AN ANALYSIS OF INTRINSIC AND EXTRINSIC FACTORS FOR IRIS BIOMETRIC SYSTEMS

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Abstract

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Iris biometric sensors and systems have advanced in complexity and performance as more detailed models of iris appearance are explored by the research community. Current research in iris biometrics works to enhance iris sensors, improve matching algorithms, and accommodate more characteristics of the human iris. However, many intrinsic human and sensor based factors and extrinsic environmental factors affect the advancement of iris biometrics. In this thesis, we examine several types of intrinsic (human and sensor based) and extrinsic (environmental) factors and their effects on iris recognitions. In particular, we study the illumination scheme of the LG IrisAccess 4000 and propose a diffuse illumination system in order to reduce the effects of specular highlights, an intrinsic sensor based factor. We also look at a human based intrinsic factor, eye dominance, as well as an extrinsic factor in the usages of the LG TD 100. Our experiments suggests that eye dominance does affect iris recognition performance, whereas variations in the use of the LG TD 100 does not.
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CHAPTER 1

INTRODUCTION

Iris biometric sensors and systems have advanced in complexity and performance as more detailed models of iris appearance are explored by the research community. The idea of identifying a human based on their iris texture information formally began with a hypothesis from Leonard Flom and Aran Safir [31]. Daugman later confirmed their hypothesis, introducing an iris matching algorithm based on the phase information in a set of texture filtered results. Current research in iris biometrics works to enhance iris sensors, improve matching algorithms, and account for factors reflecting a more sophisticated model of the human iris. However, many intrinsic (human and sensor) factors and extrinsic (environmental) factors potentially affect the advancement of iris biometrics.

1.1 Biometric Systems

A biometric system consists of several components. Given a subject’s iris, images of it must first be acquired by an iris imaging sensor. The subject’s iris can then be either enrolled or compared. Enrollment is the process of storing acquired and processed images in the gallery database. The comparison stage varies depending on whether we are considering a verification or recognition scenario.
1.1.1 Verification

In the verification scenario, a subject presents the biometric system with an identity claim and their biometric data. When using iris as the biometric, a sensor images the subject’s eye to gather the biometric data. The biometric system then retrieves previously enrolled data from the gallery which matches the claimed identification information. This gallery data is then compared to the newly acquired, probe data in a one-to-one match. If the quality of the resulting match is above a specified threshold, the identity claim is confirmed. Otherwise, the identity claim is rejected.

1.1.2 Recognition

In the recognition scenario, a subject does not provide the biometric system with an identity claim; only their biometric data is obtained. A sensor images the subject’s eye in iris recognition and then compares this new probe data with all of the data in the gallery, a one-to-many comparison. After performing all data comparisons, the biometric system uses the best match to identify the person and confirm their existence in the system. If no best match is found, the subject is classified as unknown to the system, and is rejected. This type of recognition system which can reject or identify the subject is called an open system. A recognition system which assumes all subjects who provide data are in the gallery and always assigns an identity for confirmation are called closed systems. All experiments presented in this thesis are performed within the closed recognition scenario.

1.2 Iris Sensors

The first iris images used for biometrics were taken with standard visible light cameras [21]. As the field advanced, it was seen that near-infrared illumination
provided more readily visible texture information on a broader range of light and dark irises [24]. In order to provide this type of illumination and high quality images, both industry and academia are continually working to improve imaging technology. In this thesis, three different sensors which represent the state of the art circa 2010 were used: the LG IrisAccess 4000, the LG TD 100, and IrisGuard AD 100. All of which are depicted in Figure 1.1.

1.2.1 LG IrisAccess 4000

The LG IrisAccess 4000, often referred to as the LG 4000, captures images of both eyes at the same time [40]. It makes use of two clusters of 12 near-infrared light-emitting diode illuminators of varying spectra, discovered partially by reverse engineering, which provide cross and direct illumination of both irises [38]. For acquisition to occur, a subject must be approximately 14 inches away from the sensor, with their eyes centered in the reflective acquisition window. During each acquisition session, multiple sets of iris image pairs were taken acquired.

1.2.2 LG TD 100

The LG TD 100 is a handheld face and dual iris capture sensor [34]. This sensor can also be mounted on a tripod for stationary use. A subject’s eyes must be positioned approximately 13 inches from the sensor and centered in a reflective window. Clusters of light-emitting diodes of multiple wavelengths of near-infrared illumination are used to illuminate the iris. This sensor does not prompt the subject, so during acquisition a human operator provided verbal instructions to the subject, which results in a variable acquisition time. Three sets of images per subject were acquired using this sensor during each acquisition session.
1.2.3 IrisGuard AD100

The IrisGuard AD100 is a dual-eye iris capture sensor which employs direct and cross illumination through the use of two clusters of six near-infrared light-emitting diode illuminators [4][36]. Subjects must be approximately 8 to 12 inches away from the camera for image capture to occur [26]. In the experiments employing the IrisGuard AD100, four images were taken of each eye after one audio prompt of the camera. The firmware for this sensor also aids in the quality of the acquisition process by calculating the amount of motion, measured by the level of activity of the eye, and determining whether each subject is using contact lenses or glasses and adjusts illumination accordingly.

1.3 The Human Eye

After image acquisition occurs, we now have a set of images of size 640 pixels by 480 pixels. These images contain many different features of the eye besides the iris texture data we desire. Figure 1.2 shows a typical iris image with all its parts labeled. The area around the eye is considered the periocular region. Although we
are interested in the iris, other areas of the eye are important to identify in order to achieve the most accurate segmentation of the iris texture.

1.3.1 Iris Segmentation

Many iris matching software packages include a preprocessing method in which the iris is extracted. In all matching algorithms which are later described and used, this is the case. Although each algorithm employs different techniques for segmentation, the basic steps remain the same. First, the pupil boundary and limbic boundary must be found in order to bound the area in which we find iris texture. Points in the iris texture which are occluded must then be identified and masked out. The features which occlude the iris most often are the eyelids, eyelashes, and specular highlights. Then, the masked iris texture is extracted and used to generate
a template. Each algorithm has its own method for iris extraction and creates a template unique to its matching method.

1.4 Iris Matching

Daugman proposed his initial iris matching algorithm in the early 1990s, and his approach has long been the dominant approach to iris matching. Due to the proprietary nature of that work, many algorithms have tried to mimic the general Daugman methodology, but they often differ in some details in comparison to the Daugman implementation. Others have taken original approaches to the problem. In this thesis, three algorithms are used for matching on various data sets: IrisBEE, VeriEye, and MIRLIN.

1.4.1 IrisBEE

IrisBEE is an in-house iris recognition software package based on a Daugman-like approach [41]. IrisBEE reports a normalized fractional Hamming distance for each comparison. Scores are normalized based on the number of bits used in each comparison, and the resulting match scores range from 0 to approximately 1, where 0 represents a perfect match. The scores reported from IrisBEE are symmetric. This means that the score produced by using image A as the gallery image and image B as the probe image is the same as when using image B as the gallery and image B as the probe.

1.4.2 VeriEye

The VeriEye SDK is a commercial package which performs both iris template extraction and matching [54]. We speculate that the VeriEye algorithm uses methods similar to those described in [8] and [7]. VeriEye reports an asymmetric similarity score which ranges from 0 to 9433, where 9433 indicates a perfect match. Asym-
metric scoring means that given a pair of images, VeriEye will produce a different match depending on which image is used as the probe image.

1.4.3 MIRLIN

MIRLIN is a commercial biometrics package, which is believed to be based on the Discrete Cosine Transform method proposed by Monro et al. [51]. However, no specific details regarding the segmentation or matching algorithms are publicly available. MIRLIN outputs a distance score which ranges from 0 to approximately 1, where 0 indicates a perfect match. Scores reported in MIRLIN are asymmetric.

1.5 Iris Recognition Performance

In an iris recognition system there are four possible outcomes - true accept, false accept, true reject, and false reject. A true accept occurs when the system confirms a correct claimed identity. A false accept occurs when the system confirms an incorrect claimed identity. Rather, they matched well against a different subject who was enrolled in the gallery. A true reject occurs when the system rejects an incorrect claimed identity. A false reject occurs when the system rejects a correct claimed identity. The confirmation and rejection of claims is performed by comparing the matchers’ score against a threshold. Modifying the threshold allows false accepts and false rejects to be traded off against one another.

Given a pair of labeled irises, if they are from the same subject and same eye, we call their score a match score. Otherwise, the score is a non-match score. However, in a recognition system, a subject’s identity is unknown. The first step in attempting to determine a subject’s identity in a recognition system is to first generate a representative match and non-match score distribution in which we know the identity of the probe and gallery set. A threshold is then determined in which the number of false accepts and false rejects are minimized. Then given this threshold when a
new probe image enters the system, it is compared to all other images. If a score comparison is found on the match side of the threshold, the system confirms the subjects identity in the system. Otherwise, the subject is rejected.

