
Sensor	Canon EOS 5D	Asus Eee Pad Transformer TE300T
Light sources	Natural and artificial light	Natural and artificial light

NIR ocular images. In VW ocular images, automated detection of glasses is expected to be more challenging, since, in contrast to a NIR acquisition, reflections as well as glasses frames might be less pronounced. This work complements the study of [18] by conducting a similar analysis and presenting a new glasses detection method for VW ocular images: in section II, the experimental setup is summarised. The impact of glasses on VW iris segmentation performance is evaluated in section III. Subsequently, a method to detect glasses in VW ocular images is proposed in section IV. Finally, conclusions are drawn in section V.

II. Experimental Setup

Experiments are conducted on the UBIRISv2 [20] and the MobBIO [21] iris image database, both acquired at VW. Figure 1 shows example images from the datasets, while table I provides an overview of their properties. The groundtruth labels (with/without glasses) had to be assigned to all the images, which was done manually by a single researcher via visual inspection.

For both databases segmentation groundtruth in terms of binary segmentation masks indicating iris/non-iris regions in each image are publicly available [22]. Images of both databases are processed using the iris segmentation method proposed in [10]. This algorithm has been shown to achieve state-of-the-art iris segmentation performance and is capable of performing a semantic segmentation of ocular images into several classes including iris, specular reflections and glasses, see section IV. The runtime of the algorithm is comparable to other state-of-the-art methods of iris segmentation. Two evaluations were conducted:

TABLE II
AMOUNT OF SPECULAR REFLECTIONS IN VW OCULAR IMAGES.

Database	UBIRISv2	MobBIO	same subjects
Without glasses	1.7%	3.7%	4.74%
With glasses	1.8%	5.6%	8.16%

- The impact of glasses on the sample quality (the amount of specular reflections in the images) and thereby on iris segmentation in terms of biometric performance is measured in E^1 errors, see section III. In a cross-validation over 4 folds, 400 samples for training and 100 for testing are randomly selected and the average E^1 errors are reported. The E^1 evaluation measure proposed in the first part of the Noisy Iris Challenge Evaluation (NICE.I) [5] estimates the proportion of correspondent disagreeing pixels:

$$E^1 = \frac{1}{N * m * n} \sum_{i,j \in (m,n)} G(i,j) \oplus M(i,j), \quad (1)$$

  where N, m, n are the number, length and width of test images, respectively. G and M are the groundtruth and the generated iris mask respectively, and i, j are coordinates in pixels of G and M. The symbol $\oplus$ represents the `XOR` operation to assess the mismatching pixels between G and M.
- The classification accuracy of the proposed glasses detection approach is measured in CCR, see section IV.

III. Impact on Iris Segmentation

Firstly, the amount of specular reflections present in ocular images of subjects with and without glasses is estimated. For this purpose, the iris segmentation method proposed in [10], which automatically detects specular reflections, is used. The average fraction of pixels in images showing specular reflections is calculated for both databases. In addition, a subset of 88 subjects of the UBIRISv2 database for which images with and without glasses are available is used for this calculation, see figure 2 for examples. Results are summarised in table II. A rather small increase in the amount of specular reflections present in ocular images of subjects wearing glasses can be observed for the entire UBIRISv2 database. This is due to the fact that many images in the UBIRISv2 database were captured at larger distances and therefore tend to contain a rather small amount of specular reflections. In contrast, for the subset of same subjects' images which were captured from closer distances, a significant increase of the amount of specular reflections can be observed for images with glasses. Similar results are obtained for the MobBIO database.

Secondly, E^1 errors obtained for images of subjects with and without glasses for both databases are listed in table III. Note, that the higher error rates for the MobBIO database result from errors in the groundtruth masks which do not take into account the specular reflections [10]. A relative increase of 7.6% and 11.8% in terms of E^1 segmentation error can be observed for the UBIRISv2 and the MobBIO database, respectively. Figure 3 depicts example images where specular

Fig. 2. Example images of same instances of subjects with (left) and without (right) glasses.

