Iris recognition using low resolution photographs from commodity sensors

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Abstract

Iris recognition can be a useful method of biometric identification in a multitude of applications. Previous research determined that iris recognition can be done using a smartphone camera taking iris photographs in visible light. This research attempts to determine whether iris recognition can be done at a distance using commodity sensors and the difference in matching accuracy between near-infrared light and visible light in this scenario. This is done by taking photographs of the authors' irises up close and at a distance, both with and without an infrared light filter in the camera. Furthermore, a dataset of iris photographs taken with a smartphone was obtained. Blurred copies of some photographs were made to simulate the photograph being taken at a distance and copies were made of these photographs where the red channel was isolated. These photographs were compared using John Daugman's algorithm implemented in Libor Masek's MATLAB code. The photographs of the authors' eyes at a distance did not yield any conclusive results, likely due to the camera or environment being unsuitable for iris recognition at a distance. Other experiments did indicate that near-infrared light is slightly better for matching accuracy.

Keywords: **Iris recogntion, Distance, Near-infrared light, Visible light, Hamming distance**

Contents

1 Introduction

Iris recognition can be both an accurate and convenient method of biometric identification. Since many years, algorithms for iris recognition achieved a very low false-positive rate[1]. Furthermore, iris recognition has some added advantages. For example, the pattern in the iris is an epigenetic trait[2], meaning that it is not influenced by genetics. This allows for biometrics to be used even in situations where there exist multiple people with nearly the same genes such as family or twins. Moreover, it does not require touch like fingerprint identification and hand outline identification do it also does not require the person to be identified to get as close to a scanner as with a retinal scan. Both these qualities can be desirable from a hygiene standpoint or for persons with a certain cultural background. Lastly, the pattern in the iris does not alter much over time[2]. This ensures that the template likely remains valid for much longer than for example in biometrics such as facial recognition.

Commercially, only high-grade sensors are used for iris recognition. Furthermore, these sensors are only used in controlled environments. This makes iris recognition only useful in settings such as access control, where the subject knows to identify itself and actively cooperates herein. In a forensic setting, however, it is much more interesting to identify a person that appears in images where that person does not actively try to identify himself. The first use case one might think of could be to identify suspects, but identification of victims and bystanders could be useful to forensic investigators as well. In modern society, imaging sensors are built into a plethora of devices, such as smartphones and home security systems. The ability of these devices to record images where irises can be recognized could, therefore, be of great value to forensic investigators. This ability is affected by factors such as distance to the camera, which impacts the resolution of the final image, lighting and the specular reflection of ambient light on the cornea and angle of the iris relative to the sensor. These specular reflections should be invisible to a sensor which detects light in the near-infrared wavelength spectrum but either blocks out light in the visible spectrum or records when there is very little light in the visible spectrum present.

This research will focus specifically on the type of lower grade sensors that is ubiquitous in modern society and the distance at which these sensors can still accurately detect irises. Furthermore, it will also assess if images taken in the near-infrared spectrum of light wavelengths are more accurate than images taken in the visible light spectrum. In order to make such assessments, the following research questions should be answered.

1.1 Research Questions

The main research question in this work is as follows:

How does iris recognition perform when presented with photographs taken with low-quality sensors at a distance in near-infrared light as opposed to similar photographs taken in visible light?

To answer this research question, four separate subquestions need to be answered.

- How accurately can irises be recognized in photographs from low-quality sensors taken in the visible light spectrum?

- How does distance to the camera affect the accuracy of iris recognition in photographs from low-quality sensors taken in the visible light spectrum?

- How accurately can irises be recognized in photographs from low-quality sensors taken in the near-infrared spectrum?

- How does distance to the camera affect the accuracy of iris recognition in photographs from a low-quality sensor taken in the near-infrared spectrum?

2 Related work

Daugman [1, 2, 3] has pioneered iris recognition and created a widely used iris recognition algorithm. Later, other algorithms have been developed. These algorithms would be compared to one another like in the work of Hsiung and Mohammed [4] who compared the performance of two iris recognition algorithms in the specific use-case of attendance monitoring. Some researchers attempted to use Artificial Intelligence (AI) for iris recognition, such as the work of Minaee et al. [5] who created a VGGnet based AI for iris recognition. Nguyen et al. [6] attempted a different approach using pre-trained, off-the-shelf components to create a Convolutional Neural Network for iris recognition.

