Exploring the feasibility of iris recognition for visible spectrum iris images obtained using smartphone camera

Mateusz Trokielewicz, *Student Member, IEEE*[1,2], Ewelina Bartuzi[2], Katarzyna Michowska[2], Antonina Andrzejewska[2], Monika Selegrat[2]

[1]Biometrics Laboratory, Research and Academic Computer Network, Wawozowa 18, 02-796 Warsaw, Poland;
[2]Institute of Control and Computation Engineering, Warsaw University of Technology, Nowowiejska 15/19, 00-665 Warsaw, Poland;

ABSTRACT

In the age of modern, hyperconnected society that increasingly relies on mobile devices and solutions, implementing a reliable and accurate biometric system employing iris recognition presents new challenges. Typical biometric systems employing iris analysis require expensive and complicated hardware. We therefore explore an alternative way using visible spectrum iris imaging.

This paper aims at answering several questions related to applying iris biometrics for images obtained in the visible spectrum using smartphone camera. Can irides be successfully and effortlessly imaged using a smartphone's built-in camera? Can existing iris recognition methods perform well when presented with such images? The main advantage of using near-infrared (NIR) illumination in dedicated iris recognition cameras is good performance almost independent of the iris color and pigmentation. Are the images obtained from smartphone's camera of sufficient quality even for the dark irides?

We present experiments incorporating simple image preprocessing to find the best visibility of iris texture, followed by a performance study to assess whether iris recognition methods originally aimed at NIR iris images perform well with visible light images. To our best knowledge this is the first comprehensive analysis of iris recognition performance using a database of high-quality images collected in visible light using the smartphones flashlight together with the application of commercial off-the-shelf (COTS) iris recognition methods.

Keywords: biometrics, iris recognition, color iris recognition, mobile devices, smartphones

1. INTRODUCTION

Mobile phones and devices have recently become increasingly advanced and computationally capable. The advancements in technology allow a broad range of applications beyond the primary uses - calling and texting. Smartphones are a firm connection to the world, people, knowledge, information, work, as well as to other devices, and usually contain personal and sensitive data. Over time, they have become a storage for more and more information about their owners, slowly superseding credit cards, car keys, bank tokens and such. Possible repercussions of compromising all these data could be devastating. This in turn creates a demand for reliable and convenient means of securing the sensitive data.

There are various methods for limiting the access to the device, starting with passwords, PIN numbers, patterns drawn on screen and, finally, biometric systems. A medium-length string of letters and numbers could be easily intercepted by means as simple as peeking over one's shoulder, not the mention the vulnerability of a screen drawing, that is even easier to intercept. Due to the inconvenience, most smartphone users choose to opt out of the password or passcode entirely, leaving their devices prone to zero-effort data theft. Some manufacturers have come up with solutions incorporating means of biometric authentication, such as Apple's Touch ID fingerprint reader installed in iPhone 5s and newer. The reception was very good - ease of use and security far better than the passcode are compelling enough for users to adopt the feature.

Correspondence: m.trokielewicz@stud.elka.pw.edu.pl

Human body and behavior provide many different characteristics that are both unique and complicated enough to serve as a biometric identifier for reliable identification. Apart from the aforementioned fingerprint recognition, the possibilities also include identification based on the pattern of the iris - an intricate and delicate meshwork that is a part of the uvea and serves a general purpose of controlling the pupil's aperture, and also the amount of light that enters the eyeball. Richness, uniqueness, low genetic penetrance and stability over time make iris tissue texture one of the best identifiers possible.

Hitherto, the established iris biometrics approaches have used near infrared images obtained with large and expensive equipment. Iris imaged in NIR illumination reveals its unique structure and features almost regardless of the pigmentation, hence great accuracy results. Due to hardware limitations (smartphone cameras operate in visible light) and low practicability of NIR cameras, it is essential to make the best out of visible light iris images, if the iris biometrics should be introduced into mobile devices without dedicated hardware in place. Great practicability of iris recognition under visible illumination creates an opportunity for implementation on various types of mobile devices using inexpensive cameras - for ideal safety of data and maintaining privacy.