TABLE III
E^1 SEGMENTATION ERRORS.

Database	UBIRISv2	MobBIO
Without glasses	1.43%	2.45%
With glasses	1.54%	2.74%

reflections caused by glasses lead to incorrect segmentation results. In summary, the results shown in this section demonstrate the negative impact of glasses on VW iris segmentation, which generally leads to a decrease in the overall recognition performance [1].

IV. DETECTION OF GLASSES

As previously mentioned, the proposed detection approach is based on the iris segmentation method proposed in [10]. In order to achieve a more robust iris segmentation in unconstrained environments, this method performs a semantic segmentation of ocular images into several classes listed in table IV. Semantic segmentation aims at assigning each pixel within an image to a pre-defined object class, where encouraging results have been achieved by employing fully convolutional neuronal networks (FCN) [23] in the recent past. For the task of iris segmentation, a manually annotated semantic groundtruth segmentation[1] of the training set from the NICE.I [20] database containing 500 ocular images was done by a single researcher in [10]. These publicly available annotations were built at pixel level[2], i.e. each pixel is annotated with its corresponding class number. An example of an annotated ocular image of this database can be seen in figure 4. In [10], this database is used for transfer-learning over two FCNs proposed for general semantic image segmentation[3], i.e. `fcn8s-at-once` and `fcn-alexnet`, which were fine-tuned from the pre-trained VGG-16 [24] and AlexNet [25] models, respectively. Best results were reported for using the `fcn8s-at-once` FCN with all semantic classes summarised in table IV. Note, that the list of semantic classes also includes glasses frames/edges (number 9). The size of the trained models is between approximately 256 and 512 megabytes, which makes it feasible to utilise the proposed segmentation and glasses detection systems also in mobile and embedded devices.

In order to detect glasses in ocular images, they are processed with the best segmentation method proposed in [10]. If the "glasses frames/edges" class occurs in the output of the segmentation method, then the image is classified as containing glasses, otherwise not. Hence, the detection of glasses can be seamlessly performed during the iris segmentation stage. Obtained detection accuracies are summarised in table V. As can be seen, high detection accuracy is achieved on the UBIRISv2 database. That is, the approach of [10] appears to be suitable to reliably detect glasses in ocular images, too. However, significantly lower detection accuracy is obtained on the MobBIO database. A manual inspection of misclassified images of the MobBIO database revealed that in many cases hair at the image borders was incorrectly classified as glasses frames. Such errors might be prevented by analysing the form of segmented glasses. In addition, it was found that many correctly classified images contained an

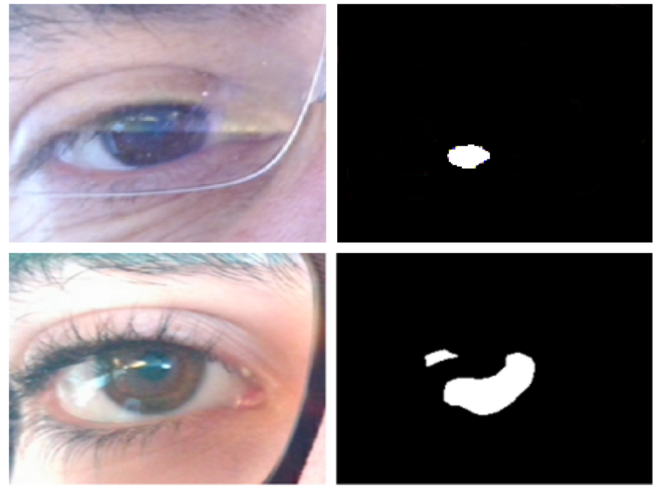

Fig. 3. Examples of incomplete iris segmentations caused by glasses. White pixels represent the detected iris texture.

