2011

Iris Recognition in Multiple Spectral Bands: From Visible to Short Wave Infrared

Raghunandan Pasula
West Virginia University

Follow this and additional works at: <https://researchrepository.wvu.edu/etd>

Recommended Citation

Pasula, Raghunandan, "Iris Recognition in Multiple Spectral Bands: From Visible to Short Wave Infrared" (2011). *Graduate Theses, Dissertations, and Problem Reports*. 4765.
<https://researchrepository.wvu.edu/etd/4765>

This Thesis is protected by copyright and/or related rights. It has been brought to you by the The Research Repository @ WVU with permission from the rights-holder(s). You are free to use this Thesis in any way that is permitted by the copyright and related rights legislation that applies to your use. For other uses you must obtain permission from the rights-holder(s) directly, unless additional rights are indicated by a Creative Commons license in the record and/ or on the work itself. This Thesis has been accepted for inclusion in WVU Graduate Theses, Dissertations, and Problem Reports collection by an authorized administrator of The Research Repository @ WVU. For more information, please contact researchrepository@mail.wvu.edu.

Iris Recognition in Multiple Spectral Bands: From Visible to Short Wave Infrared

by

Raghunandan Pasula

Thesis submitted to the
College of Engineering and Mineral Resources
at West Virginia University
in partial fulfillment of the requirements
for the degree of

Master of Science
in
Electrical Engineering

Lawrence Hornak, Ph.D.
Xin Li, Ph.D.
Arun A. Ross, Ph.D., Chair

Lane Department of Computer Science and Electrical Engineering

Morgantown, West Virginia
2011

Keywords: Iris, Multispectral recognition, Biometrics

Copyright 2011 Raghunandan Pasula

Abstract

Iris Recognition in Multiple Spectral Bands: From Visible to Short Wave Infrared

by

Raghunandan Pasula

The human iris is traditionally imaged in Near Infrared (NIR) wavelengths (700nm-900nm) for iris recognition. The absorption co-efficient of color inducing pigment in iris, called Melanin, decreases after 700nm thus minimizing its effect when iris is imaged at wavelengths greater than 700nm. This thesis provides an overview and explores the efficacy of iris recognition at different wavelength bands ranging from visible spectrum (450nm-700nm) to NIR (700nm-900nm) and Short Wave Infrared (900nm-1600nm). Different matching methods are investigated at different wavelength bands to facilitate cross-spectral iris recognition.

The iris recognition analysis in visible wavelengths provides a baseline performance when iris is captured using common digital cameras. A novel blob-based matching algorithm is proposed to match RGB (visible spectrum) iris images. This technique generates a match score based on the similarity between blob like structures in the iris images. The matching performance of the blob based matching method is compared against that of classical ‘Iris Code’ matching method, SIFT-based matching method and simple correlation matching, and results indicate that the blob-based matching method performs reasonably well. Additional experiments on the datasets show that the iris images can be matched with higher confidence for light colored irides than dark colored irides in the visible spectrum.

As part of the analysis in the NIR spectrum, iris images captured in visible spectrum are matched against those captured in the NIR spectrum. Experimental results on the WVU multispectral dataset show promise in achieving a good recognition performance when the images are captured using the same sensor under the same illumination conditions and at the same resolution. A new proprietary ‘FaceIris’ dataset is used to investigate the ability to match iris images from a high resolution face image in visible spectrum against an iris image acquired in NIR spectrum. Matching in ‘FaceIris’ dataset presents a scenario where the two images to be matched are obtained by different sensors at different wavelengths, at different ambient illumination and at different resolution. Cross-spectral matching on the ‘FaceIris’ dataset presented a challenge to achieve good performance. Also, the effect of the choice of the radial and angular parameters of the normalized iris image on matching performance is presented. The experiments on WVU multispectral dataset resulted in good separation between genuine and impostor score distributions for cross-spectral matching which indicates that iris images in obtained in visible spectrum can be successfully matched against NIR iris images using ‘IrisCode’ method.

Iris is also analyzed in the Short Wave Infrared (SWIR) spectrum to study the feasibility of performing iris recognition at these wavelengths. An image acquisition setup was designed to capture the iris at 100nm interval spectral bands ranging from 950nm to 1650nm. Iris images are analyzed at these wavelengths and various observations regarding the brightness, contrast and textural content are discussed. Cross-spectral and intra-spectral matching was

carried out on the samples collected from 25 subjects. Experimental results on this small dataset show the possibility of performing iris recognition in 950nm-1350nm wavelength range. Fusion of match scores from intra-spectral matching at different wavelength bands is shown to improve matching performance in the SWIR domain.

I was brought up with a saying, ‘Teacher’ is the first god.
I dedicate this thesis to all the *gurus*.

Acknowledgements

I have a multitude of reasons to thank my advisor Dr. Arun Ross. I will limit them to just a few for the sake of this section. At first, I would like to thank him for giving me this opportunity to conduct research and guiding me along the way. His style of teaching motivated me to learn more concepts and widen my knowledge base. As my advisor, he stood by me during my tough times and always encouraged me to stay motivated and do my best. I will never forget his unending positive support to all his students and the infectious smile with which he handles them.

I gratefully acknowledge the support and guidance given by Dr. Larry Hornak during the work on my first *real* project on ‘Iris recognition beyond 900nm’. I also like to thank Dr. Xin Li for being in my committee and I appreciate his efforts to present the image processing techniques to the students in a creative manner.

I am where I am because of the hardwork, sacrifice and vision of my parents. I cannot possibly find the words to express the amount of my gratitude and respect towards them.

I thank my cousins, Swetha, Kiran, Shobha and Ravi, and all my buddies in Morgantown for making my life in the United States a very memorable one.

Special thanks to my lab mates Raghav, Aglika, Manisha, Cunjian, Asem, Ravi, Eric, Brian and Emanuela for all the discussions and the wonderful times we have had together.

Contents

Acknowledgements	v
List of Figures	viii
List of Tables	xi
Notation	xii
1 Introduction	1
1.1 Biometrics for identity authentication	1
1.2 Components of a biometric system	2
1.3 Cross section of an eye	3
1.3.1 Anatomy of the iris	5
1.4 Iris as a biometric	6
1.4.1 Segmentation	7
1.4.2 Normalization	9
1.4.3 Feature Encoding	10
1.4.4 Matching	13
1.4.5 Challenges and scope of iris recognition	13
1.5 Motivation for this work	14
1.6 Multispectral analysis in biometrics	14
1.6.1 Face	14
1.6.2 Fingerprint	15
1.6.3 Hand	16
1.6.4 Iris	16
1.7 Contributions of the thesis	17
2 Multispectral analysis in Visible spectrum	19
2.1 Datasets	20
2.1.1 UPOL database	20
2.1.2 UBIRIS database	20
2.2 Analysis	23
2.2.1 Cross-spectral recognition in UPOL and UBIRIS datasets	23
2.2.2 Intra-spectral recognition	24
2.3 Recognition methods	24

2.3.1	Correlation method	24
2.3.2	SIFT based method	26
2.3.3	Blob based method	28
2.3.4	IrisCode method	31
2.4	Performance	31
2.4.1	ROC plots	31
2.5	Summary	35
3	Multispectral analysis in NIR and Visible spectrum	38
3.1	Datasets	39
3.1.1	WVU multispectral dataset	39
3.1.2	FaceIris database	41
3.2	Experimental Analysis	44
3.2.1	Iris in NIR and RGB channels	44
3.2.2	Matching	45
3.3	Performance	46
3.3.1	WVU multispectral dataset	46
3.3.2	FaceIris dataset	46
3.4	Summary	50
4	Multispectral analysis beyond 900nm	52
4.1	Acquisition system	52
4.1.1	Acquisition protocol	54
4.2	Image Analysis	55
4.2.1	Contrast Variation and Varying Average Brightness	55
4.2.2	Differential response of iris	57
4.2.3	Improper illumination and focus	57
4.3	Preprocessing and Matching	57
4.3.1	Segmentation	57
4.3.2	Normalization, Pre- processing and Encoding	58
4.3.3	Matching	58
4.4	Experimental Results	59
4.4.1	Data set	59
4.4.2	Definitions	59
4.4.3	Fusion	59
4.4.4	Histogram plots	60
4.4.5	Box Plots	61
4.5	Summary and Conclusions	61
5	Conclusions and Future work	70
A	Integration times for SWIR iris dataset	72
	References	74

List of Figures

1.1	Block diagram of a biometric system operating in verification mode	3
1.2	Block diagram of a biometric system operating in identification mode	4
1.3	Anatomy of eye	4
1.4	Horizontal sections of an eye	5
1.5	Sagittal section of human eye. Taken from [28]	6
1.6	Components of an iris recognition system	7
1.7	Graphic visualization of rubber sheet model for iris normalization	10
1.8	(a) Image of an eye. (b) Output of the integro-differential operator for segmentation. (c) Rubber sheet model for normalization of iris image	11
2.1	Sample images from UPOL database. The images are observed to be well focused and have minimal occlusions and spectral reflections in the iris region.	21
2.2	Segmentation of iris images in UPOL database (a) Original iris image. (b) Normalized iris image. Note that the entire normalized mask image is considered logical TRUE as there are practically no occlusions. (c) Red channel of normalized image in (b). (d) Green channel of normalized image in (b). (e) Blue channel of normalized image in (b).	22
2.3	Sample images from UBIRIS database.	23
2.4	Segmentation and normalization of iris images in UBIRIS database: (a) Original iris image (b) Automatically segmented iris image showing blackened noise regions (c) Normalized iris image (d) Normalized mask image showing black pixels for iris region and white pixels for noise.	24
2.5	RGB channel images of an image in the UBIRIS database (a) Normalized iris, (b)(c) and (d) Red, Green and Blue channel images of normalized iris in (a).	25
2.6	(i) Cross-spectral genuine matching involves matching different channel images from the same person ‘a’ taken at different times. (ii) Cross-spectral impostor matching involves matching different channel images from different persons ‘a’ and ‘b’	26
2.7	(i) Intra-spectral genuine matching involves matching same channel images from the same person ‘a’ taken at different times. (ii) Intra-spectral impostor matching involves matching same channel images from different persons ‘a’ and ‘b’	27
2.8	SIFT base matching algorithm for comparing two iris images	27
2.9	Block diagram of the blob detection algorithm [25].	29