Interest increased in creating algorithms that could do iris recognition in a more difficult environment, such as the work of Zhao and Kumar [7] who created an AI called UniNet for iris recognition based on corresponding features. Uninet was tested on a dataset of iris photographs taken in non-ideal environments. Connaughton et al. [8] researched another aspect of iris recognition, namely the sensors used to capture the photographs. They compared three different iris recognition sensors and used three different iris recognition algorithms to mitigate bias introduced by the algorithm. They concluded that the combination of a sensor and an algorithm should be considered when measuring identification accuracy, as opposed to considering these components individually. Gangwar and Joshi [9] also investigated the sensors, though instead focussed on the compatibility and accuracy of different iris sensors when old sensors are replaced with newer sensors. Liu et al. [10] tested whether photographs of different image quality can be used for iris recognition. Huang et al. [11] investigated whether AI-based image reconstruction of poor quality iris images would improve the recognition accuracy.

Yet other research focussed on specifically commodity sensors, such as the work of Trokielewicz [12] who experimented with iris photographs using the main camera of an iPhone model 5S. He found that algorithms that were created for recognizing irises in photographs taken in the near-infrared spectrum are also suitable to recognize irises in photographs taken in the visible light spectrum. Alonso-Fernandes et al. [13] also experimented on iris recognition using two different smartphone cameras as sensors. They found that when resolution had been artificially reduced, it can be enhanced again using super-resolution to improve the match rate.

3 Methods

3.1 Experiments

To answer the research question, two types of experiments were done for each of the subquestions. One of these experiments involved the author taking photographs of their own eyes at different distances. The other type of experiment involved artificially reducing the resolution and extracting red wavelengths on existing iris photographs to simulate different distances between the subject and the camera and the photo taken in near-infrared light. In total eight experiments were done, with experiments 1 and 2 addressing subquestion 1, experiments 3 and 4 addressing subquestion 2, experiments 5 and 6 addressing subquestion 3 and experiments 7 and 8 addressing subquestion 4.

Table 1 presents an overview of the experiments and their attributes. For experiment 1, the author took five close-up photographs of their own eyes to test their matching accuracy against one another. For experiment 2, five photographs of irises of the same person, taken on the same day, were tested against each other for their matching accuracy. For experiment 3, the author took photographs of their own eyes at ten different distances. These photographs are matched to the close-up photograph of the author's eyes and the matching accuracy is tested. In experiment 4, one photograph per iris was artificially blurred to four different levels. The resulting photographs were then matched to one other iris photograph and the matching accuracy relative to the matching accuracy without blurring was tested. For experiment 5, the red-light-filter of the camera was removed and the same methodology as experiment 1 was be applied. For experiment 6, the photographs of irises were converted to grayscale images using the red channel and the same methodology as experiment 2 was be applied. For experiment 7 the modification of experiment 5 was kept and the methodology of experiment 3 was applied. For experiment 8 the conversion of experiment 6 was applied and the methodology of experiment 4 was followed.

3.2 Materials

The camera chosen for this research is the Trust Spotlight Pro webcam. This camera was chosen because the infrared filter can be removed quite easily. Furthermore, it features a manual focus lens, making it easier for the author to photograph their own irises close-up. Finally, the camera has a resolution of 1.3 megapixels which is comparable to many lower resolution cameras embedded in popular devices such as selfie camera's in smartphones and webcams in laptops. Furthermore, 1.3 megapixels is about the same resolution as a screen capture of a frequently used video quality. During experimentation, however, it did turn out that the photographs were saved in a resolution of 640 x 480 pixels, which amounts to only 0.3 megapixels. It was decided to keep these photographs at

Experiment Number	Sub-research question	Iris photographs	Type of light	Distance
1	1	Author iris photographs	Visible	Close up
2	1	Smartphone iris dataset	Visible	Close up
3	2	Author iris photographs	Visible	Distance
4	2	Smartphone iris dataset	Visible	Simulated distance
5	3	Author iris photographs	Near infrared	Close up
6	3	Smartphone iris dataset	Near infrared	Close up
7	4	Author iris photographs	Near infrared	Distance
8	4	Smartphone iris dataset	Near infrared	Simulated distance

Table 1: Experiments performed in this research

this resolution because this resolution corresponds with the resolution of photographs in the dataset, which is also 640 x 480 pixels.