TABLE IV
SEMANTIC CLASSES IN OCULAR IMAGES DEFINED IN [10].

Nr.	Semantic class	Colour
1	iris	
2	pupil	
3	specular reflections	
4	sclera	
5	eyelids / eyelashes	
6	eyebrows	
7	periocular skin	
8	hair	
9	glasses frames/edges	
10	background	

[1]Multi-class iris segmentation groundtruth:
https://dasec.h-da.de/research/biometrics/MCIS/
[2]Object Labeling Tool:
http://dhoiem.cs.illinois.edu/software/
[3]FCNs for Semantic Segmentation:
https://github.com/shelhamer/fcn.berkeleyvision.org

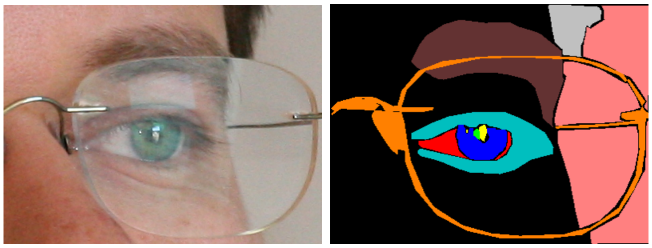

Fig. 4. Example of manually annotated semantic segmentation of [10].

TABLE V
RESULTS OF PROPOSED GLASSES DETECTION METHOD.

Database	UBIRISv2	MobBIO
CCR	98.57%	83.62%

incomplete segmentation of glasses, e.g. due to transparent or non-existent frames. Examples of these cases are shown in figure 5. Lastly, it is important to note that the manually annotated database used for transfer-learning contains only 71 images in which subjects are wearing glasses. In case more annotated training images with glasses were to be used for transfer-learning, the detection performance would be expected to improve significantly.

V. CONCLUSIONS

Glasses can have a detrimental effect on the biometric performance of iris recognition by deteriorating the sample quality and thereby making the segmentation stage more challenging. It has been shown that, on two publicly available VW iris image databases, the iris segmentation performance is significantly degraded if the data subjects wear glasses. A system capable of automatically detecting glasses in ocular images is therefore of interest, as it would allow to handle such images separately or to perform re-acquisition after requesting the data subject to remove their glasses. In this paper, an automated detection of glasses in VW ocular images based on a previously presented method for deep-learning based iris segmentation [10] has been proposed. Said approach, which performs a semantic segmentation, has been shown to be additionally capable of detecting glasses. The detection performance could potentially be further improved by increasing the amount of training data, as well as a detailed analysis of the segmentation results and errors.

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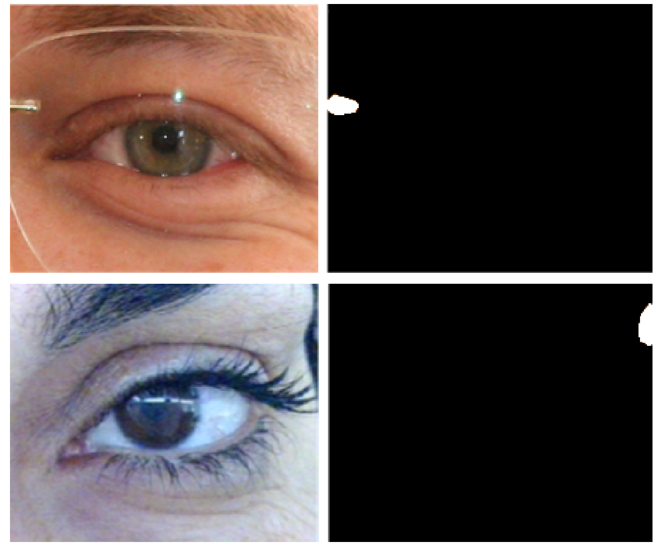

Fig. 5. Examples of incomplete (top) and erroneous (bottom) glasses segmentation. White pixels represent the detected eyeglasses areas.

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