2.10	Blob detection: (a) Original Normalized Iris image in the red channel (b) Visualizing the result of blob detection algorithm on image in (a)	30
2.11	Cross-spectral and Intra-spectral matching - ROC plots for UPOL database: (a) Correlation based (b) IrisCode based (c) SIFT based and (d) Blob based	32
2.12	Cross-spectral and Intra-spectral matching - ROC plots for UBIRIS database: (a) Correlation based (b) IrisCode based (c) SIFT based and (d) Blob based	34
2.13	Sample images of different colored iris images along with their corresponding red, green and blue channel images	35
2.14	Cross-spectral and intra-spectral IrisCode based matching on (a) Light colored irises, (b) Yellowish brown irises and (c) Dark colored iris images.	37
3.1	Absorbance spectrum of melanin. After 700 nm the observed iris region has little impact of melanin.	39
3.2	WVU multispectral dataset: Sample images of a subject in (a) NIR, (b) Red, (c) Green and (d) Blue channels captured simultaneously and hence co-registered.	40
3.3	Segmentation of iris images in WVU multispectral database: (a) NIR, (b) Red, (c) Green and (d) Blue channel images of a single sample image. Segmentation mask generated for NIR channel image was overlaid on the red, green and blue channel images.	41
3.4	Sample images in FaceIris dataset. (a) and (b) Left and Right iris images cropped from the high resolution face image. (c) and (d) are left and right iris images of the same individual in the NIR domain.	42
3.5	Examples of detected bi-ocular region and the corresponding iris images from the FaceIris Dataset	43
3.6	Segmentation of images in FaceIris dataset. (a) Acquired NIR iris image. (b) Segmented image. (c) Normalized image. (d) Enhanced normalized image. (e) Corresponding Mask image	44
3.7	Histogram of iris region in the NIR, red, green and blue channels of a sample image. NIR and red channels exhibit relatively good image contrast compared to green and blue channels.	45
3.8	ROC plots for (a) cross spectral and (b) intra spectral matching on WVU multispectral dataset	47
3.9	Histogram distribution of genuine and impostor match scores for (a) NIR vs Red, (b) NIR vs Green and (c) NIR vs Blue channel matching in WVU multispectral dataset.	48
3.10	ROC plots for cross spectral and intra spectral matching on FaceIris dataset. (a) Left eye. (b) Right eye.	49
3.11	Fusion of left and right eye match scores for (a) NIR-NIR, (b) Visible-Visible and (c) NIR-Visible matching	50
3.12	CMC curve showing rank-k identification for FaceIris dataset	51
4.1	Image acquisition setup	53

4.2	Camera photo response and its quantum efficiency shown along with the filter response of band pass filters used in the experiment. Images are obtained in 100nm spectral bands. Image courtesy XenICs and Andover Corporation. . .	54
4.3	Sample images obtained at wavelengths (a) 950nm, (b) 1050nm, (c) 1150nm, (d) 1250nm, (e) 1350nm, (f) 1450nm, (g) 1550nm, and (h) 1650nm.	56
4.4	Image histogram plots of images taken at (a) 950nm, (b) 1050nm, (c) 1150, (d) 1250nm, (e) 1350nm, (f) 1450nm, (g) 1550nm, and (h) 1650nm.	63
4.5	Images taken at wavelengths (a) 950nm and (b) 1350nm. The color of eyelashes is black at 950nm where as they turn white at 1350nm and beyond. Also note the sharp limbic boundary at 1350nm.	64
4.6	Adaptive histogram equalized images taken at (a) 1350nm, (b) 1450nm, (c) 1550nm and (d) 1650nm wavelengths. No distinct texture available at these wavelengths and also whitened eyelashes can be observed.	64
4.7	(a) Manually segmented iris image, obtained at 950nm, showing the masked pixels as black, (b) Unwrapped iris (c) Adaptive histogram equalized image of image in (b), and (d) Mask array showing whitened regions corresponding to noise.	65
4.8	Image histogram plots of images taken at (a) 950nm, (b) 1050nm, (c) 1150, (d) 1250nm and (e) 1350nm, before and after adaptive histogram equalization is applied. Contrast variation, spread in the horizontal direction, is improved after adaptive histogram equalization.	66
4.9	Normalized histogram plots of genuine cross spectral (blue dotted line), genuine intra spectral (black line) and impostor intra spectral (red line with markers) distance scores for (a) 950nm, (b) 1050nm, (c) 1150nm, (d) 1250nm, (e) 1350nm and (f) all the wavelengths combined.	67
4.10	Normalized histogram plots of genuine intra spectral and impostor intra spectral distance scores for (a) 950nm, (b) 1050nm, (c) 1150nm, (d) 1250nm, (e) 1350nm and (f) fused case. Simple fusion of scores results in good separation between genuine scores and impostor scores.	68
4.11	Box plots of genuine intra-spectral and genuine cross-spectral scores. Each boxplot shows the distribution of genuine scores when image pairs obtained at the spectral bands indicated in the row and column labels are matched. .	69

List of Tables

2.1	UPOL database	20
2.2	EER values in % for UPOL database	33
2.3	EER values in % for UBIRIS database	34
3.1	Dimension of images in FaceIris dataset.	42
3.2	EER values in % for FaceIris database	46
3.3	EER values in % for fusion of left and right eye match scores in FaceIris database	48
A.1	Integration values and eye color information for the 25 subjects in the SWIR dataset	73

Notation

The following notation and symbols are used throughout this thesis.

μm	:	micro meter
nm	:	nano meter
$\oint$	:	closed path integral
$\ \cdot \ $	:	Euclidean norm
NIR	:	Near Infrared (700nm to 900nm)
EER	:	Equal Error Rate
SWIR	:	Short Wave Infrared (900nm to 1600nm)

Chapter 1

Introduction

1.1 Biometrics for identity authentication

Biometrics refers to the science of automatically identifying or verifying an individual based on physical or behavioral traits [26, 27, 45]. Traditional methods of authentication involve the use of passcodes, passwords, magnetic tape identity cards or simple metallic keys. Though the level of security offered by these authentication systems is acceptable in certain applications, they may not prevent an impostor from gaining access to the secure facilities and circumventing the security of the system. Hence, there is a need for authentication systems that use intrinsic characteristics of an individual rather than the external tokens that he or she possesses. Biometric systems realize this goal by using intrinsic physical traits such as fingerprint, iris, face, ear and hand, or behavioral traits such as voice and gait. A good biometric trait exhibits the following characteristics [27]:

Universality

all persons should possess this trait.

Distinctiveness

any two persons should be sufficiently different in terms of the trait.

Permanence

the trait should be invariant across the period of time during which it is used for authentication.

Collectability

the biometric should be relatively easy to acquire.

Apart from the above characteristics, a biometric system should be able to deliver superior recognition performance within an acceptable amount of time. In certain societies, people may not be willing to provide some biometric traits and, therefore, a biometric should be acceptable to the individuals using it before it can be deployed in the real world. Circumventing a biometric system by means of either spoofing a biometric trait or defeating its security is also a major concern that should be addressed before the system is put to use.

Biometrics has been widely used by many an organization in varying applications including immigration, ATMs in dispensing cash¹, criminal identification, access control [1, 2, 3] and surveillance.

1.2 Components of a biometric system

A biometric system typically consists of sensor, pre-processor, feature extractor, matcher and database modules [27]. Sensor collects the raw biometric data from the user. This data is generally called a *sample*. Raw data is generally not suitable for feature extraction or matching. Pre-processor module enhances the raw data. It usually involves removing noise and enhancing the acquired data for better feature extraction. Feature extractor module extracts features from the sample and represents these features in a compact representation called as a *template*. For example, in a hand recognition system, the palm image acquired by the hand imaging sensor is the sample and the features may include length of the fingers, diameter of the palm and thickness of the fingers. Matcher module matches the features from different samples and produces a similarity or dissimilarity score. Finally, the database module stores the templates of all the users. *Enrollment* is the process of adding a new template to the database. Biometric samples or templates in the database are referred to as *gallery* while the acquired sample or template that is to be verified or identified is referred to as *probe*.

¹<http://homelandsecuritynewswire.com/europes-first-finger-vein-biometric-atms-installed-poland>

A biometric system can function in either the verification mode or the identification mode. In verification mode, a user claims an identity and the system performs a match to validate that claim. In this case, the biometric system retrieves the claimed user's template from the database and matches it with the presented template. Verification mode, by definition, is suitable for applications where an authorized user (e.g., an employee of a company) is granted access upon successful verification. This also helps in preventing multiple people from claiming the same identity. In identification mode, no claim to the identity is made and the task is to recognize the individual. If N samples are present in a database, it involves matching all the N samples against the acquired biometric ($1 : N$ matching). Identification mode is suitable for surveillance applications where the aim is to find out the identity of an individual. Identification mode also helps in detecting multiple identities for a person. A block diagram illustrating verification mode is shown in Fig. 1.1 and that of an identification mode is shown in Fig. 1.2.

Figure 1.1: Block diagram of a biometric system operating in verification mode

1.3 Cross section of an eye

Fig. 1.3 shows the image of an eye. Iris is the region between pupil and sclera. Sclera is the “white” region surrounding the iris. Pupil lies in the center of the iris region and acts

Figure 1.2: Block diagram of a biometric system operating in identification mode

as an aperture that moderates the amount of light entering the eye. Size of this aperture is controlled by the sphincter and dilator muscles of the iris. Iris is divided into two zones, viz., pupillary zone and ciliary zone that, amongst other things, contain muscles for constricting and dilating the iris (Fig. 1.3).