3.2.1 Dataset

For this research, the Warschau Biobase Smartphone Iris dataset version 1.0 was used[12]. This dataset was chosen because it was taken with the rear camera on an iPhone 5S, which is a popular smartphone which was first introduced to market in 2013 [14]. It can, therefore, be classified as a commodity sensor and fits the goal of this research. This dataset contains iris photographs of both the left and right eye of a test subject, taken up close and with the built-in flash turned on. These photographs are taken in two sessions, with the subjects blinking and looking away between photographs to introduce inter-measurement noise. The amount of photographs varies per eye, per session and person. For this research, only photographs from the first session were used. This is done to reduce the amount of data due to time restrictions. For the experiment without modification to the photograph, only five photographs per eye were used. This also excluded any iris for this experiment if there are less than 5 photographs of it in the dataset. The decision to use an equal amount of pictures was made to prevent differentiation in accuracy levels between irises due to one iris having more photographs available than the other. The number five was chosen as a balance between minimizing test subject exclusion, the sample size for each iris and limiting experimentation time.

3.3 Variables

The up-close photographs of the authors' irises were taken at a distance of around 5 centimetres to ensure that the iris is represented by a large number of pixels, while still retaining a sharp focus on each picture. As with the dataset, the author also looked away and blinked in between photographs to introduce inter-measurement noise. The distances at which the photographs at a distance

are taken increased with 10 centimetres every photograph, with the nearest and furthest distance being 10 centimetres and 100 centimetres respectively. These distances are based on an estimation of how much pixels will represent the iris taking into account the relatively low resolution of the Trust Spotlight Pro camera. The photographs were taken in the middle of the day to control lighting conditions as much as possible, though many aspects of lighting could not be controlled.

3.4 Algorithm and software

The software used in this research is presented in table 2. The experimental environment was set up on a virtual machine, using the Virtualbox software version 5.2.34 for management. The operating system on the virtual machine was Ubuntu 20.04. The software to compare irises does not appear to have an official name, but will from here on be referenced as iris recognition software. It is code written by Libor Masek in the MATLAB environment[15]. The version of the MATLAB environment installed was MATLAB R2020a. For the preparation and transformation of the iris images, ImageMagick version 6.9.10-23 was used. For the iris photographs taken at a distance, the surrounding image was cropped away. The GNU Image Manipulation program version 2.10.20 was used for this.

The iris recognition software works based on the algorithm developed by John Daugman [3]. The createiristemplate.m function, amongst other steps, detects the iris, separates it using a mask and stretches it out according to Daugman's rubber sheet model[3]. It is then encoded to a template, consisting of binary values. The code creates a template of the iris, also referred to as the IrisCode. The gethammingdistance.m function then calculates the Hamming distance of two given templates and masks. The Hamming distance is a measure of how dissimilar the two irises are. Given that it consists of binary values, a theoretical Hamming distance of 0.5 indicates two irises are randomly distant, meaning they likely are not the same iris. Two more similar, or identical irises, will have a lower Hamming distance. The discussion of which Hamming distance merits a positive identification at which confidence level is outside of the scope of this research. Instead, Hamming distances are used as values relative to one another to evaluate matching accuracy. Daugman's results of cross-iris comparison [1] can be kept in mind to estimate which values indicate a match and which values do not.

The blurring was done with ImageMagick, by applying a Gaussian blur to the images. The radius of the gaussian blur was 2 and the sigma was 1 for the first blur. For every subsequent blur both values are doubled, thereby always having a radius that is twice the size of the sigma. The largest blur was that of a radius of 32 and a sigma of 16, though this data was not adopted in the results as on average 71% of these measurements would fail. These values were chosen so that the radius would not limit the blurring and so that the furthest

working simulated distance would be found without generating so much data that it could not be processed due to time constraints. ImageMagick was also used for converting visible light images into the gray colorspace, since the iris recognition software can only take grayscale images as input. The distribution of red, green and blue color channels was kept at default for the images meant to represent images taken in visible light. For the images that were simulated to be taken in the near-infrared spectrum however, only the red color channel used was used for the conversion to the gray colorspace.