In this paper we will show how properly preprocessed visible light iris images can be successfully used with existing commercial off-the-shelf iris recognition algorithms, prepared to work with the ISO-compliant iris images. For the purpose of this study, a database of color iris images has been put together and a simple process of image conversion to the ISO/IEC-compliant format has been performed (Section 3). Then, experiments involving enrollment and matching performance of existing iris recognition methods are conducted (Section 4). Section 5 summarizes the results and proposes future work that should follow these experiments.

2. RELATED WORK

The subject of color image iris recognition has already been investigated by some researchers, with very different aspects, image types, methods, algorithms and approaches being explored. While most of the publicly available biometric datasets related to iris recognition comprise images obtained using professional NIR-illumination devices, there are several collections that comprise pictures acquired with handheld, mobile devices such as phones and tablets.

Apart from the UPOL[1] database of eye images, that was collected using an ophthalmological device, the first publicly available database to introduce noisy iris images collected in visible light with a consumer device was the UBIRISv1 dataset,[2] consisting of images collected with Nikon E5700 handheld camera. The dataset available for download comprises pictures converted to 400-by-300 pixel grayscale JPEG format, that are generally of poor quality - this was performed to simulate the unconstrained imaging procedure. Authors have later expanded their work with the UBIRISv2 database[3] that introduces images captured on-the-move and at-a-distance in visible wavelengths, which is supposed to introduce more realistic noise factors into the data. Another interesting novelty in this work was dividing the irides into three subsets corresponding to pigmentation levels. Researchers argue that the more the pigment in the iris, the more difficult it becomes to separate intra- and inter-class comparison scores between the eyes. Finally, De Marsico *et al.*[4] have recently introduced a dataset of iris images obtained using several mobile devices in unconstricted conditions - the MICHE-I dataset, comprising images taken with iPhone 5, Samsung Galaxy S4 and Samsung Galaxy Tab II. The data were captured without the flashlight. 92 subjects participated, with the resulting dataset consisting of 3732 images. Noteworthy, the database also comprises examples of 'fake' iris images (images of printouts) and videos.

Raja *et al.*[5] investigate a possibility of using a light-field color depth camera to easily obtain high quality, sharp iris images without employing large and expensive, dedicated near-infrared iris cameras. Experiments involving six iris feature extraction algorithms and authors' own database of 420 iris images (84 unique irides) show good recognition accuracy with EER reaching as low as 2.38% for the Daugman method. At the same time, the light-field camera offers an increase in recognition performance when compared to a typical, visible light compact camera, for which the Daugman method (the most accurate algorithm in this study) yielded EER=8.53%. Raja *et al.*[6] also approach the topic of smartphone-based authentication using visible light iris recognition, proposing an enhancement for the stock OSIRIS segmentation, as well as a method of feature extraction based on deep sparse filtering. This let authors achieve a good recognition performance with ERR=1.62% on a newly created database of 280 images (56 unique irides). The data were obtained using rear cameras of the iPhone 5s and Nokia Lumia 1020 phones in unrestricted conditions, with no flashlight or any assisting illumination. Authors also report a roughly 2% gain in EER over the state-of-the-art algorithms.

Radu *et al.*[7] argue that segmentation stage is the most challenging and computationally demanding when color iris recognition using noisy images is employed. Authors use a database of noisy iris images (the UBIRISv1 database) and report a segmentation error rate of about 7%. A classification system based on the multiple classifier system technique is proposed as a method for recognizing irides without database dependencies. The achieved EER values in verification scenario vary from 3.7 to 5.4%, depending on the iris feature set used. Interestingly, researchers take advantage of separate color channels and different color spaces in both segmentation and encoding stages. Frucci *et al.*[8] propose a new method for localizing the iris in images obtained from mobile device cameras. Watershed transform based algorithm is said to outperform other approaches when deployed on the MICHE database, while authors also stress the difficulty in properly segmenting noisy images obtained from mobile devices. De Marsico *et al.*[9] explore the possibility of employing iris and face biometrics on mobile devices by building an application deploying multimodal iris-face recognition, that is designed to be installed on mobile phones and tablets. Authors describe a fully working prototype optimized for computational capabilities of mobile devices and suggest possible use in mobile banking.

It is worth noticing that all of those studies concentrate the efforts on constructing new methods of image segmentation and feature extraction. This is of course a result of having to deal with images of substandard quality, as currently available iris recognition methods may not perform well with such poor quality data. Our approach, on the other hand, will focus on acquiring good quality samples, rather than on deploying advanced methods of coping with poor quality ones. In turn we hope show that it is possible to achieve optimal recognition accuracy when these data is used with existing iris recognition methods.