In order to study the nature of an iris biometric system, receiver operating characteristic (ROC) curves are developed. ROC curves plot the false reject rate against the true accept rate over a range of thresholds. The area under an ROC curve represents a measure of the threshold’s accuracy. A ROC curve with area of 1 indicates a perfect model, whereas a measure of 0.5 indicates a random model. Another metric for studying ROC curves is the equal error rate. The equal error rate of an ROC curve is the point at which the false accept rate is equal to the false reject rate. A lower equal error rates implies a better performing system. A third analysis tool for studying ROC curves is the determination of a true accept rate at a particular false accept rate. In a comparative study, the ROC curve with the largest true accept rate at the fixed false accept rate provides the better performance.

Throughout all the studies presented in the remainder of this thesis, ROC curves along with the determination of a true accept rate at a fixed false accept are used for comparing the performance of various iris recognition experiments. Further, error bars are plotted on the ROC curves. These error bars represent 95% confidence intervals calculated via bootstrapping. In particular, match and non-match scores were subsampled according to their score distributions, and an ROC curve was generated for each of 5000 bootstraps and used to create the error bars. Thus the solid curve actually represents mean ROC results. If two error bars at a particular false accept rate do not overlap, then the difference between the two curves at that false accept rate are said to be statistically significant. However, if the error bars of two curves do overlap, statistical significance cannot be determined without further testing, but the difference is likely not statistically significant. This method
is based up on the technique described by Wu et al. and implemented in house by Thompson [78][33]. By plotting this error, we can provide greater insight on whether performances of different systems or parameter settings can accurately be ordered by a true accept rate given a fixed false accept rate.

Figure 1.3 provides an example of an ROC curve. The bold black line represents the mean ROC results. For simplicity, error bars are excluded from this example. The red dot represents a true accept rate or 0.945 at a false accept rate of 0.001, and red line depicts a high security operating point for a recognition scenario where only one false accept is allowed given 1000 trials. Alternatively, the blue line depicts a more user-friendly operating point in which a 5% false rejection rate is allowed. Further, the blue point represents a true accept rate of 0.950 at a false accept rate of 0.021.

1.6 Outline

The remainder of this thesis explores intrinsic factors of both subjects and sensors as well as extrinsic factors which affect iris recognition performance. Chapter 2 discusses the impact of near infrared illumination on the iris and how diffuse illumination can be used to potentially alleviate these effects. Chapter 3 explores how the usage of a handheld mobile sensor (the LG TD 100) compares to stationary usage. Chapter 4 looks at a subject based intrinsic factor (eye dominance) which has been shown to affect iris recognition. Chapter 5 then provides concluding remarks about intrinsic and extrinsic factors can be used to improve iris recognition.
Figure 1.3. Example ROC Curve displaying two particular points of interest discussed.
Chapter 2

The Impact of Diffuse Illumination on Iris Recognition

Iris imaging for recognition purposes began with visibly illuminated frames from a video stream [21]. Since Daugman’s first iris segmentation and recognition experiments, the field has advanced to using still images, which are illuminated by light sources of various spectra- from visible to near infrared (NIR). Due to the nature of these new illumination systems, standards are now being imposed in order to best protect subjects during acquisition [2]. However, one major artifact of iris illumination which can cause variations in both the segmentation and recognition phases if not handled properly is specular highlighting. In this study we will look at the progression of iris sensors in the last 20 years, and present a new diffuse illumination system for reducing the affects of specular highlights.

2.1 Background and Motivation

2.1.1 A History of Iris Sensors

During Daugman’s initial proof of concept for iris recognition, a standard video camera, lens, frame grabber and single LED illuminator were used to gather iris images [21]. He notes that the illumination he provides is at an angle with the optical axis of the subject’s eye. He finds this to be desirable since it deflects specular reflections from glasses if present, and also eliminates the illuminator’s first Purkinje image which causes distortion, specular highlighting, in the iris texture.
In a later paper by Daugman, near infrared illumination was introduced for iris imaging due to lack of human response to the high frequency illumination [23][24]. Further, he also discusses the use of mirrors to provide the subjects with visual feedback during acquisition, which allowed subjects to better cooperate within a single camera’s field of view for dual eye imaging.

Since this development, several companies and academics have embarked on developing, testing, and advancing iris imaging systems. One of the first alternatives to Daugman’s method was published by Wildes et al [77]. This system was similar to the Daugman model, and a year later Wildes released a survey which compared his model to Daugman’s [76]. A few years later, Negin et al. presented a public and personal iris recognition system using high resolution video from two cameras using infrared illumination [53]. In their system, a low light video camera, lens, frame grabber, diffuse polarized illuminator, and reticle for operator positioning were used to develop an image acquisition rig. As the field advanced, it was seen that the use of NIR illumination provided iris images with enhanced iris texture and was also invisible to humans, decreasing their reaction to the illuminators during acquisition [23]. All the sensors presented in this thesis - LG IrisAccess 4000, LG TD 100, and IrisGuard AD 100 - employ NIR illumination. Even more recently, Venugopalan and Savvides presented an iris imaging system using an out-of-the-box Pan-Tilt-Zoom camera in conjunction with an IR filter in order to study the degree of illumination needed to acquire acceptable recognition results [73]. Their system achieved a 95% recognition rate and they believed the level of illumination could be decreased, an improvement which could be useful for commercial systems.

With all of these iris acquisition systems and algorithms appearing in the field, in 2005 and 2006 a comparative study was presented by NIST, entitled the Iris Challenge Evaluation [60][59]. The goal of this study was to analyze and compare
the results of iris recognition performance from several algorithms using a same sensor dataset. In this study the LG EOU 2200 was used to obtain iris images at several locations [35]. Although the results between the two studies were somewhat contrasting, a baseline for performance was developed, and this dataset continues to be used to test and report results for new and improved iris recognition and verification algorithms, such as in Daugman’s recent work [25]. Other studies which include a comparison of both sensors and algorithms have also appeared since the publication of the ICE studies [28][16][17].

Recently, several modifications have been made to the standard iris imaging system. With the desire to achieve the best iris texture, many have presented multispectral iris systems in order to study iris texture at different levels of infrared illumination [55][13][15][43][67][12]. In these studies, iris images are acquired in light ranging from the visible to infrared. Some of these studies aim to generate new methods for iris encoding using the fusion of various wavelengths [13][15][12][66]. Others aim to gain a better understanding of how iris texture is presented under various conditions in order to handle suboptimal images [43]. Still others are interested in using multispectral iris imaging to study anti-spoofing methods [67]. Most commercial imaging systems do currently employ multiple levels of NIR illumination. Another advancement in iris sensors can be seen in the iris-on-the-move and at-a-distance studies [44][27][75]. Here subjects can be several meters away, walking, or both during the iris imaging process. These types of systems are still being tested and improved due to the increased number of challenges. Other variations to the traditional system such as improved acquisition speed, handheld usage, and system size have also been presented [34][58].
2.1.2 Iris Imaging Safety

Around the year 2000, when iris imaging was moving from the visible spectrum to the near infrared spectrum, eye safety became of extreme importance. Many believe that prolonged exposure to infrared light can cause serious health risks, but no scientific study has shown evidence of these health risks. However, infrared light can produce extreme heats. A common use of infrared light is in lasers, when a concentration of infrared light is used to generate a beam. There are four classes of lasers. Class 1 and 2 are relatively harmless. Class 3 lasers can pose harm to a subject after prolonged exposure, and Class 4 lasers are only currently being used in military applications [56][42].

Initially, light emitting diodes (LEDs) were categorized as lasers when being inspected for safety. In 1997, an article was published which discusses the safety standard imposed upon lasers and why LEDs should be treated as separate entities [1]. Three years later the International Commission on Non-Ionizing Radiation Protection released a statement which updated the safety standards for NIR LEDs [2]. This statement became extremely important to the iris imaging community since the previous standards for imaging systems using such LEDs was subject to the stricter and less applicable laser standards.

Iris imaging safety is still an important topic in the iris biometrics community. The dangers of NIR illumination are continually being discussed and protocols advanced [74]. Corporate developers of iris sensors ensure the safety of their sensor’s users by sending their sensors to testing facilities around the world [38][39]. Academics further ensure their subjects safety when using various wavelengths of NIR illumination by following the ICNIRP standards, and reporting the power of their illuminants to their subjects and the public.
2.1.3 Image Quality and Illumination

Image quality is one of the biggest challenges in iris biometrics. Without high quality images it is more difficult to segment the desired iris texture, and thus to make an accurate iris template. Many surveys of iris biometrics identify illumination as one factor with great impact on image quality [11][37]. Image quality is a function of many factors, such as lighting, but also focus, occlusion, and many other sensor imposed artifacts. The use of NIR illumination has proved advantageous over visible illumination for iris imaging in many ways. NIR illumination produces images with more distinct texture across a larger range of iris pigments, and cannot be perceived by the human eye aiding in the control of pupil dilation. Yet, specular highlights from the illumination still appear within images of the iris.

In this study, we aim to reduce the affects of specular highlights by introducing diffused illumination the LG IrisAccess 4000 sensor. By diffusing the illumination provided by this sensor we hope to reduce the strength and number of specular highlight pixels found within both the pupil and the iris. Through the acquisition process of this new, modified system, we hope to achieve a better iris template by improving the segmentation and increasing the number of unoccluded pixels.