Software name	Version number	Distributor
Matlab	R2020a	MathWorks Inc.
Virtualbox	5.2.34	Oracle Corporation
Ubuntu	20.04	Canonical Ltd.
ImageMagick	6.9.10-23	ImageMagick Studio LLC
GNU Image Manipulation Program	2.10.20	The GIMP Team
MATLAB code for iris recognition	-	Libor Masek

Table 2: Software used in this research

		Experiment numbers							
		1	2	3	4	5	6	7	8
Comparison	Left Iris	0	96	0	228	1	49	0	116
error	Right Iris	0	96	0	181	0	32	0	91
IrisCode	Left Iris	0	11	5	11	0	2	22	2
extraction error	Right Iris	0	0	5	10	0	2	29	7
Irises	Left Iris	0	40	0	40	0	0	0	0
omitted	Right Iris	0	40	0	40	0	0	0	0
Initial amount of	Left Iris	10	700	50	700	10	350	50	350
comparisons	Right Iris	10	700	50	700	10	350	50	350
Usable	Left Iris	10	553	45	421	9	299	28	232
measurements	Right Iris	10	564	45	469	10	314	21	258

Table 3: Numbers of errors due to comparisons, numbers of errors due to IrisCode extractions, numbers of comparisons omitted due to lack of photographs, numbers of comparisons planned and the final number of usable measurements obtained for these comparisons taking the failures into account.

4 Results

In the results of experiments performed on the unaltered iris images of the dataset, some entries of the database were omitted as they did not have enough iris photographs taken in that particular session. Therefore, of person 8, 24, 29, and person 62 the left iris was omitted from test results. For person 17, 20, 24 and 29 the right iris is omitted from test results. Since the database contains iris photographs of 70 persons in total, both left and right eye, this results in 66 left irises and 66 right irises. Furthermore, the eye comparison code would fail to detect irises in some images and results for a certain eye of a certain person would not be produced by the script. These results are omitted in calculations such as means and plotting of graphs. At times when the code did successfully extract an IrisCode, it did occasionally return a NaN value instead of a numerical value to represent the Hamming distance. This likely indicates an error in the matching of the two irises, though the exact root cause could not be determined due to time constraints. The frequency of these values and the remaining legitimate values are displayed in table 3. The NaN values are also not included in the calculation such as means nor in the creation of plots. All decimal numbers are rounded down to three digits after the decimal point for readability.

The results of experiment 1 and experiment 5 are presented together in table 4. The values are Hamming distances resulting from the iris comparisons. In these results, we can see that the average Hamming distance is lower for the comparisons done in near-infrared light. However, comparisons of photographs in near-infrared light are not invariably more accurate than comparisons in near-infrared light.

Comparison	Left iris Visible light	Right iris Visible light	Left iris Near-IR light	Right iris Near-IR light
1 - 2	0.498	0.385	0.247	0.497
1 - 3	0.418	0.477	0.369	0.307
1 - 4	0.49	0.503	0.449	0.431
1 - 5	0.477	0.401	0.336	0.336
2 - 3	0.489	0.384	NaN	0.390
2 - 4	0.442	0.396	0.286	0.410
2 - 5	0.222	0.341	0.383	0.479
3 - 4	0.517	0.274	0.455	0.376
3 - 5	0.484	0.369	0.271	0.392
4 - 5	0.464	0.378	0.348	0.470
Average	0.450	0.391	0.349	0.409

Table 4: Results of experiment 1 and experiment 5, five close-up iris photographs of each eye compared to one another.