3. DATABASE OF COLOR IRIS IMAGES

3.1 Database summary

For the purpose of this work, a dataset of iris images obtained in visible light has been collected. Apple iPhone 5s was employed as a data collection device due to it's high quality camera sensor with large aperture of *f/2.2*, capable of producing images of good quality. We strongly believed that using a flashlight embedded in the phone would greatly benefit the quality of images, making them sharp and well-lit regardless of the environment, therefore flash was enabled during acquisition of every sample in the dataset. The image acquisition was performed indoors, in a moderately lit room. There were two sessions, separated by a few days (depending on the person, but less than a week). During each session at least five images were obtained for each eye. Sample images obtained directly from the sensor together with magnified regions representing the eye are shown in Figure 1. **The resulting dataset of images comprises 3192 color images of 70 people (139 different irides in the first session and 136 in the second)**.

3.2 Image preprocessing

As we intended to use commercially available recognition methods for the purpose of evaluating the performance, certain image preprocessing had to be performed on the raw images to make them compliant to the format defined in the ISO/IEC standard[10] regarding iris recognition, that is a 8-bit grayscale bitmap of VGA resolution (640x480 pixels). When converting images to grayscale, we have used the red channel only, as it allows the best visibility of details in the intricate structure of the iris tissue pattern (which is to be expected, as wavelengths corresponding to the color red are closest to near-infrared illumination employed in professional iris recognition devices).

The process of cropping images to the VGA resolution has been performed manually, as the intent of this study is to assess the recognition accuracy when presented with data obtained from the smartphone camera, and not to build an image segmentation algorithm. The advantage of this approach is that we can devise a set of samples that are similar to the ones collected with a professional iris recognition camera in constrained

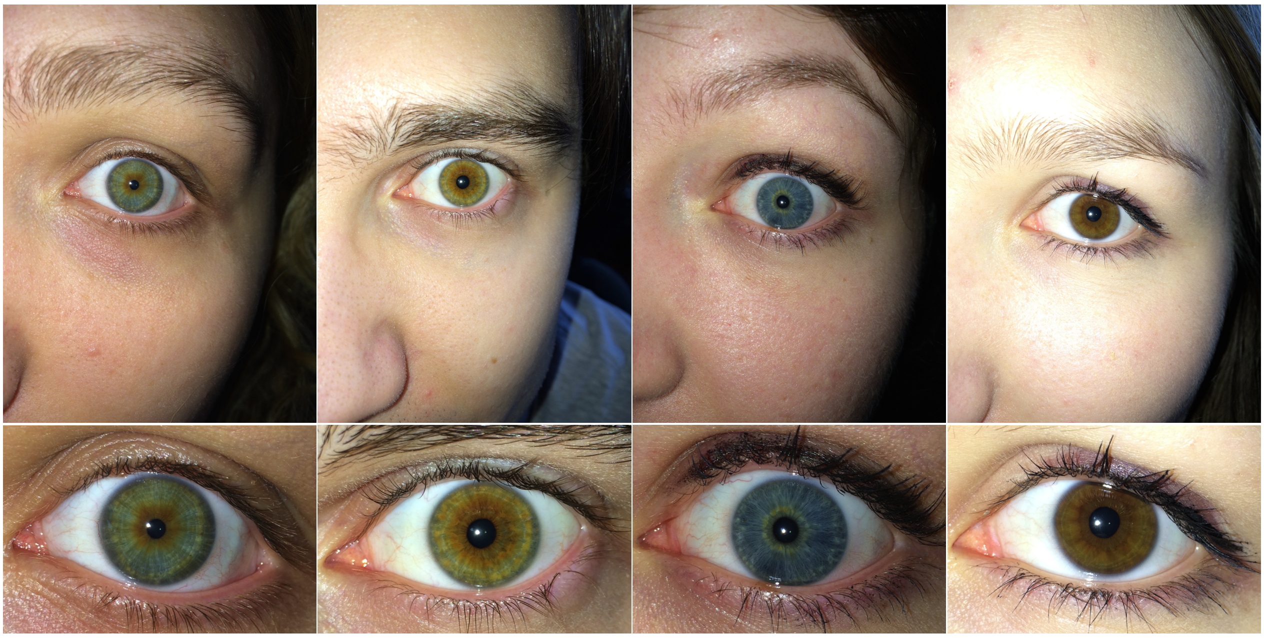

Figure 1: Upper row: sample raw images obtained during data acquisition. No image processing has been performed at this point. Lightly pigmented irides - blue-green and hazel-green (left), heavily pigmented irides - blue-grey and brown (right). Bottom row: magnified iris regions of the corresponding images in the upper row. The iris tissue pattern is easily discernible in each sample.