2.2 Hypothesis

Traditional iris illumination, specifically that emitted from the LG IrisAccess 4000, causes specular highlighting both within the pupil and iris in the resulting iris image. This lighting variation is masked in the preprocessing stage, providing fewer pixels for template creation. By removing or reducing these specular highlights, it is thought that a more complete template could be made, improving the matching results from an iris recognition system. In an attempt to reduce these specular highlights we propose an external diffuse illumination system. To determine if iris
recognition performance is enhanced by this diffuse illumination system, we will examine whether specular highlights were reduced and examine matching results obtained by several iris matching algorithms.

2.3 Designing a Diffuse NIR System

In this study, the LG IrisAccess 4000 was chosen as the sensor to alter due to the level of knowledge about the sensor, the number of sensors available to us, as well as the number of studies performed using it. Figure 2.1 shows the location of four basic hardware components of interest. The two visible LED components are not strong enough to cause an effect in the eye during acquisition if turned on. Additionally, the camera employed by this system filters for near infrared illumination such that affects of ambient illumination are reduced. The proximity sensors do not emit any visible or infrared illumination, but rather emit and receive a wavelength which determines the location of the subject which is attempting to be acquired, as diagrammed in the lower left of Figure 2.2. Figure 2.2 also shows a breakdown of the NIR LED clusters. The LG IrisAccess 4000 uses 12 NIR LEDs on both the left and right side of the sensor. 5 of the LEDs on each side, closest to the center of the sensor, are placed perpendicular to the surface of the sensor, and are used for direct illumination of the iris. The other 7 LEDs are placed at an angle, and are used for cross illumination of the iris. Both 770 nm and 870 nm of NIR illumination is used in order to achieve the desired level of iris texture for various ranges in iris coloring [38]. Given the particular sensor used, the wavelength intensities of a single cluster of 770 nm and 870 nm LEDs is shown in Figure 2.3 through the use of a spectrometer. The peaks of these readings are not perfectly centered at the desired wavelength. This is due to the nature of LED manufacturing.

The original configuration of the LG IrisAccess 4000 places a tinted plate of glass
Figure 2.1. Components of the LG IrisAccess 4000.

Figure 2.2. Further breakdown of the components of the LG IrisAccess 4000.
Figure 2.3. Spectrometer reading of LEDs from the LG IrisAccess 4000.
in front each LED cluster. In order to diffuse the produced illumination, a set of
diffusing lenses produced by Edmund Optics were purchased and positioned carefully
in front of the LED clusters on the outside of the sensor [3]. These lenses are 25
mm circular cuts of sandblasted glass, all with a transmission efficiency greater than
85%. Three levels of diffusion were used in this study, 20 degree, 25,and 30, based
on a previous smaller study. The level of diffusion describes at what angle light
entering perpendicular to the lens will leave after passing through. Additionally,
each lens diffuses light in a spectral range from 400 nm to 1600 nm, thus covering
the NIR spectrum provided by the sensor.

In order to create our diffuse illumination system, a set of two lenses of the same
degree of diffusion were used. Clips secured by a base were used to position and hold
the lenses in place over each LED cluster. Figure 2.4 depicts the diffuse illumination
setup. The lenses are placed several inches away from each other’s center, and at a 10
degree angle towards the center of the sensor. By placing them at this location and
angle we assured that all illuminators were covered and that both direct and cross
illumination were effected without compromising the proximity sensors. During the
acquisition process, an unaltered LG IrisAccess 4000 was used to acquire images of
a subject’s irises first, followed by images of the same irises using a separate LG
IrisAccess 400 with the diffuse illumination system in order to best compare the two
systems.

2.4 Dataset

The data collected using the unaltered LG IrisAccess 4000, labeled as the tra-
ditional data or subjects in the remained of this study, and the diffuse illumination
system, was gathered over 6 months from November 2010 to April 2011. Each set
of illuminators was used in two different sessions, which extended over a period of
Figure 2.4. Diffuse Illumination System Setup Diagram.
three days. The positioning of the lenses was checked periodically to ensure consistency in the altered diffuse illumination system. Table 2.1 describes the breakdown of images and subjects per session across the entirety of the study. A noticeable variation is found in the lack of images and subjects between the diffuse and traditional categories for session 4. This was due to a loss of one day’s worth of data due to technical errors. Other, smaller variations between the number of images and subjects between the two categories are due to failures to enroll with a particular sensor. In all cases, the diffuse illumination system has somewhat smaller image counts, which can be attributed to a possible disruption in proximity due to small movements in the diffusing lenses.

Figure 2.5 shows images from the different acquisition scenarios. The top row shows the traditional illumination results. As you go down the rows, the level of diffuse illumination increases from 20 to 25 to 30. By visual inspection one may notice various differences. For instance, as you increase the level of diffusion the contrast in the images appears darker. Additionally, the diffused images often have more padding, the gray borders, along the sides of the image. This is due to how

### Table 2.1

<table>
<thead>
<tr>
<th>Session Number</th>
<th>Degree of Diffusion</th>
<th>Number of Diffused Images</th>
<th>Number of Traditional Images</th>
<th>Number of Diffused Subjects</th>
<th>Number of Traditional Subjects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Session 1</td>
<td>25°</td>
<td>1106</td>
<td>1095</td>
<td>287</td>
<td>287</td>
</tr>
<tr>
<td>Session 2</td>
<td>30°</td>
<td>1230</td>
<td>1835</td>
<td>287</td>
<td>339</td>
</tr>
<tr>
<td>Session 3</td>
<td>30°</td>
<td>1122</td>
<td>1703</td>
<td>234</td>
<td>208</td>
</tr>
<tr>
<td>Session 4</td>
<td>20°</td>
<td>702</td>
<td>1624</td>
<td>90</td>
<td>205</td>
</tr>
<tr>
<td>Session 5</td>
<td>20°</td>
<td>1999</td>
<td>1999</td>
<td>251</td>
<td>252</td>
</tr>
<tr>
<td>Session 6</td>
<td>25°</td>
<td>1897</td>
<td>1918</td>
<td>239</td>
<td>242</td>
</tr>
</tbody>
</table>
Figure 2.5. Right (a) and Left (b) eyes from traditional illumination. Right (c) and Left (d) eyes from 20 degrees of diffuse illumination. Right (e) and Left (f) eyes from 25 degrees of diffuse illumination. Right (g) and Left (h) eyes from 30 degrees of diffusion. All images are from subject 06005 across various sessions.
the sensor zooms and crops the image during the acquisition process to assure the correct size and average iris area in each image. These, and other quality variations, will be critically examined in the results of this study.

2.5 Diffuse Illumination and the Reduction of Specular Highlights

There are two types of specular highlighting of interest here: highlights within the pupil and highlights within the iris. By reducing specular highlights within the pupil, particularly highlights close to the pupillary boundary, we can improve pupil detection and segmentation. Similarly, by reducing specular highlights near the scleral boundary we may improve the accuracy of the boundary detected between the iris and sclera. Additionally, by reducing the specular highlights in the iris we may reduce the number of masked pixels, potentially improving the template created by an image segmenting and matching algorithm.

2.5.1 Within the Pupil

In order to determine whether specular highlighting was reduced within the pupil, average histograms of all pupils were generated. Specifically, the segmentation information provided by the IrisBEE preprocessing stage was used to examine the pixel data from inside the pupil. These pixel intensities were found for each image category per week, and plotted in a normalized histogram for comparison. Figure 2.6 show the resulting histograms from the traditional and diffuse illumination systems per session. The x-axis of this histograms represents pupil intensity, where 0 is black, and 255 is white. In the traditional illumination histograms, almost all of the histograms are centered around 50, with a small peak around 125, and larger peak at 255. Comparatively, in the diffused illumination histograms the largest peak is centered to the left of 50, no peak is found around 125, but a peak is still seen at 255. These peaks at 255 represent the strength of the specular highlight. The small
peaks at 125 in the traditional histograms represents the halo around the strongest point of the specular highlight. The fact that this type of peak is not present in the diffused illumination pupil histograms proves that the effect of specular highlighting has been reduced. Further, the largest peak being shifted to the left in the diffused illumination graph speaks to the fact that the contrast is darker in the diffused images, making the pixel intensities in the pupil, and over all the image, shifted closer to zero.

2.5.2 Within the Iris

To analyze the resulting specular highlights within the iris texture, connected components were used to describe highlight regions’ pixels. Using the segmentation information provided by the IrisBEE preprocessor, the iris region alone was extracted from each image. A histogram of all the pixels in this region was then developed. The top 3% of pixels closest to white were considered to fall around a
specular highlight component. A mask of only these pixels was then used to determine connected components of an appropriate size which best described the specular highlights. Components which were too large were excluded since this often is descriptive of eyelid and eyelash occlusion. In contrast, regions which were too small were eliminated since these may describe the iris texture. Many iris recognition algorithms provide their own methods for segmentation and masking occlusion and specular highlights. Since IrisBEE’s preprocessing information was used, our results were compared to the results of IrisBEE’s segmentation and masking. Figure 2.7 shows an image which compares our specular highlight detection in blue and IrisBEE’s detection in yellow. In order to ensure that none of the specular highlight is included when filtering the resulting iris region, the masked bits are subjected to an additional dilation step in IrisBEE. Thus our results appear smaller, but are more accurately describing only the specular highlight.