Figure 1 displays a box-and-whisker plot of the average Hamming distance calculated per iris for both experiment 2 and experiment 4. The top and the bottom line of the box represent the first and the third quartile of these values. The line in the middle of the box represents the median. The caps at the end of the whiskers represent the highest and lowest average Hamming distance found in these experiments, outliers excluded. Outliers are represented as circles, with outliers defined as being more than one and a half times the interquartile range above the third quartile or below the first quartile. The total average of all these measurements in experiment 2 is for the left eye 0,283 and for the right eye 0,299. In experiment 4 the total average of all measurements is 0,268 for the left eye and for the right eye it is 0,291. These averages indicate a slightly lower average Hamming distance for photographs taken in near-infrared light. The box-and-whisker plot seems to support this, with only minute differences between the medians and inter-quartile ranges of comparisons in visible light and the comparisons in near-infrared light.
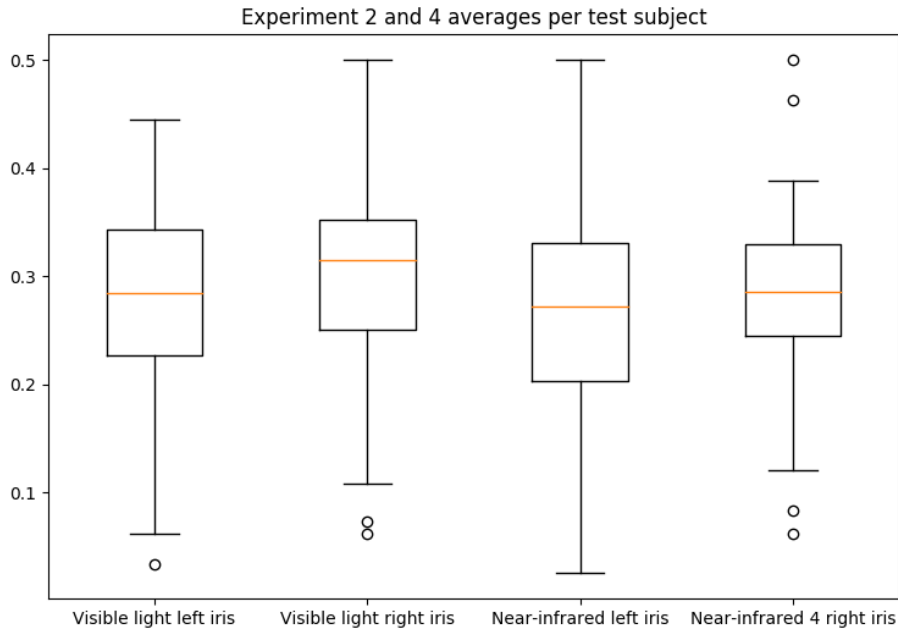
Figure 1: Box-and-whisker plot representing the medians, interquartile ranges and outliers of the averages taken of the 10 comparisons for each iris.

Average result values of experiment 3 and experiment 7 are displayed in table 5. Missing values are due to one of the photographs at a distance failing to be processed by the iris recognition software and therefore all matches to close up photographs failing. In this experiment, we see relatively high Hamming distances, with no clear variance at a greater distance as opposed to a short distance. Hamming distances in comparisons in near-infrared light are slightly higher in most values, though the difference is small.

For experiment 6 and 8, the averages of the Hamming distances in the blurred images are presented in table 6. In these results, we see that the average Hamming distance mostly increases with the level of blurring, save for the comparisons of the right eye in near-infrared light. We also see that the average Hamming distance is generally better for comparisons done in near-infrared light. Finally, we see that in some cases the Hamming distance even decreased at higher levels of blurring in comparisons in near-infrared light. Box-and-whisker plots representing the individual measurements of experiment 6 and 8 are presented in figure 2 for the left iris and figure 3 for the right iris. Again the line in the middle of the box represents the median of the measured Hamming distances and the top and the bottom line of the box represent the third and first quartile respectively. The outliers are represented as circles and defined as more than one and a half times the interquartile range below the first quartile

Distance in cm	Left eye Visible light	Left eye Near-IR light	Right eye Visible light	Right eye Near-IR light	Difference Left eye	Difference Right eye
10	0.433	0.428	0.427		-0.005	
20	0.457	0.404	0.422	0.426	-0.053	0.004
30	0.424		0.410			
40	0.450	0.429	0.455	0.428	-0.021	-0.027
50	0.420	0.439		0.415	0.019	
60			0.420			
70	0.430	0.389	0.432	0.429	-0.043	-0.002
80	0.469		0.440	0.466		0.026
90	0.429	0.404	0.463	0.387	-0.025	-0.075
100	0.478		0.455			

Table 5: Averages of measurement values of self-taken iris photographs taken at a distance when compared with photographs taken close-up. Last two columns indicate the difference between averages of the visible light spectrum and the near-infrared spectrum. Negative numbers indicate a lower Hamming distance in the near-infrared spectrum.

or above the third quartile. These plots do not indicate as clear a trend as the averages do however, with both higher and lower means and interquartile ranges in near-infrared light compared to visible light.