conditions (and thus should be accepted by the commercial off-the-shelf algorithms), but represent different data. Figure 2 presents converted versions of the sample images. Samples prepared in such manner should therefore perform well when used with existing iris recognition technologies.

Figure 2: Grayscale converted and cropped images of the corresponding pictures in Figure 1. Using the red channel of the RGB color space enables good visibility of the iris pattern even in the dark, heavily pigmented irides.

4. BIOMETRIC SYSTEM PERFORMANCE ASSESSMENT

4.1 Iris recognition methods

In this study we employ two well known and established, commercially available iris recognition methods, namely: **MIRLIN**[11] from SmartSensors and **VeriEye**[12] from Neurotechnology. The first method, proposed by Monro *et al.*,[13] derives the iris features from zero-crossings of the Discrete Cosine Transform (DCT) calculated for overlapping angular patches of the iris region. This method yields comparison scores in a form of Hamming Distance, thus the output values reach from 0 (a perfect match) to 1 (a perfect non-match, yet a typical score for different irides should be about 0.5, as a score of 1 means that every bit of information is an exact opposite of the corresponding bit in the second image - resulting in a perfect negative). The second algorithm - VeriEye - employs an unpublished feature extraction technology that is only said by the manufacturer to not follow the typical Gabor filtering and approximate the iris and pupil boundaries using non-circular approaches. This method provides a similarity scores between the two samples that are different from MIRLIN, starting with zero for entirely different samples and reaching unknown, higher values when same-eye images are compared. In our experiments the highest similarity value we encountered was 990.

4.2 Enrollment performance

The very first stage of any biometric system is the enrollment. This translates to extracting the feature set from the *iris image*, therefore creating a mathematical representation of these features - the *iris template*. In cases when the template cannot be extracted from the image, a failure-to-enroll error is acknowledged. Calculating the FTE for both algorithms is helpful in assessing the initial performance of the system at the enrollment stage, that is to relate the percentage of samples that failed to provide a valid iris template. See Table 1 for FTEs in respect to algorithms and data acquisition sessions. Obtained values are low and generally in line with what we usually observe for datasets comprising samples obtained in NIR illumination with a dedicated device.

Table 1: Columns 2 and 3 show the number of samples and unique irides in each session. Columns 4 and 5 present FTE rates obtained for each session and each algorithm.

Acquisition session	**Number of irides**	**Number of images**	FTE for MIRLIN	FTE for VeriEye
First	139	1632	1.27%	0%
Second	136	1560	1.12%	0.11%
Total	–	**3192**	–	–

4.3 Matching performance

With iris templates in place, we have employed the two iris recognition methods to generate full comparison score distributions by comparing every possible pair of same-eye and different-eye samples. Each pair of images was used only once, *i.e.,* if sample A from a pair was compared against sample B, then sample B was not compared against sample A, as this would just double the data load without contributing to the shape of the distributions (order of samples can be reversed in both methods and output values would remain the same). Figures 3 and 4 present cumulative distribution functions for same-eye and different-eye comparison scores for session 1 and session 2, respectively.

FNMR[*] values at the acceptance threshold where FMR[†] equals zero (later on referred to as *FNMR@zeroFMR*), *i.e.,* a threshold at which no different-eye images were accepted as genuine, same-eye images, were calculated. *FNMR@zeroFMR* were 2.23% and 5.44% for session 1 data and MIRLIN and VeriEye methods, respectively. EER[‡] values have also been calculated. EER equaled 1.80% for the MIRLIN method and 4.80% for VeriEye.

Figure 4 presents analogous comparison score distributions, but obtained from the samples acquired during the second session of the data collection process. *FNMR@zeroFMR* values were 2.20% and 8.32% for MIRLIN and VeriEye, respectively. Corresponding EER values equaled 1.19% and 7.33%.