Figure 2.8 (a) shows a comparison in the number of connected components found during diffuse illumination acquisition compared to the number of connected components found during traditional acquisition. The means in these boxplots are all maintained around two. This is due to the illumination pattern placed on the eye which often causes highlights at the extreme top and bottom of the iris from reflections off the eyelid. Other specular highlights can often be found on the pupillary boundary and elsewhere throughout the iris. Some specular highlights can even be caused by reflections off the nose. Although we appear to not be reducing the number of specular highlight components, we are not increasing them on average when using diffuse illumination. The increase in standard deviation is most likely due to differences in contrast.

In Figure 2.8 (b), we further illustrate the impact of specular highlights in the iris region by comparing the number of pixels found which describe a specular highlight.
Figure 2.7. Sample eye image with overlaid specular highlight detection.
Figure 2.8. Traditional Iris and Diffused Iris Specular Highlight boxplots. Here 20, 25, and 30 refer to degrees of diffusion used for the represented subset of data. Similarly, LG refers to a traditionally illuminated subset of data. (a) Shows the number of specular highlight connected components were found within the iris. (b) Shows the sum of the area these components occupied within the iris.
The average area consumed by specular highlights within the iris region for all cases is around 125 pixels. Again we find the means statistically the same between traditional and diffuses data, such that mean of the diffuse data falls within one standard deviation of the traditional data. This is consistent with the number of specular highlights found. However, it does seem that we are not reducing the impact of specular highlights as much within the iris as within the pupil when using diffuse illumination. Testing in a recognition scenario will further explore the results of our diffuse illumination system.

2.6 Effects of Diffuse Illumination on Iris Recognition

Since each algorithm available for use employs a different segmentation and matching method, each was used to analyze the results of the diffuse illumination system. In particular, given the diffuse and traditional dataset, for each algorithm, templates were made and three different types of experiments were performed. In the first experiment, the probe and gallery sets contained images acquired from the diffuse illumination system. Similarly, in the second experiment, the probe and gallery sets contained images acquired from the unaltered LG IrisAccess 4000. The third type of experiment used the traditional LG IrisAccess 4000 images as the gallery and the diffuse images as the probe set. Due to the fact that two of the matching algorithms provide asymmetric scoring, in the experiments which compare the same type of illumination, the older of the two image sets was used as the gallery set.

2.6.1 MIRLIN

2.6.1.1 Performance Results

Figure 2.9 shows ROC curves for the three types of experiments performed on the diffuse and traditionally illuminated data. Each experiment is labeled such
that Session XvY implies that images from Session X formed the gallery set and images from Session Y formed the probe set. The top figure shows comparisons performed within a single session between diffuse illumination images and traditional illumination images. All six experiments have mean ROC results between a true accept rate of 0.985 and 0.975 at a false accept rate of 0.002. Further, all error bars are overlapping. Thus it is unlikely that these experiments are statistically significant from one another. Hence, it appears that all experiments at different levels of diffusion perform about the same.

Figure 2.9 (b) shows comparisons between similar illumination schemes, where the traditional illumination schemes were further broken down into the same session comparison as the corresponding diffuse illumination experiments. Here we see the traditional illumination experiments collected above a cluster of diffuse illumination experiments. Within the group of the traditional illumination experiments, comparisons from Sessions 1v6 and Sessions 4v5 have a similar mean ROC as well as overlapping error bars. However, the comparisons from Sessions 2v3 have a greater mean ROC and do not have error bars which overlap any other experiment. This variation could be due to the DCT method potentially employed by MIRLIN, which cuts off curtain frequencies which may be of interest in the diffused but not traditionally illuminated images. In contrast, the diffuse illumination experiments have mean ROC true accept rates between 0.965 and 0.95 at a false accept rate of 0.002 and all error bars overlap all other error bars. Thus, these results are likely not statistically significantly different from one another. Figure 2.9 (c) further elaborates this results. Namely, that traditional illumination statistically significantly outperforms all the diffuse illumination experiments and that the diffuse illumination experiments perform at approximately the same recognition rate.
Figure 2.9. Bootstrapped MIRLIN ROC Curves representing results from (a) comparisons from traditional to diffuse illumination images from the same session, (b) comparisons from same degree of diffusion across sessions and traditional illumination comparisons from the corresponding diffuse comparison sessions, and (c) comparisons from same degree of diffusion and all traditional illumination data.
2.6.1.2 Quality Analysis

In order to determine the cause of these recognition results, several quality metrics outputted by MIRLIN were analyzed. MIRLIN provides the user with a sharpness measure, contrast measure, average image gray level, saturation level, occlusion percentage, and signal-to-noise ratio. Figure 2.10 depicts boxplots of the occlusions percentage and sharpness measure for both the traditionally illuminated and diffuse illuminated image sets. When comparing the occlusion percentage per image on both data subsets, the diffuse illumination set consistently shows lower levels of occlusion, implying a larger number of usable iris code bits. However, the mean of the diffuse illumination set is within a standard deviation of the traditional illumination set for each comparison, and is thus likely not significant.

The same type of comparison for the sharpness measure as reported by MIRLIN is reported in Figure 2.10 (b). The sharpness of an image describes the clarity of the details within the image and can be defined by the boundaries between different areas of shades or colors. There are several ways to calculate this measure, and the method employed by MIRLIN is unknown. However, it is known that larger values of sharpness provide a "sharper" and more desirable image. When comparing our diffuse data to the traditionally illuminated data we find the mean sharpness value for all diffuse data falls outside of one standard deviation of the corresponding traditional data distribution. Thus these value are statistically different from one another. Further, the mean sharpness value for the diffuse data falls below the mean saturation value found for the traditional data, implying the images captured by the diffuse illumination system are less sharp. The lack in sharpness here could be a affected by the variation in contrast between the diffuse and traditional data, causing MIRLIN to find the diffuse data of a lower quality.

Given these metrics, it can be determined that although the diffuse illumination
Occlusion Percentage for LG 4000 and Diffused Images (According to MIRLIN)

Note: Smaller Values are Better

Sharpness Measure for LG 4000 and Diffused Images (According to MIRLIN)

Note: Larger Values are Better

Figure 2.10. (a) Occlusion Percentage and (b) Sharpness Measure for each data subset as reported by MIRLIN.
data provides MIRLIN with more iris pixels to create templates, a better quality image is not necessarily achieved. Due to variations in sharpness, potentially caused by differences in contrast, the traditional images appear to provide a higher quality image than the diffuse images, allowing for potentially better match comparisons. Therefore, diffuse illumination does not improve iris recognition when using the MIRLIN segmentation, template creation, and recognition algorithms.

2.6.2 VeriEye

2.6.2.1 Performance Results

VeriEye is the second iris segmentation and matching algorithm used to analyze the recognition rate of diffuse and traditionally illuminated iris data. Figure 2.11 shows the results for each comparison experiment. The top figure depicts the results from comparing each week’s traditional illumination data to the diffuse illuminated data. Considering only the mean ROC curves, without error bars, it appears that when comparing 25 degrees of diffusion to traditionally illuminated images the best results are seen given a false accept rate of 0.002. 30 degrees of diffusion then follows, with 20 degrees of diffusion comparisons at the lowest recognition rate. However, the error bars of all experiments overlap three or more other experiments, reducing the likelihood that these results are statistically significantly different from one another.

Figure 2.11 (b) depicts the results of same illumination scheme comparisons by week. Considering only the diffuse illumination system experiments mean ROC results at false accept rate of 0.002, 25 degrees of diffusion performs the best, followed by 30 degrees of diffusion, and finally 20 degrees of diffusion. These results agree nicely with those from the initial same session experiments. Yet, the errors bars of the diffuse illumination experiments overlap, reducing the likelihood of a statistically significant difference. When looking at the traditionally illumination comparison results, we find that two ROC curves perform almost perfectly, but the traditional
Sessions 4v5 experiment performs with a true accept rate of about 0.999 at a false accept rate of 0.002. Sessions 1v6 and Sessions 2v3 have errors bars which overlap with one another, but no other experiments. However, Sessions 4v5 performs about as well as 25 degrees of diffusion with error bars that completely overlap.

To better study the relationship between degrees of diffusion and traditional illumination, the bottom graphic in Figure 2.11 shows the combined recognition results of the traditionally illuminated dataset. Here we more clearly see that the traditionally illuminated experiment outperformed all of the diffuse illumination experiments. However, the error bars of the traditionally illuminated experiment results somewhat overlap the 25 and 30 degrees of diffusion ROC results. Thus, diffuse illumination does not appear to improve the recognition results of the LG IrisAccess 4000 when using VeriEye for segmentation and matching.