Figure 1.3: Anatomy of eye

Figure 1.4: Horizontal sections of an eye

1.3.1 Anatomy of the iris

Eye is a three dimensional entity that is convex in shape. Fig. 1.5 shows a graphical view of the sagittal cross section of a fully developed human eye. This section describes the components of the iris starting from the exposed part of the eye to the posterior pigment epithelium that forms the base of the iris. Outermost layer or the exposed surface of iris is called cornea that is a transparent mass of cell and proteins. Cornea covers both iris and pupil. Cornea accounts for most of the focusing power of the human visual optical system. It is followed by anterior chamber, a region between cornea and iris, that is filled with a watery substance called aqueous humor that maintains the optimal pressure of the eye. This aqueous humor is produced by ciliary body in the posterior chamber of iris and extends out into anterior chamber and provides nutrients to the ocular tissues enroute. Stroma is a dense network of iris vessels, nerves, chromatophores, and other cellular components. Stroma also contains a color inducing pigment called Melanocytes. Darker or brown irides have higher concentrations of melanocytes than blue or light colored irides. Sphincter muscle is usually visualized as thick streaks encircling the pupil that forms the edge of the pupil. Sphincter muscle is a primary component of pupillary zone. Dilator muscle of the iris lies beneath the sphincter muscle and is anchored on the posterior pigment epithelium. Posterior pigment epithelium is an opaque substance that is dark in both light and dark colored irises. Iris could be visualized as a layered structure of these components. The unique texture pattern exhibited by iris is a result of light reflected and scattered from all these layers. Human

iris texture is believed to be a result of a random morphogenesis and it may be considered stochastic².

Figure 1.5: Sagittal section of human eye. Taken from [28]

1.4 Iris as a biometric

Iris is a nearly universal biometric, though there exists a small fraction of the population that is affected by *aniridia* resulting in absence of the iris [37]. Iris has a rich textural content and is believed to be unique to each individual and even differs between two eyes of the same person [22]. The textural pattern is believed to be permanent throughout an individual's life after stabilizing at 2 years. The permanence of the iris in terms of template consistency has been recently challenged [5, 21]. Traditional iris recognition systems operate in the near infrared (NIR) domain, thus minimizing the inconvenience to the user during iris image acquisition. Light in NIR domain penetrates the surface of the eye and reveals the intricate texture patterns even for dark colored irides [45]. State-of-the-art iris recognition

²<http://www.cl.cam.ac.uk/jgd1000/anatomy.html>

systems are able to perform millions of matches in a second. All these advantages make iris an extremely sought after biometric.

The block diagram for a typical iris recognition system is shown in Fig. 1.6.

Figure 1.6: Components of an iris recognition system

A typical image acquisition system captures the iris image using an NIR camera. Pre-processor module removes the noise and enhances the acquired image for segmentation. Segmentation detects the actual iris region devoid of occlusion due to eyelids or eyelashes. Normalization module transforms the segmented iris image into a normalized image space. Another pre-processing module is used optionally to enhance the normalized image to account for varying ambient illumination conditions during image acquisition. Feature encoding module extracts features from the iris region and encodes them into a template. Matching module matches the probe with the gallery template to produce a match score based on which a decision is made. The following section explains, in detail, the concept of segmentation, normalization, feature encoding and matching in the context of iris recognition.

1.4.1 Segmentation

Segmentation is the process of localizing the limbic and pupillary boundaries of the iris. Segmentation also involves detection of eye lids and eye lashes thereby isolating the true iris region. Daugman [17] approximates the limbic boundary and the pupillary boundary with circles and uses the integro-differential operator to detect these boundaries. Integro-differential operators search for a maximum cumulative radial image gradient on a blurred image over the circumference of a circle. Integro-differential operator is represented as

$$\max_{(r,x_o,y_o)} \left| G_\sigma(r) * \frac{\partial}{\partial r} \oint_{r,x_o,y_o} \frac{I(x,y)}{2\pi r} ds \right| \quad (1.1)$$

where $I(x, y)$ is the intensity value at location (x, y) in the iris image and G is a smoothing function with variance σ . The operator smoothens the image with blurring factor σ and searches for a maximum in the partial derivative for various circular arcs of radius r , centered at (x_0, y_0) . The algorithm starts with the application of a smoothing function with large σ and iteratively searches for a large circular edge. As the sclera is typically brighter in intensity than the iris region, the limbic boundary separating the iris from sclera is detected first. Now this region within the limbic boundary is searched for the next prominent circular boundary that would ideally be the pupillary boundary. For an iris image with uniform illumination and reasonable quality, this technique results in accurate localization of these two boundaries.

Wildes [61] constructs a gradient edge map and uses the circular hough transform to detect the limbic and pupillary boundaries. Circular Hough transform converts a circular edge into a bright intensity point in the transformed space. For a particular radius, bright points are observed in the transformed space depending on the number of edge points available in a circular boundary. The edge map is weighed in the vertical direction for circular boundaries and in horizontal direction for eyelid detection. Several others [35] [32] [36] have used Hough transform with minor variations to detect limbic and pupillary boundaries. As these boundaries are not exactly circular, the authors in [51] approximated the boundaries to be elliptical.

Ritter et.al [44] make use of active contours to localize the pupil-iris boundary while Ross and Shah [47] use geodesic active contours to detect iris-sclera boundary. Ross and Shah detect the pupil using simple thresholding, and the limbic boundary is found by initializing a circular contour near the pupillary boundary. This contour evolves outward and stops at the iris-sclera boundary using image gradient as the stopping function. Apart from these methods, many a group has made use of a series of thresholding and morphological operations to achieve fast and robust segmentation for constrained datasets. A survey of iris segmentation techniques can be found in [42].

Kong and Zhang [30] classify eyelashes into two categories: individually separable eyelashes and multiple eyelashes. Separable eyelashes are easily isolated in the image which are observed as scattered eyelashes. Since the convolution of a separable eyelash with a 1-D Gaussian function is very small, they can be removed by thresholding. Multiple eyelashes are observed when eyelashes overlap in a small region and a point is assumed to be part of an eyelash if the variance of pixel intensities within a small window centered on that point is low. Wildes [61] detects upper and lower eyelids by constructing a binary edge map with horizontal weighting, and searching for an elliptical curve in a circle formed by the limbic boundary. Masek [36] searches for a horizontal line in the edge map to detect eyelids, and uses simple thresholding to detect dark eye lashes.

1.4.2 Normalization

Normalization is the process by which two iris images to be compared are mapped to the same geometric domain to facilitate feature extraction and matching. This step is optional in an iris recognition system. Methods exist in literature to match two iris images without the normalization step [64, 6]. Normalization accounts for variations in iris size due to incident illumination. Pupil dilates or contracts to the incident illumination and oscillates even for uniform illumination [17]. The *Rubber sheet model* proposed by Daugman[17] converts all iris images, irrespective of the size of the iris region, to a doubly dimensionless projected polar coordinate system. The advantage of this system is that it accounts for change in iris due to pupil dilation and constriction. This also transforms eye rotation due to head tilt or random oscillations into a simple translation operation in the transformed domain which is more easily dealt with. Rubber sheet model remaps each pixel (x, y) in the iris region to a point (r, θ) in a fixed size rectangular region. Here r varies from $[0, 1]$ and θ varies from $[0, 2\pi]$. This remapping of image $I(x, y)$ in original coordinates to (r, θ) in polar coordinates is represented as

$$I(x(r, \theta), y(r, \theta)) \rightarrow I(r, \theta) \quad (1.2)$$

where

$$x(r, \theta) = (1 - r)x_p(\theta) + rx_l(\theta)$$

$$y(r, \theta) = (1 - r)y_p(\theta) + ry_l(\theta)$$

Here, $x_p(\theta), y_p(\theta)$ and $x_l(\theta), y_l(\theta)$ are a set of pupillary boundary points and limbic boundary points. Smaller iris sizes results in a highly smoothened normalized image when r is much greater than the iris radius, because same pixel value gets mapped to multiple points in the rectangular region [42]. For this reason the value of r is chosen judiciously. Fig. 1.7 shows a graphic visualization of Daugman's rubber sheet model. Fig. 1.8 shows an example of applying of Daugman's integro differential operator for segmentation and Daugman's rubber sheet model for normalizing an iris image.

Figure 1.7: Graphic visualization of rubber sheet model for iris normalization

Apart from the rubber sheet model, a system developed by Wildes [61] uses image registration to geometrically warp an acquired image to match an image already present in the database, and the system developed by Boles [8] scales the iris images to have the same diameter.

1.4.3 Feature Encoding

Feature encoding is the process of extracting discriminating features and encoding them into a *template*. It involves identifying the discriminating features from the iris region and constructing a feature vector. Depending on the feature encoding method, a corresponding matching method is chosen to generate the similarity or dissimilarity score between two templates. Daugman's *IrisCode* method generates a binary code by convolving the normalized iris image with a set of Gabor filters and quantizing the output. The logic behind the appli-

(a)

(b)

(c)

Figure 1.8: (a) Image of an eye. (b) Output of the integro-differential operator for segmentation. (c) Rubber sheet model for normalization of iris image

cation of family of Gabor filters is as follows. Fourier transform provides knowledge about the occurrence of frequencies in a signal without providing any clue about their location. Short time Fourier transform, on the other hand, provides frequency information in piecewise locations. Wavelets provide a complete description of frequency information at varying sizes of piecewise locations. Hence, Daugman makes use of a family of 2-D quadrature phasor filters [15] also known as 2-D Gabor filters that approximate a 2-D Gabor wavelet. Gabor filter is basically a Gaussian function modulated by a sinusoidal plane wave. Daugman also proves that this set of filters are co-jointly optimal [16] in representing the maximum possible information regarding the frequency information and the local (spatial) information. 2-D Gabor filter has the form

$$G(x, y) = e^{-\pi[(x-x_o)^2/\alpha^2+(y-y_o)^2/\beta^2]} e^{-2\pi i[u_o(x-x_o)+v_o(y-y_o)]}$$

where (x_o, y_o) is the location of pixel in the image, α and β specify width and length of the filter, and, u_o and v_o specify the modulation defined by $w_o = \sqrt{(u_o^2 + v_o^2)}$.