4.4 Possible sources of errors

One of the stages of biometric authentication process that are most prone to errors is the iris localization and subsequent image segmentation. If the iris is localized incorrectly, then the encoding that follows will be performed on the data that do not necessarily represent the iris portion of the image, causing the entire

[*]False Non-Match Rate – proportion of incorrectly rejected same-eye samples to the overall number of same-eye comparisons.

[†]False Match Rate – proportion of incorrectly accepted different-eye samples to the overall number of different-eye comparisons.

[‡]Equal Error Rate – quality metric of (any) classification system's performance, defined as a point where FNMR equals FMR.

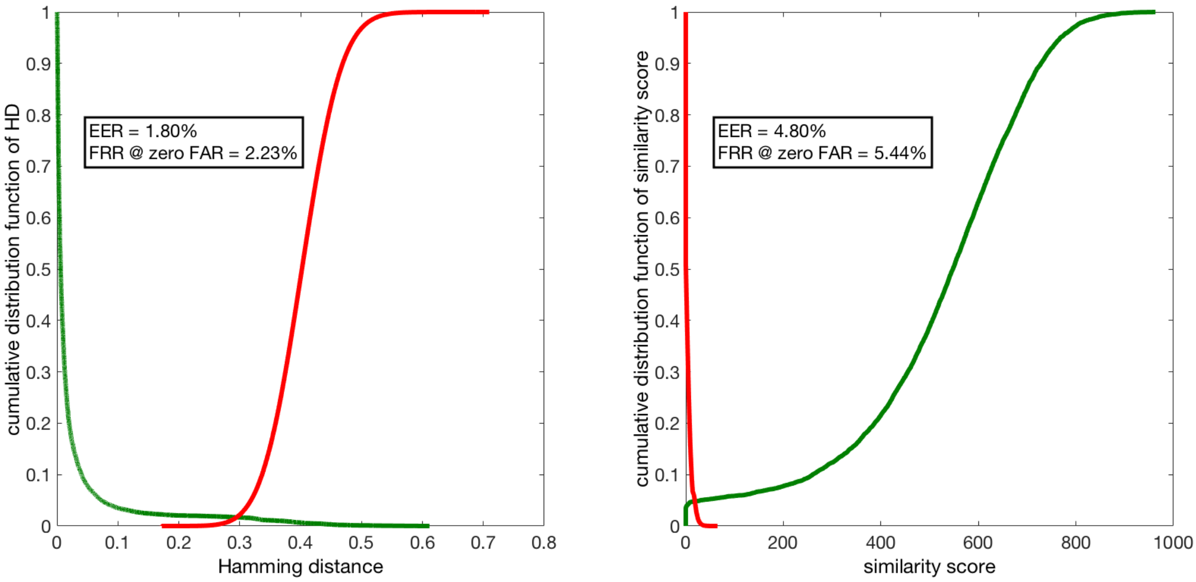

Figure 3: **Left:** cumulative distribution functions for same-eye (green) and different-eye (red) comparison scores obtained from the MIRLIN method and session 1 data. The lower the score, the better the match between two samples. **Right:** analogous distributions, but for the VeriEye method. The higher the score, the better the match.