2.6.2.2 Quality Analysis

As an investigation into the reason behind the slightly decreased results when using diffuse illumination, several quality metrics provided by VeriEye were studied. VeriEye provides a list of quality metrics as output including gray level spread, iris scleral contrast, iris pupil contrast, interlace, sharpness, and signal-to-noise ratio. A generalized quality score is also provided. Figure 2.12 shows the distribution of signal-to-noise ratio for each dataset per week as well as reports the generalized quality score. In Figure ?? (a), all the traditionally illuminated datasets have higher mean signal-to-noise ratios than that of all the diffused illumination datasets from the same session. These results are statistically significant since the mean value of the diffuse illumination data, when compared to the traditional illumination data, falls outside of the standard deviation limiting bars.

Figure 2.12 (b) depicts the results of VeriEye’s generalized quality metric. When
Figure 2.11. Bootstrapped VeriEye ROC Curves representing results from (a) comparisons from traditional to diffuse illumination images from the same session, (b) comparisons from same degree of diffusion across sessions and traditional illumination comparisons from the corresponding diffuse comparison sessions, and (c) comparisons from the same from same degree of diffusion and all traditional illumination data.
Figure 2.12. (a) Signal-to-Noise Ratio and (b) Quality Measure for each data subset as reported by VeriEye.
studying VeriEye’s quality scoring it is important to note that larger quality values are better. When comparing the quality metrics between datasets of the traditional and diffuse illuminated data, the traditional images have overall better quality than the diffuse illumination images. Both of these results are reasonable implications as to why the LG IrisAccess 4000 traditional comparisons outperform the diffuse illumination system when using VeriEye.

2.6.3 IrisBEE

2.6.3.1 Performance Results

The final algorithm used to study our diffuse illumination system is the in-house algorithm IrisBEE. Figure 2.13 shows the results of the IrisBEE system for this study. Figure 2.13 (a) shows the experimental results of same session traditional to diffuse illumination comparisons. These ROC results are less conclusive than that of the commercial algorithms. The sessions that use 30 degrees of diffusion cluster well, with a true accept rate of 0.98 at a false accept rate of 0.002. However, one of the sessions for both 20 and 25 degrees of diffusion fall above this cluster while the other falls below, providing a less conclusive ordering of traditional to diffuse illumination comparisons.

Figure 2.13 (b) depicts same illumination comparisons by session. When looking at the mean ROC results alone, at a false accept rate of 0.002, 20 degrees of diffusion performs the best, followed by 30 degrees of diffusion, 25 degrees of diffusion, then all the traditionally illuminated experiments. To more clearly analyze these results, the bottom figure shows the combination of the traditionally illuminated comparisons. Here, all of the diffuse illumination experiments outperform the traditional illumination experiment. Further, the traditional illumination ROC curves’ error bars only overlap 25 degrees of diffusion before around a 0.0035 false accept rate. This shows that the diffuse illumination system, regardless of degree of diffu-
sion, likely statistically significantly outperforms the traditional LG IrisAccess 4000. However in contrast, the diffuse illumination experiments all have overlapping error bars, reducing the likelihood of statistical significance between degrees of diffusion.

2.6.3.2 Quality Analysis

Since IrisBEE is an in-house segmentation and matching algorithm, we can extract many more meaningful quality metrics. The first two metrics we explored were dilation ratio and external padding. In Figure 2.14 (a) we look at the dilation ratio of traditional and diffuse illumination data by session. By looking at this data we can ensure that the illumination projected onto the eye has no effect on pupil dilation. This is in fact the case, since the mean and standard deviation of each dataset are approximately the same. Figure 2.14 (b) then shows the percentage of padding within an image for each dataset per session. There is a wide variation in the results shown within this set of boxplots. In Session 1 and Session 2 we see three subsets of data which have significantly higher mean values and larger standard deviations than the remainder of the results. This is due to a change in acquisition software. These variations in padding provide us with some insight into the reasoning for a lack of clustering in the same session traditional to diffuse illumination experiments.

Additionally, IrisBEE provides as output the number of bits used when comparing two templates. Figure 2.15 shows the number of bits used during a match, and in contrast for a nonmatch, for both diffuse and traditional illumination systems. In Figure 2.15 (a), we see that the mean number of bits matched for 20 and 25 degrees of diffusion are slightly above the means for traditional illumination, whereas 30 degrees of diffusion has approximately the same mean number of matching bits as traditional illumination. However, the mean falls within one standard deviation of traditional illumination for all cases, and is thus not statistically significant. The
Figure 2.13. Bootstrapped IrisBEE ROC Curves representing results from (a) comparisons from traditional to diffuse illumination images from the same session, (b) comparisons from same degree of diffusion across sessions and traditional illumination comparisons from the corresponding diffuse comparison sessions, and (c) comparisons from the same from same degree of diffusion and all traditional illumination data.
Figure 2.14. (a) Dilation Ratio and (b) Padding Percentage for each data subset as reported by IrisBEE
same observation can be made for nonmatch comparisons in Figure 2.15 (b). Thus, even though we are increasing the average number of bits available for comparison on average when using diffuse illumination, and improvements are seen in both matches and nonmatches, these results are not statistically significantly different from those results from traditional illumination comparisons.

2.7 Effects of Direct and Cross Illumination on Iris Recognition

An additional area of exploration provided by this study is the effect of direct and cross illumination on iris recognition. Several sensors available for iris imaging provide more than one illumination pattern during acquisition. For example, the LG IrisAccess 4000 used in this study provides both direct and cross illumination using different combinations of NIR LEDs. In order to analyze whether the diffusing lenses affected direct and cross illumination in a similar fashion, the two illumination patterns were separated into two subsets. Unfortunately, due to a software upgrade which occurred in the middle of the acquisition process of this study, this could only be done for 20 degrees of diffusion and traditional illumination. During each acquisition, 8 sets of images of a subjects eyes were taken - 4 images of the right eye directly illuminated, 4 images of the right eye cross illuminated, 4 images of the left eye directly illuminated, and 4 images of the left eye cross illuminated.

ROC curves were then generated to study these results as shown in Figure 2.16. Since no error bars overlap when comparing either the 20 degrees of diffusion direct to cross illumination and the traditional direct to cross illumination, we can say that direct illumination is statistically significantly different from cross illumination. Further since the mean ROC curves for both direct illumination studies are above both cross illumination mean ROC curves, we can say that direct illumination outperforms cross illumination in both the traditional and diffuse illumination...
systems. Additionally, as expected, the experiment which considers both direct and cross illuminated images falls between the direct and cross illumination ROC curves in both instances. However, the error bars of these baseline experiments overlap with the error bars of the respective cross illumination experiments, but not those of the respective direct illumination experiments. Thus, although the baseline is statistically significantly different from the direct illumination experiment, we cannot say that the baseline and cross illumination are statistically significant from one another.

In spite of the lack of diffuse data, this experiment has showed us that both direct and cross illumination act in a similar fashion regardless of diffusion or traditional illumination settings. Yet, it is interesting that direct illumination so clearly outperforms cross illumination, begging the question of why cross illumination is provided. This problem requires more investigation in the future. One speculation is that cross illumination may move highlighting caused by glasses away from the iris.

2.8 Conclusions

This study set out to accomplish three goals - (1) develop a diffuse illumination system based on an existing system, (2) determine if diffuse illumination can reduce specular highlights, and (3) analyze whether diffusion can aid in iris recognition. In our diffuse illumination system, we use various levels of external diffusing lenses in order to diffuse the illumination emitted by the LG IrisAccess 4000. By then analyzing the specular highlights within in the pupil and iris, we determined that we were successful in diffusing the illumination with this system. Additionally, the specular highlights from the pupil appear less prominent, allowing for the probability of increased segmentation accuracy and stronger template generation.
Given the creation of a diffuse illumination system based on the LG IrisAccess 4000 with reduced specular highlighting, various matching algorithms were then used to study the resulting diffused image templates. Some matchers showed no or little improvement when using diffuse illumination, as shown in the MIRLIN and VeriEye results. However, when using the Daugman-style IrisBEE matcher, particular levels of diffusion showed statistically significant improvement over the traditional illumination system. Several quality metrics were studied for each matcher to further explain these variations in iris recognition performance.

In conclusion, we have seen how a manufactured intrinsic factor (a sensor’s illumination scheme) can be positively affected by an external factor (diffuse lenses). Although not all matchers used in this study showed improved performance, the reduction of specular highlights should prove to be beneficial for any segmentation algorithm.

2.9 Potential Future Works

We hope this study is in the future considered when manufacturing new and updated iris sensors. A more extensive study could show the exact level of diffusion that should be used for a particular illumination scheme, which one could then internally integrate into the system. Further, one could then show how this new type of system affects various segmentation algorithms due to the reduction of specular highlights.
Figure 2.15. Boxplots showing the number of bits used for comparing (a) Match Pairs and (b) Nonmatch Pairs as reported by IrisBEE.
Figure 2.16. (a) Match Score Distribution and (b) ROC Curves for Direct, Cross, and Combined Illumination schemes for the LG IrisAccess 4000
CHAPTER 3

EFFECTS OF DOMINANCE AND LATERALITY ON IRIS RECOGNITION

Eye dominance, the tendency to prefer to process visual input from one eye over the other, is a little discussed topic in iris biometrics. In previous studies, it has been shown that one eye often has improved performance over the other. One possible cause of this variation in performance could be due to the distribution of eye dominance among the subject population. In the following study, we explore the effects of eye dominance on an iris recognition system. We also show how eye dominance can be used to guide the development of a single-eye recognition system. A preliminary exploration of laterality, specifically the correlation between eyedness and handedness, is also presented.