	Average Hamming distance measured			
	Left eye Visible light	Left eye Near-IR light	Right eye Visible light	Right eye Near-IR light
Original	0.259	0.251	0.297	0.286
2x1 blur	0.276	0.264	0.314	0.299
4x2 blur	0.277	0.294	0.293	0.281
8x4 blur	0.315	0.273	0.31	0.289
16x8 blur	0.405	0.355	0.362	0.285

	Average difference between original and blur			
	Left eye Visibile light	Left eye Near-IR light	Right eye Visibile light	Right eye Near-IR light
2x1 blur	-0.002	-0.036	0.008	-0.015
4x2 blur	0.019	-0.049	-0.003	0.011
8x4 blur	0.059	-0.064	0.018	0.003
16x8 blur	0.165	-0.157	0.05	-0.051

Table 6: Average values and differential values of the difference between the Hamming distance of the original comparison and comparison of the blurred image for experiments 6 and 8. In blur values, the first digit indicates the radius and the second digit indicates the sigma of the Gaussian blur.
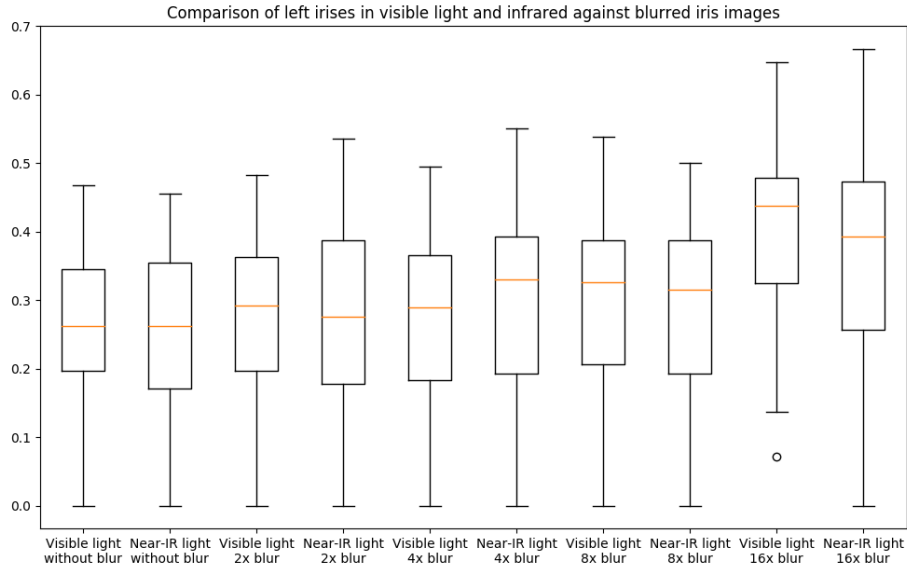

Figure 2: Box-and-whisker plot representing the medians, interquartile ranges and outliers of the Hamming distances in the individual measurements of the left iris in experiment 6.
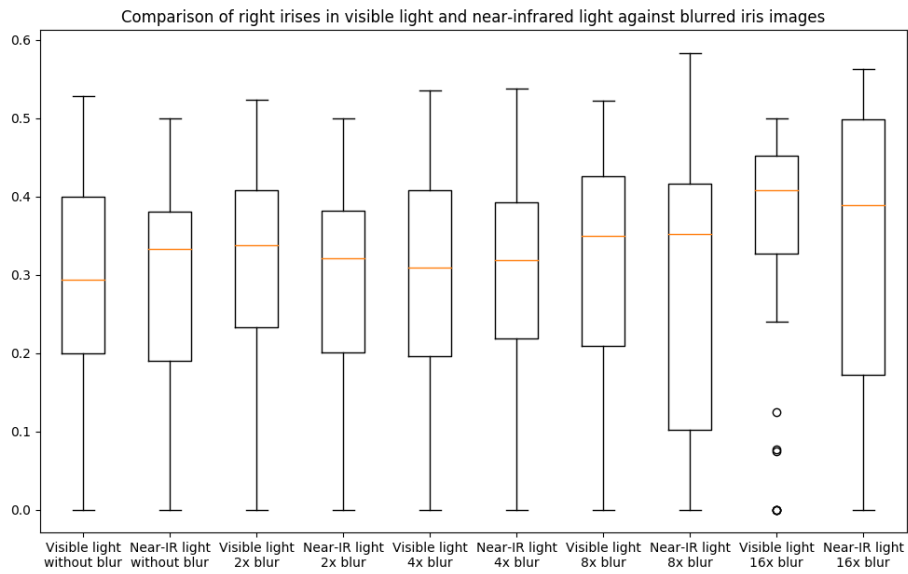
Figure 3: Box-and-whisker plot representing the medians, interquartile ranges and outliers of the Hamming distances in the individual measurements of the left iris in experiment 8.