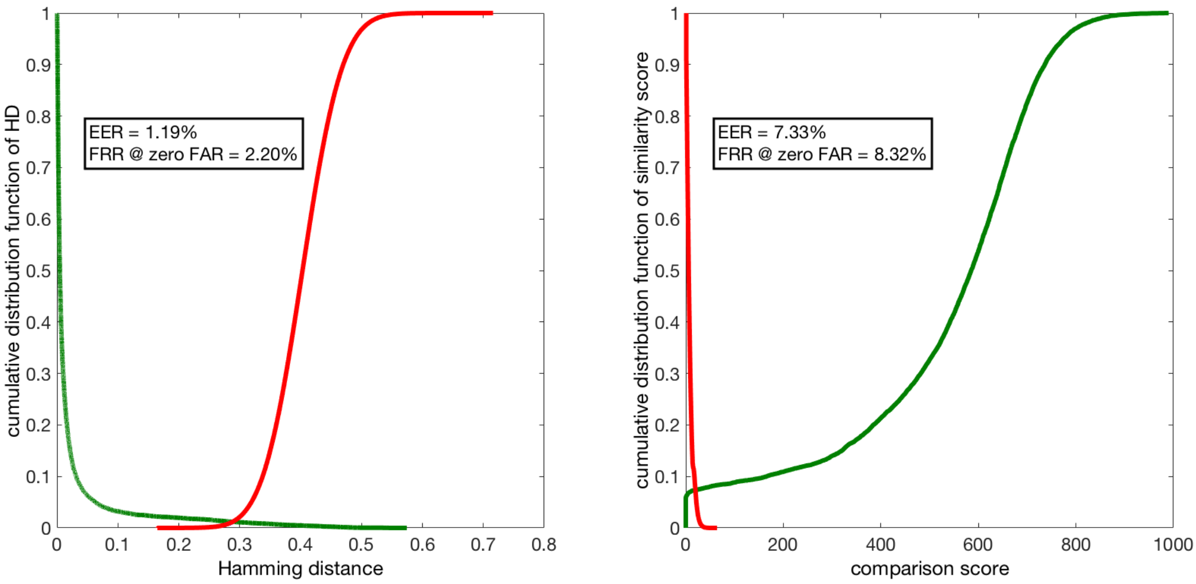

Figure 4: Same as in Figure 3, but for the second acquisition session data.

recognition to produce incorrect results (usually manifested with false rejecting same-eye samples). Thanks to the possibility of printing out the localization results of the MIRLIN algorithm we are able to see if there are images that were incorrectly segmented, and if the answer to that is affirmative, then if these images affect comparison scores in a way that has a potential of degrading the performance of the entire system.

Figure 5 presents different outcomes of the segmentation stage that we have come across, including cases

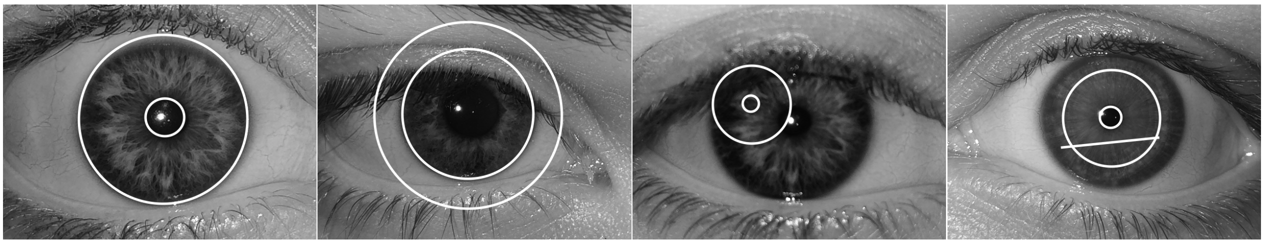

Figure 5: Sample images with denoted results of the iris localization performed by MIRLIN algorithm. First image on the left presents a correctly localized iris. The following three images present irides that were incorrectly localized.

with iris localized incorrectly. There were a total of 64 samples with incorrect localization. To know if these errors are the main cause of non-perfect accuracy of the system, we looked at those parts of comparison score distributions that contain worst scores, *i.e.,* these similarity scores for same-eye samples that were worse than the worst (*e.g.,* lower, for Hamming distance) different-eye score for a given algorithm and dataset. When inspecting the samples we learn that the majority of exceptionally bad scores can be attributed to the iris localization errors, but also to images being blurred (both due to motion blur and out of focus) or having eyelash/eyelid occlusion. This is to be expected, however, still a correct segmentation is confirmed to be a vital part of a successful iris recognition.

5. CONCLUSIONS AND FUTURE WORK

The experiments regarding iris recognition performance conducted in this study managed to provide insight concerning several interesting issues. We have shown that it is perfectly viable to employ a smartphone's camera (provided it is of good quality) for the purpose of iris pattern imaging. Images we acquired are of good quality, and with appropriate image preprocessing allowed us to use two commercially available iris recognition methods with low error rates. The enrollment performance is good, with sample rejection rates of about 1% (yet we managed to even achieve 0% FTE with the VeriEye method and session 1 dataset). We may thus hazard a guess that the enrollment stage is barely affected by the fact that different type of data is deployed to the algorithm instead of typical NIR samples.