3.1 Background and Motivations

Eye or ocular dominance, often referred to as eyedness, is the tendency to prefer to process visual input from one eye, the dominant eye, over the other, the nondominant eye. It has been seen that about 67% of the population is right eye dominant, and the other 33% of the population is left eye dominant [29][10][62]. The relationship of eyedness to other dominant features of a person, such as handedness, is a frequently discussed topic in the psychology and medical fields. This relationship between dominant features is typically associated with the concept of laterality, the preference to use on side of the body. In psychology, eye dominance and laterality
are examined for use in disorder diagnosis as well as in the study of child development [57][10]. Neuroscientists use studies in this area to explore imbalances in the brain for diagnosis of particular diseases. Sports scientists have explored the effects of eye dominance in golf, shooting, and other eye hand coordination activities [6][70][52]. However, no one has yet explored the impact of eye dominance or laterality on iris biometrics. It is at least plausible that eye dominance could affect the performance of an iris biometric system based on, for example, the ease of a usage which a user experiences when presenting one eye or the other for imaging.

Throughout the last century, many psychologists have explored the phenomenon of eye dominance. The earliest work on eye dominance that we are aware of was in 1593 by Porta [64]. In 1928, Miles established the basis for the determination of eye dominance [48][49][47]. Several other methods involving either single-eye focus or fixation have been developed and explored since then [65][62][72][50]. The determination of the dominant eye has been used in several psychological studies. Banister used eye dominance to explore rifle usage and then expanded it to assess soldierliness [6]. In the 1970’s, psychologists began to focus on determining the relationship between eyedness and handedness. In particular, Coren and Porrac published multiple papers exploring the topic in different settings with various populations [18][19][62][63]. The strength of the relationship between eyedness and handedness is still debated, and many conclude that the correlation is only slightly better than chance [61][14][20]. Yet it is agreed that childhood pressures to be right handed in many cultures often opposes the body’s natural disposition to laterality. This may be the cause of the psychology based discrepancy.

In iris biometrics, right and left eyes are often considered together. However, when right and left eyes are considered separately, a variation in performance is sometimes seen. For instance, in the ICE 2005 report a verification rate of 0.995 at
a false accept rate of 0.001 was reported for right eyes [60]. Left eyes only showed a verification rate between 0.990 and 0.995 at the false accept rate of 0.001. However, when new comparisons were presented in the ICE 2006 and IRIS 2006 reports, the same relative performance for both left and right eyes was exhibited [59][5]. In contrast, a recent study by Mehrotra et al. showed the left eye performing with a verification rate around 0.94 at a false accept rate of 0.01, whereas the right eye only performed at a verification rate of 0.93 [46]. Thus, there is no consensus for the general population whether right or left eyes alone provide a higher verification rate.

Many iris sensors are built to acquire both eyes of a subject at approximately the same time, disregarding the possible affects of eye dominance or laterality. In a technical publication regarding the usage of a single eye sensor however, a phenomenon regarding the subjects’ eye dominance was reported [9]. During the enrollment process subjects typically presented their dominant eye first, and were easily enrolled. But when they then presented their nondominant eye, many subjects had difficulty aligning their eye for proper enrollment. To overcome this challenge, many had to cover their dominant eye and attempt to be reacquired. This effect begs the question of how eye dominance affects enrollment in dual eye systems.

3.2 Hypothesis

In this study, we explore the effects of eye dominance and laterality on the performance of an iris recognition system. We conjecture that subjects might present their dominant eyes more accurately than their non dominant eye, which causes discrepancies on whether right or left eye performs more accurately in an iris biometric system. Further, we analyze whether a subject’s laterality impacts a their performance in the same iris biometric system.
3.3 Impact of Eye Dominance on Iris Recognition

3.3.1 Dataset

The LG IrisAccess 4000 system was used to collect all of the iris images used in this study. During the acquisition process, the sensor was placed on a tripod and adjusted to each subject’s height. For this experiment, left and right iris data was acquired for 421 subjects of which 231 of the subjects were male and 190 were female. Data was collected over a period of four weeks during September and October of 2011.

For each subject, eye dominance was determined by a Miles Test [47]. In the original Miles Test, subjects held a truncated metal cone over their faces while both eyes were open. It was then aimed at a point in the distance. Each eye was then closed individually, and whichever eye most clearly saw the distant point was recorded as the dominant eye. This test has been transformed in many ways, most popularly through the hole-in-card test. In our study, subjects form a triangle with their hands and focus on a poster in the center of a distant wall. They then close one eye at a time and identify the eye through which they saw the majority of the poster.

Using this variant of the Miles Test, 271 subjects determined themselves to be right eye dominant and 150 reported left eye dominance. Of the right eye dominant subjects, 151 of them were male, and 120 were female. Within the left eye dominant set, 80 subjects were male, and 70 were female. Subjects reported eye dominance each week that they had images acquired and no subjects reported a change in their dominant eye during the entirety of the study. Figure 3.1 depicts images from this dataset. Given this set of images, there is no obvious visual difference between dominant and non-dominant eyes.
Figure 3.1. Images of irises taken by the LG IrisAccess 4000 during the same session. (a) Right eye image from a Right Eye Dominant Subject. (b) Left eye image from a Right Eye Dominant Subject. (c) Right eye image from a Left Eye Dominant Subject. (d) Left eye image from a Left Eye Dominant Subject.

3.3.2 Results

The initial experiment in this study explores the difference in iris recognition performance between left and right eyes of subjects with a particular eye dominance. The image dataset was thus partitioned into four subsets - right eyes of right eye dominant subjects, left eyes of right eye dominant subjects, right eyes of left eye dominant subjects, and left eyes of left eye dominant subjects as described by Table 3.1. Figure 3.2 shows the results of these experiments, and Table 3.2 contains the match and nonmatch score counts. It is seen that both cases involving right eye dominant subjects outperform both cases of left eye dominance. However, within each dominance subset, some variations are seen. For right eye dominant subjects, it appears that there is no statistically significant difference in performance between eyes since the error bars of both right eye dominant tests overlap, although the mean ROC curves appear different. In contrast, there is a statistically significant difference between the two left eye dominant tests. Namely, the dominant left eye has an improved recognition rate over the right eye, and the error bars for these experiments do not overlap.

The match score distribution for each experiment provides some insight into
### TABLE 3.1

GENDER OF SUBJECTS BY EYE DOMINANCE

<table>
<thead>
<tr>
<th>Dominance</th>
<th>Males</th>
<th>Females</th>
<th>Total Subjects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Right Eye Dominant</td>
<td>151</td>
<td>120</td>
<td>171</td>
</tr>
<tr>
<td>Left Eye Dominant</td>
<td>80</td>
<td>70</td>
<td>150</td>
</tr>
</tbody>
</table>

### TABLE 3.2

NUMBER OF MATCH AND NONMATCH COMPARISONS FOR THE EYE DOMINANCE COMPARISONS

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Matches</th>
<th>NonMatches</th>
</tr>
</thead>
<tbody>
<tr>
<td>Right Eye Dominance Right Eyes</td>
<td>92,864</td>
<td>20,251,746</td>
</tr>
<tr>
<td>Right Eye Dominance Left Eyes</td>
<td>91,252</td>
<td>19,928,848</td>
</tr>
<tr>
<td>Left Eye Dominance Right Eyes</td>
<td>39,776</td>
<td>4,439,796</td>
</tr>
<tr>
<td>Left Eye Dominance Left Eyes</td>
<td>39,326</td>
<td>4,398,016</td>
</tr>
</tbody>
</table>

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Figure 3.2. ROC Curves with error bars for the four initial eye dominance experiments. Here, the experiments with right eye dominant data, outperform the experiments employing left eye dominant data.

why this effect is seen. Figure 3.3 shows the match score distributions for each dominance subset. For match score distributions of the dominant eye subsets, the scores appear more evenly distributed in a Gaussian fashion, than the distributions for the nondominant eye subsets. In particular, for right eyes of left eye dominant subjects, the peak in match scores appears closer to the nonmatch distribution and other scores extend out towards 4000. A similar phenomenon is present for the left
Figure 3.3. Match and NonMatch Distributions for the initial eye dominance experiments. The red dashed curve depicts the nonmatch distribution and the black solid curve depicts the match distribution for the Right Eye Dominant Right Eye Experiment (Top Left), Right Eye Dominant Left Eye Experiment (Top Right), Left Eye Dominant Left Eye Experiment (Bottom Left), and Left Eye Dominant Right Eye Experiment (Bottom Right).

eyes of right eye dominant subjects.