In the context of iris recognition the equivalent polar form of the filter is given by

$$G(r, \theta) = e^{-iw(\theta-\theta_o)} e^{-(r-r_o)^2/\alpha^2} e^{(\theta-\theta_o)^2/\beta^2}$$

Here r_o and θ_o specify the bandwidth of 2-D frequency-selective quadrature filters. As this filter is complex valued, the response of the image to this filter bank is also complex valued. The real part of the response is adjusted to have a zero dc response which indirectly removes the effect of illumination. Phase response is symmetric around zero by principle. This complex valued response is projected on to a 2-D coordinate system where each complex value lies in one of the four quadrants. Each quadrant is assigned a two bit binary code. This quantization results in good compression of iris data and can be represented as [14]

$$h_{Re,Im} = \text{sgn}_{Re,Im} \int_{\rho} \int_{\phi} I(\rho, \phi) e^{-iw(\theta-\phi)} e^{-(r-\rho)^2/\alpha^2} e^{(\theta-\phi)^2/\beta^2} \rho d\rho d\phi,$$

where $I(\rho, \phi)$ is the intensity of the normalized iris image at location (ρ, θ) . So a normalized iris image of size $m \times n$ will result in $m \times n \times 2$ bits of iris code. A normalized mask image is generated along with the iris template in which the bits corresponding to the noisy pixels (eyelids, eyelashes and specular reflections .etc) are set to “0” and the bits

corresponding to the valid iris region are set to “1”. The images displayed in this thesis corresponding to binary mask images are inverted for the purpose of better visualization.

Several other encoding schemes include convolving the normalized iris image with Gaussian filter [58], dyadic wavelet transform [34] and Laplacian of Gaussian filter [12] etc. A detailed survey can be found in [10].

1.4.4 Matching

Matching is the final step that produces a similarity/dissimilarity score based on which a decision is made. The type of matching algorithm is directly dependant on the encoding method used to generate a template. A fractional Hamming distance is used [14] to compare two iris codes [17]. Hamming distance, HD, between two iris codes $code_A$ and $code_B$ with masks $mask_A$ and $mask_B$, respectively, is given by

$$HD = \frac{|| (code_A \otimes code_B) \cap mask_A \cap mask_B ||}{|| mask_A \cap mask_B ||}.$$

Here, $\otimes$ is an exclusive-OR operator that results in a logical 0 if both the bits are equal and a logical 1 if the bits are unequal. So only the those bits that are not part of the mask are counted and summed up and the count is divided by the total number of bits compared to give a normalized dissimilarity score. Matching is computationally less expensive as all the operations are bit wise operations. Rotation of eye between gallery and probe images is account by calculating the Hamming distances at various translational shifts of $code_A$ and selecting the least Hamming distance.

1.4.5 Challenges and scope of iris recognition

Though iris recognition systems have achieved equal error rates (EER) as low as 0.07% [34] this performance is based on images acquired in highly constrained environments. There is a need for a robust system that can perform iris matching in varying ambient illumination when the subject is unconstrained and not looking directly at the camera. Major challenges for iris recognition systems include matching iris at a distance, matching iris on the move and ability to extract sufficient information from the iris in low illumination scenarios. Another

type of challenge is to determine the efficiency of matching iris images in the visible spectrum against those obtained in NIR spectrum.

1.5 Motivation for this work

Iris has been traditionally imaged in the NIR spectrum as the effect of color inducing pigment, melanin, is minimized in this band and good texture patterns are visible even for dark colored irides. Matching two iris images is possible with high degree of confidence when both the gallery and probe images are acquired in the NIR spectrum. Research has also been carried out to see if iris images obtained in the visible spectrum can be successfully matched [52] [56]. However the work in [41, 42] was constrained to the ‘Red’ channel image or the gray scale equivalent of the RGB image.

The motivation for this thesis is to explore, analyze and possibly quantify the response of human iris at different wavelengths ranging from the visible spectrum to traditional NIR spectrum to SWIR (short-wave infrared) wavelengths. For example, as part of this thesis work, images obtained in the visible spectrum are matched against images obtained in the NIR spectrum. Multispectral analysis has been beneficial for other biometric traits including face, fingerprint and hand etc. The following section presents a brief overview of multispectral work on face, fingerprint, hand and iris biometric traits.

1.6 Multispectral analysis in biometrics

1.6.1 Face

Face has been traditionally imaged in the visible spectrum by commercially available digital cameras. It is hypothesized that humans differentiate between two face images based on the shape and texture of the eyes, nose, mouth, ears, facial hair and other facial features [7, 19]. All these features are reasonably discernible in the visible spectrum. Humans also have the ability to recognize individuals under a variety of expression and pose changes, including caricatures [43]. On the other hand, an automated face recognition system is very sensitive to variations in pose, illumination, expression (PIE problem) and presence

of occlusions in a face [60, 4], that are known to greatly reduce the performance of a face recognition system.

In the absence of ambient visible light, a human or a machine has no data to process as facial information is not clearly discernible. In some cases, non-uniform illumination causes the performance of a face recognition system operating in visible domain to drop significantly. Hence, in low visible illumination conditions or non-uniform illumination conditions, face images can be captured at NIR or SWIR [9] wavelengths. However, the problem of occlusion is still not resolved as the acquired image is still dependent on the reflected light from the face. To overcome this problem, thermal IR imaging uses Long Wave Infra Red (LWIR) wavelengths in the order of $8\mu m$ to $12\mu m$ to capture heat signature of the face which is nearly resilient to occlusion, expression and illumination [62]. This heat signature has been shown to be a potential biometric [53]. Fusion of visual and thermal signatures has been explored to achieve robust face recognition [24]. An exhaustive survey of face recognition technology can be found in [63].

1.6.2 Fingerprint

Multispectral imaging has been used for spoof detection [39] and image enhancement [49] in fingerprint systems. One of the most widely used sensor for fingerprint image acquisition is the optical sensor. A traditional camera can be regarded as an optical sensor. In an optical sensor based image acquisition, the finger is placed on a platen, known as touch surface, and it is illuminated by a visible light source and the reflected light is captured by pixel arrays to reproduce the fingerprint. The major disadvantages of this imaging method are that imaging fails for fingerprints with dry superficial skin and residues on the touch surface result in large amount of noise on the acquired image. Multispectral imaging, on the other hand, illuminates the surface with multiple wavelengths and uses the images acquired at different wavelengths to enhance the final image. This method also provides robustness against spoofs by observing the change in reflectance across multiple wavelengths for a live finger and an artificial finger.

1.6.3 Hand

Rowe et al. [50] used multi spectral images to enhance the hand image and achieve better performance. Authors in [23] used a touch-free sensor to acquire six hand images from ultra violet to infrared channels and fused the information from all the images to enhance hand verification accuracy. Most discriminative features are extracted using multiscale decomposition and their coefficients are combined to result in a compact representation of feature vector. The authors in [23] also show that discriminative features like principal line and wrinkles are available in visible images while features like blood vessels are prominent in infrared images.

1.6.4 Iris

There is very little multispectral work carried out in the iris domain. The pioneering work by on iris recognition by Daugman [17] suggests that NIR wavelength band from 700nm to 900nm is ideal for capturing iris texture of different eye colors. Recently, Ngo et al. [38] reiterated the importance of NIR spectrum for iris biometric by acquiring multispectral images of iris at different wavelengths spread out from 405nm to 1550nm and showing that wavelengths around 800nm are ideal for iris recognition.

There has been a lot of work done on iris images obtained in visible spectrum [41, 42, 57] but most of this work is constrained to either converting RGB images into a grayscale image or using the ‘R’ channel image and then performing iris recognition. However, the information from different spectral bands were not exploited or analyzed.

Boyce et al. [11] initiated multispectral iris recognition work by cross-matching red, green, blue channel images with iris images acquired in the NIR spectrum. Multispectral information is exploited to improve the accuracy of iris segmentation. Boyce et al. also observed that the farther the spectrum of the two images, the lower the match score would be for a genuine match. As a result intra class variation is observed to be large across spectral bands.

1.7 Contributions of the thesis

This thesis attempts to provide a comprehensive overview of iris recognition performance at wavelengths ranging from 450nm in visible spectrum to 1600nm in SWIR spectrum. The contribution of this thesis is threefold.

1. A detailed analysis of iris recognition performance in visible spectrum is undertaken. Cross spectral and intra spectral matching is done between Red, Green and Blue channels of an RGB image obtained in visible spectrum. A novel blob based iris matching method is proposed that generates a match score based on the similarity between blob like structures in the iris images. Traditional IrisCode method and SIFT-based method are also used to analyze the matching performance on iris images in visible spectrum. 2-D correlation matching is used as a baseline performance to compare blob-based, SIFT-based and IrisCode methods. UPOL [18] and UBIRIS [41] databases are chosen for the purpose of this study.
2. The efficacy of matching iris images obtained in visible spectrum against those obtained in traditionally in NIR spectrum is investigated. WVU multispectral dataset [11] and a proprietary “FaceIris” dataset are used to conduct the experiments. While the visible and NIR iris images in the WVU multispectral dataset are co-registered, the visible and NIR iris images in FaceIris dataset are captured using different cameras at different times under different ambient illumination conditions.
3. To our knowledge, this is the first attempt to investigate iris recognition at SWIR wavelengths. Traditionally iris has been imaged in NIR wavelengths (700nm - 900nm) as the absorbance coefficient of color inducing component called melanin decreases³ after 700nm, thus enabling the NIR sensors to capture intricate details of iris textural pattern. However, no work has been undertaken to investigate the iris beyond 900nm. The following is accomplished as part of the thesis:
 - An acquisition set up is designed to collect multispectral images from 900nm - 1600nm.