We have also managed to get satisfactory results in the matching stage (actually comparing the samples). With *FNMR@zeroFMR* value of a little more than 2% for the MIRLIN method we could expect false rejecting two samples in a hundred, with no false accepted samples, which can be considered a good performance. Moreover, the MIRLIN method yields better results than the competing VeriEye algorithm, which may suggest that it employs technology that is less susceptible to different types of input data, however, the fact that VeriEye's manufacturer does not enable access to the localization results, it is hard to know the underlying reasons of inferior performance given by their method. However, for the MIRLIN matcher such possibility exists, and visual inspection of the samples producing exceptionally bad similarity scores revealed that in most cases the erroneous localization is to blame, and therefore, the encoding and comparing the samples work well most of the time, and it is the image segmentation that needs improvement.

In future work we hope to develop a method that would allow reliable localization of the eye region and automatic cropping of the images to the desired format. This would in turn enable running experiments that would more accurately mimic a real-world deployment scenario and provide more insight on the recognition accuracy and system performance that can actually be achieved. With more data and research we will be able to get closer to answering the fundamental question, that is if we can fulfill the promise of effortless, inexpensive and reliable iris recognition, that can be deployed on any device or platform.

ACKNOWLEDGMENTS

The authors contributed to this study as follows: MT came up with a general idea, devised and conducted the experiments involving iris recognition software and wrote most of the paper; EB and KM participated in

gathering the database, manual image conversion to ISO/IEC format, making charts and plots, performance review; AA contributed to the data collection and writing of the introductory part of the paper; MS conceived a MATLAB script to automate image conversion to the ISO format and contributed to data collection.

Each person who volunteered to participate in the data collection process has been provided with information about the purpose of this study and informed consent has been obtained. The authors would like to thank all participants for their commitment and help with collecting the data.

Study described in this paper is a part of the project realized by the Biometrics Scientific Club at the Warsaw University of Technology in Warsaw, Poland.

REFERENCES

[1] Dobes, M., Machala, L., Tichavsky, P., and Pospisil, J., "Human eye iris recognition using the mutual information," *Optik* **115(9)**, 399–404 (2004).

[2] Proenca, H. and Alexandre, L. A., "UBIRIS: A noisy iris image database," *Technical Report, ISBN: 972-99548-0-1, University of Beira Interior, Portugal* (2005).

[3] Proenca, H., Filipe, S., Santos, R., Oliveira, J., and Alexandre, L. A., "The UBIRIS.v2: A Database of Visible Wavelength Iris Images Captured On-The-Move and At-A-Distance," *IEEE Transactions on Pattern Analysis and Machine Intelligence* **32(8)**, 1529–1535 (2010).

[4] De Marsico, M., Nappi, M., Riccio, D., and Wechsler, H., "Mobile Iris Challenge Evaluation (MICHE)-I, biometric iris dataset and protocols," *Pattern Recognition Letters* **57**, 17–23 (2015).

[5] Raja, K., Raghavendra, R., Cheikh, F., Yang, B., and Busch, C., "Robust Iris Recognition Using Light Field Camera," *The Colour and Visual Computing Symposium 2013, IEEE* (2013).

[6] Raja, K., Raghavendra, R., Vemuri, V., and Busch, C., "Smartphone based visible iris recognition using deep sparse filtering," *Pattern Recognition Letters* (2014).

[7] Radu, P., Sirlantzis, K., Howells, G., Hoque, S., and Deravi, F., "A Colour Iris Recognition System Employing Multiple Classifier T echniques," *Electronic Letters on Computer Vision and Image Analysis* **12(2)**, 54–65 (2013).

[8] Frucci, M., Galdi, C., Nappi, M., Riccio, D., and Sanniti di Baja, G., "IDEM: Iris DEtection on Mobile devices," *22nd International Conference on Pattern Recognition, IEEE* (2014).

[9] De Marsico, M., Galdi, C., Nappi, M., and Riccio, D., "FIRME: Face and Iris Recognition Engagement," *Image and Vision Computing* **32**, 1161–1172 (2014).

[10] ISO/IEC 29794-6, "Information technology – Biometric sample quality - Part 6: Iris image data (FDIS)," (August 2014).

[11] Smart Sensors Ltd., "MIRLIN SDK, v. 2.23," (2013).

[12] Neurotechnology, "VeriEye SDK, v. 4.3," (2012).

[13] Monro, D. M., Rakshit, S., and Zhang, D., "DCT-Based Iris Recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence* **29(4)**, 586–595 (2009).