Hence, when considering eye dominance in an iris recognition system, right eye dominance shows improved performance rates over left eye dominance data. Fur-
ther, when looking at left or right eyes only for each dominance type, which eye is used does not make a statistically significant difference for right eye dominance. In contrast, left eyes for left eye dominant subjects exhibit improved performance over their corresponding right eyes.

3.4 Single Eye Systems

Given that the performance of the right eye dominant subjects, regardless of eye used, was better than that of the left eye dominant subjects, and that left eyes of left eye dominant subjects performed better than the right eyes of those subjects, there is an expected outcome for a single eye system from this data. Namely, when using only right eyes or only left eyes, regardless of dominance, left eyes alone should perform better.

3.4.1 Dataset

Using the previously described dataset, three new subsets of data were formed. All right eye images from the 321 subjects were used in the right eye system subset, and similarly, all left eye images were used in the left eye system subset. Further, we generated a subset of the data to simulate a single eye iris recognition system which considers dominance. Namely, a subject would identify their dominant eye, and this eye alone would be enrolled. Thus, matches in this system consists of left eye matches from left eye dominant subjects, and right eye matches from right eye subjects. Further, nonmatches are derived only from left eye to left eye nonmatch comparisons and right eye to right eye nonmatch comparisons. By not allowing right to left eye nonmatch comparisons we can reduce the expense of the system.
3.4.2 Results

In Figure 3.4, we see the comparison of the described eye dominance system and right and left single eye systems. The left eye system performs statistically significantly better than the right eye system. This is consistent with the recent findings by Mehrotra et al., but is not a consistent result in the history of iris recognition systems.

Figure 3.4. ROC Curves for single eye iris recognition systems. The Left and Right Eye Systems do not consider eye dominance whereas the Eye Dominance System contains only the dominant eye of each subject.
biometrics. Further, the eye dominance system performs as well as the left eye dominance system.

Through the use of a single eye system which considers the eyedness of each subject, we have sustained the performance of the left eye only system while including right eye matches. Additionally, we have improved the efficiency and cost of a traditional iris recognition system. Since we only store one eye for each subject we decrease the size of our gallery by half. Further, since we know which eye a subject is presenting based on dominance, we need only compare to other eyes of that type, decreasing the computational cost of a traditional system.

3.5 Laterality and Iris Recognition

To further explore the effects of eye dominance, we also examined the notion of how handedness in conjunction with eyedness affects an iris recognition system. Few works in hand based biometrics report or study a person’s handedness, and none appear to have looked at the performance rate of a subject’s dominant hand in comparison to their nondominant hand [30][68].

3.5.1 Dataset

Using the same set of data for which subjects reported eye dominance, we determined each subject’s dominant hand. In order to determine handedness, for each subject we viewed videos of them performing various activities, such as picking up a telephone, tossing a bean bag, picking up a toy gun, and holding a golf club. This activity based approach of determining handedness is similar to much of the research which determines the accuracy of self reported handedness and its’ correlation to eyedness [6][20]. If a subject performed all activities with the same hand, that hand was marked as the dominant hand. Otherwise, that subject was marked as neither right nor left handed, and was excluded from this experiment. Table 3.3 shows the
subject breakdown given the reported eyedness and determined handedness. This breakdown of handedness is representative of the reported handedness of the world population with about 10% of the population being left handed [32].

To explore the effects of hand dominance we created four new subsets of data: right eyes from right eye dominant right handed subjects, right eyes from right eye dominant left handed subjects, left eyes from left eye dominant left handed subjects, and left eyes from left eye dominant right handed subjects.

<table>
<thead>
<tr>
<th>Subject Set</th>
<th>Number of Subjects</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Right Eyed Right Handed</td>
<td>241</td>
<td>88.93%</td>
</tr>
<tr>
<td>Right Eyed Left Handed</td>
<td>13</td>
<td>4.80%</td>
</tr>
<tr>
<td>Right Eyed Neither Handed</td>
<td>17</td>
<td>6.27%</td>
</tr>
<tr>
<td>Left Eyed Right Handed</td>
<td>116</td>
<td>77.33%</td>
</tr>
<tr>
<td>Left Eyed Left Handed</td>
<td>34</td>
<td>22.22%</td>
</tr>
<tr>
<td>Left Eyed Neither Handed</td>
<td>0</td>
<td>0%</td>
</tr>
</tbody>
</table>

3.5.2 Results

Figure 3.5 depicts the results from the hand dominance based experiments. Three of the experiments - Right Eye Right Handed, Right Eye Left Handed, and Left Eye Left Handed - perform nearly perfect with similar mean ROC curves and overlapping error bars. In contrast, the Left Eye Right Handed experiment performs statistically significantly worse than the other three experiments, including Left Eye Left Handed. Since the performance of right eye dominant subjects was already nearly perfect this is not unexpected. Further, in the laterality studies, those using the same eye and hand, perform as well or better than those using opposite
Figure 3.5. ROC Curves for the correlation between hand and eye dominance experiments. All experiments except Left Eye Dominant Right Handed perform nearly perfectly after bootstrapping.
eye and hand. This suggests the possibility that those who are same side dominant present their eyes better to the sensor than those who are not.

3.6 Conclusions

In this study, we show the results of an experimental investigation into the relationship between eyedness, or eye dominance, and handedness as an extrinsic affect on iris recognition. Our results suggest that the concepts of laterality, eye dominance and handedness, are correlated with iris biometric recognition performance. This is a novel area of investigation in iris biometrics, and much work remains to be done, but we have obtained interesting and intriguing initial results.

We first subdivided our overall iris image dataset according to the eye dominance of the subjects. We found that for subjects who are right eye dominant, there is not a statistically significant difference in iris recognition accuracy between the left iris and the right iris. However, for subjects who are left eye dominant, we found that iris recognition performance for the left iris was statistically significantly better than for the right iris.

For an iris recognition system that is designed to use one iris, the initial implication is that it is better to base it on the left iris than on the right iris. Alternatively, but more complex, the system could use the dominant eye for each subject. For an iris recognition system that is designed to use both irises, an implication is that the left and right iris results for a left eye dominant subject could be unequally weighted.

We then also considered eye dominance in combination with handedness. We considered the recognition performance of (1) the right iris for right eye dominant and right handed persons, (2) the right iris for right eye dominant and left handed persons, (3) the left iris for left eye dominant and left handed persons, and (4) the
left iris for left eye dominant and right handed persons. We found that recognition performance was essentially the same in 3 of the 4 cases, but that recognition was noticeably poorer for the left iris of subjects who were left eye dominant and right handed.

We conjecture that the results we observe may be due to some difference in how easily subjects with different eye dominance can present the non-dominant eye for imaging. However, the particular mechanism remains to be explained.

3.7 Potential Future Work

This work could be extended in several ways in the future. Initially, it would be desirable to gather a larger dataset and determine eyedness and handedness more accurately. In order to determine eyedness and remove some of the human error possibly caused by determining handedness in our current method, the use of the hole-in-card method of Miles Testing would be beneficial [47]. In conjunction with subject activity analysis, a future study should also include self reported handedness. An analysis of the affects of gender, ethnicity, and other covariates which may correlate well with the effects of eye dominance may also provide further insight into reasons why the variations in performance occur. Lastly, a study comparing the features of dominant and nondominant eyes in order to determine eye dominance without subject aid would be of interest in order to develop a more subject aware sensor or algorithm.
CHAPTER 4

HANDHELD VERSUS TRIPOD USAGE OF THE LG TD 100 IRIS SENSOR

4.1 Background and Motivations

As the usage of biometrics grows, the need for more portable technologies also increases. Many iris biometric systems are stationary, such that a subject approaches the fixed location sensor and attempts to be recognized. However, in the world outside of a stationary setting, it is also desirable to have the ability to verify or recognize a person’s identity. For instance, in India’s UID project, handheld iris imaging devices are being used for e-governance applications and iris enrollment [71]. Additionally, police forces have been using hand held devices to identify subjects in the field during arrests and other policing activities [69]. The military also uses handheld biometric devices in the field [45].

Due to the increased field usage of handheld iris sensors, it is important to study the differences in performance between handheld and stationary systems. Few studies have been done in which handheld sensors are compared to stationary sensors. Connaughton et al. provides the most recent and extensive study in which the LG IrisAccess 400, LG TD 100, and IrisGuard AD 100 sensors are compared using three different matching algorithms [16][17]. However, currently no study has been done to compare images taken using a handheld sensor, in its intended usage as well as in a stationary scenario. Further no analogous study has been performed for other biometrics.
4.2 Hypothesis

In this study, we hope to show that no statistically significant difference is seen in iris recognition when using the LG TD 100 as a handheld, versus a stationary, iris sensor. The usage of an iris biometric system has yet to be studied. It is hoped that performance remains the same regardless of system usage.