³<http://www.cl.cam.ac.uk/~jgd1000/anatomy.html>

- The characteristics of iris images obtained at SWIR wavelengths are explained and the hypothesis for observed phenomena is presented.
- Cross spectral and intra spectral recognition matching is performed and the results are reported.
- Fusion of match scores from cross spectral matching is shown to improve recognition performance.

Chapter 2

Multispectral analysis in Visible spectrum

Visible spectrum in this work refers to the wavelengths in the 450nm to 700nm range of the electro magnetic spectrum. Active illumination from natural sources like sun and artificial sources like fluorescent bulbs radiate light in visible spectrum. Human retina contains cone cells and rod cells that are responsible for vision. Rod cells are sensitive to illumination intensity and help in low intensity vision. Cone cells are sensitive to color and are active during bright illumination. Typically, retina has three types of cone cells whose sensitivity peaks near 564 - 580 nm, 534 - 545 nm, and 420 - 440 nm, respectively [55]. The response of three types of cone cells is transmitted to the brain via optical nerves which forms a composite vision of the scene. In the same way, a typical digital camera has three monochromatic sensors densely arranged in a certain pattern. The reflected light from a scene is incident on these sensors and the output is combined to form an image. Red (R), green (G) and blue (B) are considered additive primary colors [48] because a wide range of colors can be reproduced by adding weighted quantities of R,G and B.

This chapter reports the recognition performance of iris matching on images obtained in the blue, green and red channels of visible spectrum. Section 2.1 describes the UPOL and UBIRIS databases in detail. Section 2.2 describes the concept of cross-spectral and intra-spectral matching in visible spectrum. Novel blob based iris matching method along with traditional iris matching procedures are explained in section 2.3. Matching performance

is reported in terms of receiver operating characteristic (ROC) plots and equal error rates (EERs) in section 2.4. Finally summary is presented in section 2.5

2.1 Datasets

2.1.1 UPOL database

The UPOL dataset [18] is a publicly available database which contains iris images obtained in visible spectrum. The details of the dataset are presented in Table 2.1. These irises were obtained using the TOPCON TRC50IA optical device connected to a SONY DXC-950P 3CCD camera ¹. The iris images in this data set are ideal in the sense that the images are well focused and occlusions or spectral reflections are minimal. Sample images from UPOL database are shown in Fig. 2.1. Each image has a resolution of 576×768 pixels.

Table 2.1: UPOL database

Number of subjects	64
Number of eyes per subject	2
Number of images (samples) per eye	3

Pre-processing

All the images in the UPOL database are manually segmented and then normalized using Daugman's rubber sheet model [17] into a doubly dimensionless projected polar coordinate system. The radial and angular resolution are chosen to be 150 and 720, respectively. As the UPOL database had minimal occlusions the mask is chosen to be logical TRUE or 1s for all the pixels. An example of the normalized image is shown in Fig. 2.2.

2.1.2 UBIRIS database

UBIRIS dataset contains iris images that replicate iris images acquired in real world scenarios to a reasonable extent. A subset of the UBIRIS database [41] containing 5×66 (5

¹<http://phoenix.inf.upol.cz/iris/>

Figure 2.1: Sample images from UPOL database. The images are observed to be well focused and have minimal occlusions and spectral reflections in the iris region.

sample images each for 66 subjects) color images is chosen for this thesis work. These images were captured ² with a Nikon E5700 camera using the E5700v1.0 software. In contrast to the UPOL database, the images in this database are non-ideal and obtained under unconstrained environments. This database contains images with varying focus, occlusions and spectral reflections and exhibits large intra-class variations. Sample images from the UBIRIS database are shown in Fig. 2.3. Each image in this database has 800×600 pixels.

Pre-processing

Images in the UBIRIS database are automatically segmented using Daugman's integro differential operator to detect pupillary and limbic boundaries, and approximating the upper and lower eyelids with horizontal lines. Specular reflections are masked out using simple thresholding. The red channel image is used for segmentation purpose and the mask thus generated is overlaid on the corresponding green and blue channel images. Next, the images are unwrapped into a doubly dimensionless projected polar coordinate system using Daugman's rubber sheet model [17]. The radial and angular resolution are chosen to be 144 and 720, respectively. As the UBIRIS database contained images with varying degrees of

²<http://iris.di.ubi.pt/ubiris1.html>

Figure 2.2: Segmentation of iris images in UPOL database (a) Original iris image. (b) Normalized iris image. Note that the entire normalized mask image is considered logical TRUE as there are practically no occlusions. (c) Red channel of normalized image in (b). (d) Green channel of normalized image in (b). (e) Blue channel of normalized image in (b).

occlusion it is important to determine the masked pixels that do not contribute to the iris region. Fig. 2.4 shows the segmented iris image along with its normalized and mask images.

Fig. 2.5 shows the red, green and blue channel images of a normalized image in the UBIRIS dataset.

Figure 2.3: Sample images from UBIRIS database.

2.2 Analysis

2.2.1 Cross-spectral recognition in UPOL and UBIRIS datasets

Three channel images namely, R,G and B, are available for each iris sample. Cross-spectral genuine matching is done between images from two different channels pertaining to different samples of the same person. Cross-spectral impostor matching is done between images from two different channels pertaining to two different persons. For each of the above matching scenarios, cross-spectral matching is done as shown in Fig. 2.6.

Figure 2.4: Segmentation and normalization of iris images in UBIRIS database: (a) Original iris image (b) Automatically segmented iris image showing blackened noise regions (c) Normalized iris image (d) Normalized mask image showing black pixels for iris region and white pixels for noise.

2.2.2 Intra-spectral recognition

Intra-spectral matching is performed to provide a base line performance. Intra-spectral genuine matching is done between images from the same channel but pertaining to *different* samples of the same person. Intra-spectral impostor matching is done between images from the same channel but pertaining to two different persons. This procedure is shown in Fig. 2.7.

2.3 Recognition methods

2.3.1 Correlation method

To provide a baseline performance measure for comparing the results obtained using other matching techniques, a simple correlation measure is used to assess the similarity between

(a)

(b)

(c)

(d)

Figure 2.5: RGB channel images of an image in the UBIRIS database (a) Normalized iris, (b)(c) and (d) Red, Green and Blue channel images of normalized iris in (a).

Figure 2.6: (i) Cross-spectral genuine matching involves matching different channel images from the same person 'a' taken at different times. (ii) Cross-spectral impostor matching involves matching different channel images from different persons 'a' and 'b'

two normalized iris images. Correlation, r , between two images A and B is computed as

$$r = \sum_x \sum_y \frac{(A_{xy} - \bar{A})(B_{xy} - \bar{B})}{\sqrt{(\sum_x \sum_y (A_{xy} - \bar{A})^2)(\sum_x \sum_y (B_{xy} - \bar{B})^2)}}$$

where, A_{xy} denotes the intensity value of image A at location (x, y) ,

B_{xy} denotes the intensity value of image B at location (x, y) ,

$\bar{A}$ is the mean intensity value of image A , and

$\bar{B}$ is the mean intensity value of image B .

2.3.2 SIFT based method

This method involves finding Shift Invariant Feature Transform (SIFT) keypoints [33] in the normalized iris image. Publicly available code ³ is modified to extract these keypoint locations along with their descriptors. Each location is represented by the (x, y) , location of the keypoint along with σ and θ , the scale and orientation, respectively, at which the

³<http://www.cs.ubc.ca/~lowe/keypoints/>

Figure 2.7: (i) Intra-spectral genuine matching involves matching same channel images from the same person 'a' taken at different times. (ii) Intra-spectral impostor matching involves matching same channel images from different persons 'a' and 'b'

keypoint is found. According to [31], the scale at which the keypoint is found is representative of the size of the feature. Keypoints detected at very low σ , corresponding to minute noisy regions, are eliminated. The remaining keypoint descriptors of the two images are matched to generate a normalized match score.

This process is shown in Fig. 2.8

Figure 2.8: SIFT base matching algorithm for comparing two iris images

The SIFT matching is implemented as follows. Consider two images, Image 1 and Image 2, with n_1 and n_2 number of keypoint descriptors, respectively. The distance/dissimilarity

between two descriptors is simply the Euclidean distance between the keypoint descriptor vector. Nearest neighbor is defined as the keypoint with the minimum Euclidean distance for the keypoint descriptor [33]. A positive match occurs when the first nearest neighbor is significantly closer to than the closest incorrect match. For each descriptor in Image 1, a matching descriptor is searched in descriptors for Image 2. If there are m matches found, then the normalized match score, s , is computed as

$$s = \frac{m}{\text{minimum}(n_1, n_2)}.$$

2.3.3 Blob based method

Blob in a gray scale image may be refer to a region that is brighter or darker than its surroundings [31]. Iris matching using blobs is an attempt to match two iris images by finding point-to-point correspondences between two iris images rather than a similarity score based on a textural response. Here, “point” refers to a blob that is to be localized.

Blob detection

This method is applied to a gray scale iris image representing the red channel. The contrast of a normalized iris image is enhanced using Contrast Limited Adaptive Histogram Equalization (CLAHE)[65]. The normalized iris image in Fig. 2.10 shows blob like structures which could correspond to radial furrows, crypts, macro features [59] or any other prominent element. In this work, the blob extraction algorithm developed by Jahangiri et.al. [25] is used to detect perceptually prominent regions in the image. The input image is enhanced using an edge preserving Toboggan enhancement algorithm [20]. An edge map is then generated by applying Gaussian filters at different scales. The interest map is binarized by selecting a global thresholding using an automatic thresholding algorithm [40]. The blobs are detected by applying a series of image filling and morphological operations (opening and closing) and removing the less prominent regions. A bounding box is used to visualize the result of blob detection. A flowchart highlighting the steps involved in the blob detection algorithm is shown in Fig. 2.9. The result of blob detection is shown in Fig. 2.10.