5 Discussion

As presented in the results, the photographs taken at a distance with the Trust Spotlight Pro had relatively high Hamming distances and these values differed little in relation to the distance at which the photograph was taken. This indicates that this camera in combination with the environment is likely not suitable for iris recognition at a distance. In this experiment the positioning was done so that relatively bright light to the surrounding shone through a window directly into the iris, creating only a specular reflection in the pupil, so it is likely not specular reflection that made this experiment unsuccessful. It could be related to lens quality or possibly the photograph was slightly blurred or the iris was at a slight angle relative to the camera due to the author being both the subject in the photograph and photographer simultaneously. With the knowledge that this experimental set-up is imperfect, we can also infer that the improvement in the Hamming distance in photographs taken at a larger distance is likely due to measurement error. This result was not supported by the similar experiment done on the dataset and the improvement was small enough to infer that it is due to measurement error. Also, knowing that this set-up was unsuitable for iris recognition at a distance, we cannot infer anything about the difference between using Gaussian blur to simulate distance and having physical distance to the subject in photographs.

The experiments of the close-up photographs taken with the Trust Spotlight Pro, the experiments on the dataset and the blurred version of the dataset photographs all seemed to indicate that iris recognition does, in general, yield more favorable Hamming distances. While the sample size of the experiment on the blurred dataset photographs is relatively large, only two specific photographs per iris were used. This decision had been consciously made to reduce the amount of data to process, but more iris photographs compared per iris would have yielded more accurate results. In the case of the photographs taken of the authors' irises, photographs of a larger number of irises would have yielded more accurate results. This was unfortunately not possible since this research was done during a global pandemic which prevented the author from taking iris photographs of volunteers. It should be noted that experiments with greater Gaussian blurs were also planned. However, in the experiment using a Gaussian blur with a radius of 32 and a sigma of 16 around 71% of the measurements failed on average. After reviewing these preliminary results the experiment with even greater Gaussian blur was scrapped due to time considerations. While these measurements are not incorporated into the results of this research, they are a clear indicator that around that level of blurring iris recognition no longer functions.

The accuracy of this research could be impacted by the fact that the used methodology did not allow for fine-grained control over the exact wavelengths of light used to image the irises. Furthermore, while genealogy seems to have little effect on the pattern in the iris, the color of the iris is determined by genet-

ics. Brown eyes get their color from the melanin pigment, but blue eyes do not contain this pigment and get their color from Rayleigh scattering instead[16]. Because near-infrared light excites melanin, the results of this experiment can vary between differently coloured eyes. Therefore it should be noted that the irises of which photographs were used in this research likely come from a very narrow demographic, due to the use of volunteers for a specific research project at one specific, localized institute.

6 Conclusion

While matching accuracy did decrease at further simulated distances, the used iris recognition software can still recognize iris images at a moderate distance. Though depending on desired insult threshold, it could be undesirable to use at longer distances especially when making use of cheaper, lower-quality sensors. Though no exact conclusions can be drawn about the prerequisites of iris recognition at a distance, controlled lightning conditions and a medium quality sensor are likely desired.

The use of red light seems to have a slightly positive effect on average matching accuracy, though not in every individual case was matching accuracy better. A slight absolute decrease of the Hamming distance can contribute greatly to the confidence level of a match though, due to the steepness of the bell curve of random comparisons listed in Daugman's research [1].

The results of the iris comparisons against photographs taken at physical distances resulted in a sample size too small and results too inconsistent to draw any conclusions about the difference between physical distance and simulated distance through Gaussian blur.

6.1 Future work

This research has focused on the accuracy of finding a positive match. Further research could focus on the accuracy of non-matches and how to lower the fraud rate of biometric identification. Both of these aspects are required to accurately do identification based on iris recognition. While this research has been very general, it would be valuable to do further research for a specific use case, where desired insult and fraud rates are known. This way more clarity can be had about what constitutes an accurate recognition for that specific use-case.

Furthermore, this research has been limited by the datasets currently available. Ideally, similar experiments would be repeated with a dataset of iris photographs taken at a distance, in different lighting or of people on the move. While the UBIRIS datasets of the University of Beira Interior[17] do provide this, these photographs are taken with higher quality camera's and therefore cannot provide deeper insight into the usefulness of commodity sensors.

Another interesting avenue of research is to test which wavelengths of red or near-infrared light are best for iris recognition, especially considering the specific iris color of the subject. This information would be very valuable to enable, for example, iris recognition in security cameras, as night vision footage can be supplemented with infrared light.

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