4.3 Dataset

To compare the uses of the LG TD 100, 4 sessions worth of data were collected from October 2010 to January 2011. During the first two sessions of acquisition, an operator was used to control the LG TD 100 as a handheld iris sensor. Namely, the operator would begin the acquisition and position the sensor in the correct orientation for imaging to occur while the subject remained still. In the last two sessions, the LG TD 100 was placed on a tripod during acquisition. Instead of the operator positioning the sensor, subjects approached the sensor, and adjusted it using a crank, such that they were looking directly into the reflective mirror. Since this sensor does not provide audio cues, the operator then instructed the subject to move closer to or farther away from the sensor for acquisition to occur. Table 4.1 further describes the acquisition sessions by number of images and subjects.

Figure 4.1 provides examples of image pairs from the subject during both the handheld and stationary setup. Through visual inspection of these images, no obvious difference in image quality is seen. All images have some image padding at the bottom edge and appear to have the same illumination pattern and contrast.

4.4 Results

The preprocessing and recognition experiments in this study were all performed using the VeriEye SDK. First, all images from both types of data acquisition were
TABLE 4.1

BREAKDOWN OF IMAGES AND SUBJECTS BY SESSION FOR HANDHELD VS. TRIPOD STUDY.

<table>
<thead>
<tr>
<th>Session</th>
<th>Usage</th>
<th>Number of Images</th>
<th>Number of Subjects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Session 1</td>
<td>Handheld</td>
<td>932</td>
<td>144</td>
</tr>
<tr>
<td>Session 2</td>
<td>Handheld</td>
<td>1262</td>
<td>181</td>
</tr>
<tr>
<td>Session 3</td>
<td>Tripod</td>
<td>1579</td>
<td>269</td>
</tr>
<tr>
<td>Session 4</td>
<td>Tripod</td>
<td>1568</td>
<td>267</td>
</tr>
</tbody>
</table>

Figure 4.1. Right (a) and Left (b) eye image pair taken by the LG TD 100 in a handheld setting. Right (c) and Left (d) eye image pair taken by the LG TD 100 on a stationary setting. All images are from subject 02463.
segmented and made into templates. During the matching, the older of the two templates was used as the gallery, and the other as the probe. Hence, there are three types of experiments, handheld to handheld, tripod to tripod, and handheld to tripod. There is no tripod to handheld experiments because the handheld images were taken before the tripod images. It is important to establish this ordering since VeriEye employs asymmetric scoring.

Figure 4.2 (a) displays the match and non-match score distribution for each experiment. Here the numbers 1 and 2 describe which session of that type we are referencing. No obvious variations are seen when comparing these distributions. Figure 4.2 (b) then shows the corresponding ROC curves for these experiments. Given the two same type experiments, handheld to handheld and tripod to tripod, we see that they provide us with two of the best performing results with mean ROC curve true accept rates of approximately 1.0 and 0.9995 at a false accept rate of 0.002. However, the errors bars for these two results overlap, implying that they are not statistically significantly different from one another, thus providing equivalent performance regardless of usage.

The remaining experiments in Figure 4.2 (b) show the handheld to tripod results. The mean ROCs range from a true accept rate of 0.9975 to 0.9995 at a false accept rate of 0.002. Many of the error bars for these experimental results overlap each other, showing that they are likely not statistically significantly different from one another. Additionally, some experiments of the handheld to tripod type, such as Handheld 2 v Tripod 2, have error bars which also overlap the handheld to handheld and tripod to tripod experiments. This implies that one may achieve the same performance from a mixed type experiment as with a same type experiment, a desirable effect.

Figure 4.3 shows the generalized results from these experiments, where all the
Handheld and Tripod
Match and NonMatch Score Distributions

![Graph showing match and nonmatch score distributions for handheld and tripod comparisons.](a)

ROC Curves for Handheld v Tripod data using VeriEye

![ROC curve for handheld and tripod comparisons.](b)

Figure 4.2. (a) Match and NonMatch Distributions for Handheld and Tripod Comparisons. (b) ROC curve for Handheld and Tripod Comparisons by acquisition session comparison.

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mixed type experiments are grouped together in the Handheld v Tripod experiment. Examining only the mean ROC curve results, at a false accept rate of 0.002, the Handheld v Handheld labeled experiment performs the best with a true accept rate of approximately 1.000, followed by the Tripod v Tripod experiment with a true accept rate of about 0.9995. Lastly, the Handheld v Tripod average ROC provides us with a true accept rate of about 0.9975 at the given false accept rate. Thus it appears that on average it may be best to use the LG TD 100 sensor as intended, then if need be on a tripod, and if necessary, one could mix uses and still see acceptable recognition rates. However, since all error bars overlap, it is likely that these results are not statistically significantly different from one another, and any usage or combination of uses would provide approximately the same and acceptable results.

4.5 Conclusions

In this study we looked at two different usage scenarios for the LG TD 100. The intended usage of this sensor is as a handheld iris imaging system. When using images gathered in this scenario in both the gallery and probe sets, we achieve the best mean ROC performance. Sometimes it is desirable to have a stationary, rather than mobile, iris image system. To simulate this scenario, we placed the LG TD 100 on a tripod for acquisition. When using these images in both the gallery and probe sets we achieved mean average ROC results with a true accept rate of 0.9995 at a false accept rate of 0.002, slightly lower than that of the handheld scenario. In order to determine whether a mixture of these scenarios would also provide acceptable performance, the handheld images acquired were used as the gallery set and the tripod images used as the probe set. This experiment had a lower mean ROC than both the handheld only and tripod only, but still achieved a high true accept rate.
Figure 4.3. ROC Curves for each category of experiment for Handheld and Tripod Comparisons.
Further, when performing bootstrapping on these experiments, the error bars of each experiment were overlapping with one another. Thus all scenarios are likely not statistically significant from one another. Hence, any usage of the LG TD 100 should produce acceptable and similar results. This is a desirable result for any mobile imaging sensor.

4.6 Potential Future Work

In the future, it would be advantageous to perform the same experiment on a larger dataset with more subjects over a greater number of sessions. This would allow for more same scenario comparisons, as well as more different scenario comparisons. Other sensors, such as the IrisGuard AD 100 are also intended for mobile use. It would be interesting to gather similar data using other mobile sensors, perform the same experiments, and compare the results, to see if all mobile sensors provide the same accuracy across usages. Additionally, it would be beneficial to compare the overall performance of several handheld iris sensors.
In this thesis, we have presented an exploration of several intrinsic and extrinsic factors which affect iris biometrics in various ways. We first discussed iris sensor illumination schemes, an intrinsic factor due to the nature of the sensor’s hardware and its inability to be easily changed. Specular highlights are an issue encountered by all iris biometric systems. In order to alleviate some of these strong contrast variations within the pupil and iris, we externally altered an existing system, the LG IrisAccess 4000, by adding diffusing lenses in front of the clusters of NIR LEDs used to illuminate a subject’s eyes during acquisition. We found that with our new system we reduced specular highlighting within the pupil. However, specular highlights within the iris still just as present as those from the traditional system. Further, when introducing images gathered by our diffuse illumination system into an iris segmentation and matching algorithm for recognition purposes, results varied based on the algorithm. For two commercial matchers, diffusion appeared to have no affect or reduced the recognition rate in comparison to traditionally illuminated images. However, for the in-house IrisBEE matcher, diffusion improved the recognition rate in comparison to traditional illumination. Illumination and the need to address specular highlights are problems which will continue to drive the field of iris biometrics due to their impact in both the segmentation and matching stages of recognition.
We then explored eye dominance, an intrinsic factor stemming from the subjects rather than the sensor. Here was saw that eye dominance does in fact impact iris recognition performance, a possible explanation for a discrepancy in performance between left and right irises. Those who are right eye dominant perform better than those who are left eye dominant. We then looked at single eye systems and an eye dominance based system using the same data where we found left eyes only, without dominance, performed statistically significantly better than right eyes only without dominance, and that our eye dominance system performs as well as the left eye only system. This eye dominance based system also has the added benefit of being more space and search efficient. In a further investigation we also looked at the laterality of the subjects within this dataset. An additional covariate, handedness, was added to the eye dominance study. Due to the reduced dataset size, many experiments performed nearly perfectly, with the exception of one cross laterality experiment. This implies that laterality may also improve iris recognition, but further investigation with a larger dataset and more accurately reported handedness data is needed. The study presented here is the first study of eye dominance within the setting of iris biometrics. Due to the nature of these results, we feel that a larger study might be able to drive sensor development and allow us to better understand the nature of eye dominance in an iris based context.

The final study presented here looks at the usages of the LG TD 100, an extrinsic factor determined by the operator. This sensor is intended to be a handheld iris sensor, but it can also easily be used in a stationary scenario. The findings of this study imply that regardless of usage, the LG TD 100 provides similar results for both handheld and stationary settings. As the scenarios in which iris imaging occur change from stationary, to mobile, to on the move, studies which verify and compare the performance of these type of sensors uses will remain important.
Only a few of the many covariates, both intrinsic and extrinsic, are examined in this thesis. Further, all of these studies, as with most, could be expanded into much larger works and branch studies. The field of iris biometrics is ever changing, and with that, new challenges will arise, such as these, for examination.
BIBLIOGRAPHY