Figure 2.9: Block diagram of the blob detection algorithm [25].

Blob matching

Each blob may be considered as a 3-dimensional vector represented by its location, (x, y) , area, A and shape, Sh . The similarity measure, SM , between two blobs (x_P, y_P, A_P, Sh_P)

Figure 2.10: Blob detection: (a) Original Normalized Iris image in the red channel (b) Visualizing the result of blob detection algorithm on image in (a)

and $Q(x_Q, y_Q, A_Q, Sh_Q)$ is given by

$$SM = w_1 * S_{xy} + w_2 * S_A + w_3 * S_{sh},$$

where,

$$S_{xy} = \text{inverse} \left(\sqrt{(x_P - x_Q)^2 + (y_P - y_Q)^2} \right),$$

$$S_A = \frac{\min(A_P, A_Q)}{\max(A_P, A_Q)},$$

$$S_{Sh} = \text{shapesim}(S_P, S_Q).$$

Here, *shapesim* is the inverse of the Procrustes shape distance [54]. This requires that the two shapes are first aligned with respect to their respective centroids with one-to-one point correspondence. The Procrustes distance, P_d between two shapes, x_1 and x_2 is given by

$$P_d = \sqrt{[(x_{j1} - x_{j2})^2 + (y_{j1} - y_{j2})^2]}.$$

Now, consider image X with blobs $(x_1, x_2, x_3, \dots, x_n)$ and image Y with blobs $(y_1, y_2, y_3, \dots, y_m)$ whose centroids do not fall in the masked noise region. Now a table of size $m \times n$ is constructed that computes blob similarity $SM_{1 \leq j \leq n, 1 \leq k \leq m}(x_j, y_k)$. Similarity values below a certain threshold are ignored. Point-to-point correspondences are found by iteratively removing rows

and columns corresponding to the highest similarly value. This ensures that a blob in image X is matched to at most one blob in image Y . Once the number of correspondences, N_{XY} , is found, the blob based similarity, S_{Blob} between images X and Y computed as

$$S_{Blob}(X, Y) = \frac{N_{XY}}{\min(n, m)}$$

2.3.4 IrisCode method

Iris images are first segmented and then normalized as described in the previous section. Masek's code [36] is used to encode the normalized iris into an iris code. Each row of the normalized iris pattern, corresponding to a circular ring on the actual iris, is convolved with a 1D Gabor wavelet and the output is phase quantized to four levels as described in Daugman's work [17]. Each filter produces two bits of data for each phasor and thus each iris code contains a total of 150x720x2 bits. A normalized mask is also encoded to represent valid iris bits as 1's and noisy regions as 0's.

Modified Hamming distance [36] is used to measure the distance (or) dissimilarity score between two iris templates. Hamming distance, HD , between templates X and Y with corresponding noise masks Mx and My is calculated as

$$HD = \frac{\sum_{i=1}^N \sum_{j=1}^N X_{ij}(XOR)Y_{ij}(AND)Mx_{ij}(AND)My_{ij}}{\sum_{i=1}^N \sum_{j=1}^N Mx_{ij}(AND)My_{ij}}$$

where N is the number of bits represented by each template.

Hamming distance is computed at various left and right offsets of the iris codes with respect to each other. This is to account for rotations of the actual iris that translate into column shifts in the pseudo polar domain. Of all the hamming distances thus computed, the lowest value is chosen to be the best match.

2.4 Performance

2.4.1 ROC plots

The recognition performance is evaluated by plotting receiver operating characteristic (ROC) curves for all possible scenarios. Plots for three cross-spectral matching cases, R-G,

G-B and R-B are generated along with three intra-spectral matching cases, R-R, G-G and B-B.

UPOL database

Fig. 2.11 shows the ROC plots for both cross-spectral and intra-spectral matching using correlation, IrisCode, SIFT-based and blob-based matching on the UPOL database.

Figure 2.11: Cross-spectral and Intra-spectral matching - ROC plots for UPOL database: (a) Correlation based (b) IrisCode based (c) SIFT based and (d) Blob based

Equal error rates (EER) for all the plots in Fig. 2.11 are presented in Table 2.2. It is observed that simple correlation method gives good performance on the UPOL database even in the cross-spectral scenario as shown in Fig. 2.11. This is because the samples in

the UPOL database have very minimal intra-class variation. IrisCode method also seems to perform better due to the same reason. Blob-based method gives an EER of 2.82 % for R-R matching which proves that this method may be used as a novel matching technology especially in the presence of partial iris. However SIFT and blob based methods did not perform as well as the IrisCode method in the cross-spectral matching scenario. This poor performance may be attributed to varying visual structures in different channels.

Table 2.2: EER values in % for UPOL database

UPOL	Correlation	IrisCode	SIFT based	Blob based
R-R	1.92	0.26	6.31	2.82
G-G	3.05	0.39	8.52	3.2
B-B	9.58	2.28	25.00	6.74
R-G	3.92	0.45	16.22	12.94
G-B	9.98	1.16	27.20	18.08
R-B	18.25	1.92	34.74	30.98

UBIRIS database

Fig. 2.12 shows the ROC plots for both cross-spectral and intra-spectral matching using correlation, IrisCode, SIFT-based and blob-based matching on the UBIRIS database.

Equal error rates (EER) for all the plots in Fig. 2.12 are presented in Table 2.3. The noticeable difference from the previous database is that IrisCode method did not perform well as it did in the UPOL database. This may be due to the characteristic of the image acquisition system resulting in varying levels of texture in different channels along with variations in the degree of focus, occlusion and specular reflections. The red and blue channel images of a normalized iris in UPOL database are visually very similar as shown in Fig. 2.2, whereas there is a lot of textural difference between the red and blue channel images of a normalized iris in UBIRIS database as shown in Fig. 2.4.

Dependence on eye color

EER values for IrisCode method on UBIRIS dataset indicate very good performance even in the cross-spectral scenario. In this experiment the efficiency of IrisCode method is studied

Figure 2.12: Cross-spectral and Intra-spectral matching - ROC plots for UBIRIS database: (a) Correlation based (b) IrisCode based (c) SIFT based and (d) Blob based

Table 2.3: EER values in % for UBIRIS database

UBIRIS	Correlation	IrisCode	SIFT based	Blob based
R-R	7.34	0.7	13.71	14.22
G-G	5.12	1.1	14.89	13.68
B-B	4.21	4.6	16.67	25.66
R-G	13.61	1.3	18.04	28.73
G-B	7.67	2.3	18.10	25.03
R-B	19.23	5.3	23.66	38.77

on three categories of colored irises. The dataset is divided into groups of 31 light colored irises, 81 yellowish brown irises and 117 dark colored irides. Fig. 2.13 shows examples of

light, yellowish brown and dark iris images, and Fig. 2.14 shows the performance of IrisCode method in these three different cases. The cross-spectral matching for light colored irides results in very low EERs indicating very good matching performance. However, the cross-spectral matching performance gradually decreases as the darker irides are matched against each other. This phenomena can be observed in Fig. 2.14.

Figure 2.13: Sample images of different colored iris images along with their corresponding red, green and blue channel images

2.5 Summary

Correlation method does seem to yield good performance for this limited dataset though it is clearly evident that this method will fail in differing non-uniform illumination conditions.

IrisCode method performs significantly well in the non-ideal UBIRIS dataset even in the cross-spectral scenario. One major factor that ensures this success rate is the method of segmentation that was employed for the UBIRIS dataset. If the segmentation mask of the red channel is not overlaid on the corresponding green and blue channel images but instead segmentation of red, green and blue channel images are done independently, then the performance may be severely affected. SIFT-based method and blob-based method provide a novel approach to iris matching. These methods may be successfully used in intra-spectral matching with reasonable accuracy while these two methods did not perform as well as IrisCode methods in cross-spectral matching. Red to Red matching gave the best matching performance and Red to Blue matching resulted in poor performance for all eye colors on both the datasets.

(a)

(b)

(c)

Figure 2.14: Cross-spectral and intra-spectral IrisCode based matching on (a) Light colored irises, (b) Yellowish brown irises and (c) Dark colored iris images.

Chapter 3

Multispectral analysis in NIR and Visible spectrum

In the previous section, the iris is analyzed entirely in the visible spectrum. Though it is shown that the red channel is sufficient to perform successful matching between two irides with high confidence, it may not be good enough for darker irides. In some cases, it becomes difficult to segment the pupillary boundary in darker irides when the iris is imaged in visible spectrum. For this reason, iris is traditionally imaged in NIR spectrum in 700-900 nm range. Darker eye colors are a direct result of high concentration presence of color inducing pigment called *melanin*. But light absorbance property of melanin decreases rapidly beyond 700nm [29] as shown in Fig. 3.1

The observed iris region has little dependence on color of the iris when imaged beyond 700nm. Most of the observed texture may be attributed to the intricate structures in the iris. WVU multispectral database and a proprietary “FaceIris” database are used to investigate the feasibility of matching iris images obtained in visible spectrum against those obtained in NIR spectrum.

This chapter is organized as follows. Section 3.1 describes the databases used for this study. Section 3.2 analyzes the differences in response of iris to wavelengths in the visible and NIR spectrum, and describes the cross spectral and intra spectral matching scenarios. Experiments and results are presented in section 3.3. Finally the chapter is summarized in section 3.4.

Figure 3.1: Absorbance spectrum of melanin. After 700 nm the observed iris region has little impact of melanin.

3.1 Datasets

3.1.1 WVU multispectral dataset

WVU multispectral dataset contains multi spectral images in NIR (near infrared), red, green and blue channels respectively. All these images are spatially co-registered for a single sample. The images are captured using a Redlake MS3100 multispectral camera [11] that uses three band pass prisms along with three CCDs to capture images from four wavelength bands. Native resolution of the captured iris images is 1040×1392 . This is a very small dataset with 26 subjects and 3 samples in four channels for each subject. This dataset contains almost equal proportions of dark brown, yellowish brown and blue irises.

Segmentation and pre-processing

The images in this dataset are manually segmented to ensure that improper segmentation would not hinder the analysis across the spectral bands. The illumination evident in the center of the iris was masked out using a simple thresholding scheme. All the pixels whose intensities greater than 240 in a 8-bit depth grayscale image are considered as part

Figure 3.2: WVU multispectral dataset: Sample images of a subject in (a) NIR, (b) Red, (c) Green and (d) Blue channels captured simultaneously and hence co-registered.

of illumination/ specular reflection. The procedure for conducting the manual segmentation is critical as it plays a major role in the overall performance. IR channel image is used for manual segmentation of the pupillary boundary, the limbic boundary, eye lids and eyelashes. As the corresponding red, green and blue channel images are spatially co-registered, the same mask generated from the IR channel is used for segmenting the images from the red, green and blue channels. The reason for doing this is that for dark iris colors, the precise location of the pupil boundary is very hard to detect by visual inspection in the red, green and blue channels (see Fig. 3.2 (d)). Example of marked noise regions along with pupil and limbic boundaries is presented in Fig. 3.3

Next the images are unwrapped into a doubly dimensionless rectangular grid using Daugman's rubber sheet model [17] with radial resolution of 144 and angular resolution of 720, respectively. The normalized iris is then subject to adaptive histogram equalization and

Figure 3.3: Segmentation of iris images in WVU multispectral database: (a) NIR, (b) Red, (c) Green and (d) Blue channel images of a single sample image. Segmentation mask generated for NIR channel image was overlaid on the red, green and blue channel images.

encoded using Mask’s method [36] as explained in the previous section.

3.1.2 FaceIris database

FaceIris dataset is a proprietary dataset consisting of high resolution face images along with iris images obtained in NIR domain for 406 subjects. Each subject has two samples of face images, two samples of NIR images for the left eye and two samples of NIR image for the right eye. The idea is to match the cropped iris image from high resolution face image against close up shot of iris image in NIR domain. Both sets of images are captured with different sensors at different times under different illumination conditions. Moreover, most of the NIR iris images are obtained under non-uniform illumination. The dimensions of iris images is shown in Table 3.1.

Fig. 3.4 shows sample iris images from the cropped face image and the corresponding

Table 3.1: Dimension of images in FaceIris dataset.

Parameter (in pixels)	Visible domain	NIR domain
Image resolution	2448×3264	640×480
Average iris diameter	75	212
Average pupil diameter	25	73
Inter-pupil distance	382	-

NIR iris images. The face image is not displayed as the dataset is proprietary.

Figure 3.4: Sample images in FaceIris dataset. (a) and (b) Left and Right iris images cropped from the high resolution face image. (c) and (d) are left and right iris images of the same individual in the NIR domain.

Automatic eye region detection on face image

To extract the iris information from the face image, the eye region needs to be detected. Trained Haar classifier is used for detecting the bi-ocular region (Fig. 3.5). In this case, the size of the detected eye pair region is 690×190 (Fig. 3.5). The detected iris region occupies 1.46% of the original face space based on the pixel information extracted. As can be seen,

the iris information presented on face images are very small thus presenting a challenge to match the extracted visible-light iris image against the NIR iris image. The *red channel* image is selected empirically to represent the visible-light image. Henceforth, in this section on FaceIris dataset, the term visible-light iris image refers to the red channel iris image extracted from the high resolution face image.

Figure 3.5: Examples of detected bi-ocular region and the corresponding iris images from the FaceIris Dataset

Iris segmentation

The eye regions in FaceIris database are automatically segmented by using Daugman's integro differential operator to detect the pupillary and limbic boundaries. The upper and lower eyelids are approximated with horizontal lines in the Hough space. Specular reflections are removed by thresholding. Incorrect segmentations are manually identified and are not considered for matching. A new dataset containing successfully segmented iris images is formed. Later the images in the new dataset are unwrapped into a doubly dimensionless projected polar coordinate system using Daugman's rubber sheet model [17]. The radial and angular resolution are chosen to be 20 and 360, respectively. Fig. 3.6 shows the segmented iris image along with its normalized and mask images.

Figure 3.6: Segmentation of images in FaceIris dataset. (a) Acquired NIR iris image. (b) Segmented image. (c) Normalized image. (d) Enhanced normalized image. (e) Corresponding Mask image

3.2 Experimental Analysis

3.2.1 Iris in NIR and RGB channels

Upon visual inspection, it is clearly evident that the NIR channel contains rich textural patterns followed by the red, green and blue channels, respectively. Images in blue channel do not reveal much texture and are very different from images in the red channel for dark

irides, while they are reasonably similar to red channel images for light colored (blue) irides. The histograms of the individual channels of the iris image in Fig. 3.2 are shown in Fig. 3.7.

Figure 3.7: Histogram of iris region in the NIR, red, green and blue channels of a sample image. NIR and red channels exhibit relatively good image contrast compared to green and blue channels.

The mean intensity of blue and green channel images is lower than NIR and red channel images. Variance in NIR and red channel is greater than green and blue channels.

3.2.2 Matching

Cross spectral and intra spectral matching is performed on NIR, red, green and blue channels, as described earlier in the thesis, on the WVU multispectral dataset. In the FaceIris dataset, the NIR iris image is matched only against the red channel of the iris image from the cropped face image. The red channel of the cropped face image is labeled as *visible*. The IrisCode matching technique developed by Masek [36] and described in section 2.3 is employed to evaluate the performance of cross spectral and intra spectral matching.

3.3 Performance

3.3.1 WVU multispectral dataset

ROC plots are generated for all possible cross spectral scenarios involving NIR, red, green and blue channels. ROC plots are also generated for intra spectral matching for all the channels. Fig. 3.8 shows the plots for IrisCode-based matching on the WVU multispectral dataset.

As the dataset is very small and EER is 0% for all the cases, histogram plots are generated for cross spectral match scores. Fig. 3.9 shows the histogram distributions of the genuine and impostor scores for NIR-Red, NIR-Green and NIR-Blue matching cases.

3.3.2 FaceIris dataset

Fig. 3.10 shows the ROC plots for Visible vs Visible, NIR vs NIR and NIR vs Visible matching cases. The dataset is further divided into two datasets containing images of left eye only and images of right eye only. Matching is done independently on these datasets.

EER values for the above ROC plots are shown in Table 3.2.

Table 3.2: EER values in % for FaceIris database

Matching (408 subjects)	EER for left eye	EER for right eye
NIR-NIR	8.52	7.84
Visible-Visible	14.84	13.22
NIR-Visible	25.81	24.34

Fusion

As the iris samples for both the left and the right eye are available for all the subjects, an experiment is conducted to fuse match scores from matching the left eyes and right eyes independently. A new dataset is derived from the FaceIris dataset containing subjects for whom correctly segmented samples of both the left and right eyes in both NIR and visible domain are available. The original dataset is trimmed down to a new dataset consisting

Figure 3.8: ROC plots for (a) cross spectral and (b) intra spectral matching on WVU multispectral dataset

of 116 subjects who satisfied the above condition. The fusion process can be visualized as follows. Given a probe and gallery image for the left and right eyes, match scores are generated by matching the left probe with the left gallery and the right probe with the right

Figure 3.9: Histogram distribution of genuine and impostor match scores for (a) NIR vs Red, (b) NIR vs Green and (c) NIR vs Blue channel matching in WVU multispectral dataset.

gallery and the resulting scores are added to give a fused score. Fig. 3.11 shows ROC plots for fusion of match scores for the NIR-NIR, Visible-Visible and NIR-Visible matching cases.

EER values for the above ROC plots are shown in Table 3.3

Table 3.3: EER values in % for fusion of left and right eye match scores in FaceIris database

Matching (116 subjects)	EER for left eye	EER for right eye	EER after fusion
NIR-NIR	6.83	11.97	1.64
Visible-Visible	9.83	7.12	3.07
NIR-Visible	16.73	16.9	11.85

(a)

(b)

Figure 3.10: ROC plots for cross spectral and intra spectral matching on FaceIris dataset. (a) Left eye. (b) Right eye.

Rank-k Identification

A Cumulative Match Characteristic (CMC) curve is generated to represent rank-k identification rate for the FaceIris dataset. For this task, a selective database for left iris images

Figure 3.11: Fusion of left and right eye match scores for (a) NIR-NIR, (b) Visible-Visible and (c) NIR-Visible matching

is formed. This dataset has 189 subjects where each subject has 2 samples each of NIR iris images and 2 samples each of left iris images from the face. Fig. 3.12 shows the rank-k identification rate for this dataset for both cross spectral and intra spectral matching. An identification accuracy of 70.37% is achieved for NIR-Visible matching at rank-15.

3.4 Summary

It is shown that cross spectral matching is feasible when the probe and gallery images are acquired by the same sensor with almost the same iris diameter, as in the WVU multispectral

Figure 3.12: CMC curve showing rank-k identification for FaceIris dataset

dataset. EER for all the cross spectral cases in the WVU multispectral dataset is zero, though this performance may degrade on a larger database with poor quality iris samples. Segmentation plays a major role in determining the efficiency of cross spectral matching. As observed in Fig. 3.2, it is very hard to locate the pupil boundary. If the pupil boundary is not properly localized, then the normalization step will result in a non-linear deformation of the actual iris region which would degrade the performance immensely.

FaceIris dataset presented a unique problem of matching visible spectrum face images with NIR iris image. An attempt was made to match iris images from a high resolution face image with traditionally acquired NIR iris images. The results indicate some promise towards achieving that goal with several challenges to overcome. Some of the main challenges include matching images captured by different sensors, obtained at different resolutions and under varying ambient lighting conditions. Simple fusion of match scores of left and right iris images resulted in a good improvement in performance in cross spectral matching.

Chapter 4

Multispectral analysis beyond 900nm

Iris is traditionally imaged at NIR wavelengths of 750nm - 900nm. This chapter explores iris at SWIR wavelengths of 900nm - 1700nm to study the feasibility of iris matching beyond 900nm. This will give an understanding of the iris recognition in the presence of invisible passive illuminators [46]. The tasks accomplished in this chapter are,

1. An acquisition system is designed to capture iris at different spectral bands from 900nm - 1700nm.
2. The response of iris to multispectral wavelengths is analyzed.
3. Cross spectral and intra spectral matching are performed, and the possibility of fusion is addressed.

This chapter is organized as follows. Section 4.1 describes the acquisition setup and the acquisition protocol. Section 4.2 analyzes the acquired iris images. Section 4.3 describes the applied pre-processing and matching techniques used to perform cross spectral and intra spectral matching. Experimental results are presented in section 4.4 and the chapter is summarized in section 4.5.

4.1 Acquisition system

The image acquisition setup is shown in Fig. 4.1. A XenICs XEVA-818 camera, with an Indium Gallium Arsenide (InGaAs) sensor and a 320×256 Focal Plane Array (FPA) with

30 μ m pixel pitch and 98% pixel operability and three stage thermoelectric cooling, is used to acquire the iris images. The XEVA-818 has a relatively uniform spectral response from 950 - 1700 nm wavelength (e.g. the Short Wavelength Infrared (SWIR) band) across which the InGaAs FPA has largely uniform quantum efficiency (see Fig. 3). Response falls rapidly at wavelengths lower than 950 nm and near 1700 nm [46].

The setup to achieve this acquisition is shown in Fig. 4.1. A Tungsten-Krypton DC light source is used as the broadband source to illuminate the eye. The 300 - 2200 nm wavelength output of the source is relatively flat over the camera's spectral response range, decreasing towards longer wavelengths. The broadband output of this source is cut with a cold mirror to exclude visible wavelengths below 750 nm for the comfort of the subject and to promote pupil dilation. The broadband light is then delivered to the eye using a ring illuminator with bandpass sufficient for the experiment's spectral range. The reflected light from the subject's eye is then collected through the center of the ring light, through a bandpass filter and imaged by the XEVA-818 camera using a conventional macro zoom lens.

Figure 4.1: Image acquisition setup

Eight, 100 nm FWHM, 4-cavity non-polarizing band pass filters centered at 950, 1050,

1150, 1250, 1350, 1450, 1550, and 1650 nm were fabricated to specification by Andover Corporation and used in sequence to image a subject's eye in spectral slices across the SWIR band under this broadband illumination. Peak transmission of these filters on Borofloat glass substrates ranges from 87 percent at 950 nm to 74 percent at 1650 nm. Refer to Fig. 4.2.

Figure 4.2: Camera photo response and its quantum efficiency shown along with the filter response of band pass filters used in the experiment. Images are obtained in 100nm spectral bands. Image courtesy XenICs and Andover Corporation.

A similar optical transmission efficiency through the macro zoom lens is expected at these wavelengths. As a result, as low as 50 percent transmission to the camera's FPA can be expected at the experiment's longest wavelengths.

4.1.1 Acquisition protocol

Iris images are obtained in SWIR domain using the following protocol.

Step 1: The bandpass filter is placed between the camera and the illumination source as shown

in Fig. 4.1.

Step 2: The subject is asked to place his/her head on the chin rest.

Step 3: A still image is captured by the camera when the subject is staring straight into the camera. Integration time is varied on the XenICs x-control software to show an image with reasonable good contrast. The image is then saved on the computer using XenICs x-control software.

Step 4: The subject is asked to remove the head from the chin rest.

Step 5: Repeat step 2, step 3 and step 4 to obtain 5 samples for one bandpass filter.

The above protocol is implemented for 7 bandpass filters centered at 950, 1050, 1150, 1250, 1350, 1450 and 1550 nm; and for left and right eye of 25 subjects. Fig. 4.3 shows sample images obtained for a subject using 7 bandpass filters.

4.2 Image Analysis

This section presents an analysis of the acquired iris images in SWIR domain.

4.2.1 Contrast Variation and Varying Average Brightness

There is a gradual change in image contrast and average brightness across the examined spectral bands as shown in Fig. 4.4. This pattern can be reasonably explained with the water absorption spectrum ¹ of the aqueous humour, a thick watery region between the lens and cornea. The water absorption spectrum indicates high coefficients for 1350nm - 1650nm wavelengths compared to 950nm - 1250nm. This is believed to be the reason for darker images after 1350nm wavelengths. According to [13] absorption co-efficient for water peaks at 1450nm and decreases slightly thereafter. This results in a relatively “darker” image at 1450nm compared to the image obtained at 1550nm.

However, this does not completely explain the photometric nature of these multi spectral images. For example, if the explanation above based on water absorption were to be the sole

¹<http://www.lsbu.ac.uk/water/vibrat.html>

Figure 4.3: Sample images obtained at wavelengths (a) 950nm, (b) 1050nm, (c) 1150nm, (d) 1250nm, (e) 1350nm, (f) 1450nm, (g) 1550nm, and (h) 1650nm.

reason for the "dark" images, then the samples obtained using the 1550nm band pass filter would be expected to be darker than the images taken using the 1650nm band pass filter; but the images at 1550nm filter are observed to be a little "brighter", as can be observed in the histogram plot shown in Fig. 4.4(g). It must be noted that the average power incident on the eye varied as a function of the wavelength used. This could have also impacted the quality of the images procured at different bands, particularly the images beyond 1450nm. This also gives rise to the possibility of other contributing factors, such as the different absorption properties of individual components of the iris structure and the optical properties of the lens system used in the camera, to the overall brightness and contrast.

4.2.2 Differential response of iris

Different components of the iris seem to respond differently at multiple spectral bands for dark colored irides. One such prominent observation is the presence of a blurred limbic boundary at 950nm and a sharp limbic boundary at 1350nm. So, images at 1350nm could potentially be used for segmentation (due to the prominent limbic edges) while the images taken at smaller wavelengths could be used for extracting the iris texture. Also, eyelashes that are observed to be dark at 950nm, appear grey at 1350nm and white beyond 1350nm (Fig. 4.5). Thus, if these multi spectral images were obtained simultaneously (i.e., if they are co-registered), then segmentation could be significantly improved due to the differential response of the various ocular structures at different spectral bands.

Even after applying enhancement techniques like adaptive histogram equalization it is observed that the textural information of the iris varied across the different spectral bands. The images after applying adaptive histogram equalization are shown in Fig. 4.6.

4.2.3 Improper illumination and focus

Although the focus is manually adjusted each time an image was acquired, there are a few out of focus images due to the movement of the subject's head on the chin-rest. Similarly, as the ring illuminator is manually adjusted, identical illumination across all subjects is not guaranteed. However, these factors do not drastically alter the structure of the iris image since, for the most part, utmost care is taken to impose uniformity in the data collection process across subjects.

4.3 Preprocessing and Matching

4.3.1 Segmentation

In order to decouple the effect of inaccurate segmentation on the performance of iris recognition, the irides in the acquired images are manually segmented. The pupil boundary and limbic boundary are assumed to be circular although they are not usually concentric. Noisy regions including eyelashes and occlusions are manually marked in the image as shown

in Fig. 4.7. This ensured that segmentation was not a confounding factor for further investigation.

4.3.2 Normalization, Pre- processing and Encoding

Daugman’s rubber sheet model is used to unwrap the iris from Cartesian coordinates to a pseudo-polar coordinate system. The mask denoting the segmented iris is also unwrapped into this new coordinate system. The normalized image is subject to adaptive histogram equalization as part of pre-processing, see Fig. 4.7. Adaptive histogram equalization improves the contrast of the image by transforming the grayscale values of an image using contrast-limited adaptive histogram equalization (CLAHE). This algorithm stretches the histogram of local group of pixels, called tiles, rather than stretching the histogram of entire image (Fig. 4.8). This ensures that the overall shape of histogram of the entire image is not overly modified. This also ensures that not much noise is induced in the grayscale values of the image. Each row of the normalized iris is considered as a 1-D signal and log Gabor filters are applied to this signal resulting in a complex valued output. The frequency response of a Log-Gabor filter is given as;

$$G(f) = \exp \left[\frac{-(\log(f/f_o))^2}{2(\log(\sigma/f_o))^2} \right]$$

where f_o represents the center frequency, and σ gives the bandwidth of the filter. The output of the filter is phase quantized to four grey levels (with 0’s and 1’s) using Daugman’s method. This binary feature vector is referred to as the ‘iris code’. Note each row corresponds to a circular ring on the iris and maximum independence occurs in the angular direction, i.e., along the columns in the pseudo-polar coordinate system. Masek’s code [36] is modified to process the obtained images and also used to normalize, encode and match the iris images.

4.3.3 Matching

In order to generate a match score, the Hamming distance between two iris codes is computed after taking into account the masked bits corresponding to noise due to eyelashes, eyelids, occlusion, etc. The Hamming distance between two iris codes, codeA and codeB,

with corresponding mask arrays, maskA and maskB, is given as [17]:

$$HD = \frac{||(\text{code}A \otimes \text{code}B) \cap \text{mask}A \cap \text{mask}B||}{||\text{mask}A \cap \text{mask}B||}$$

4.4 Experimental Results

4.4.1 Data set

A dataset containing samples from 25 subjects is used to conduct the following study. Only five spectral bands corresponding to 950, 1050, 1150, 1250 and 1350nm are used in the experiment as the textural clarity of the images from the remaining bands is too low to be of benefit for this study. More research is required in order to establish the utility of these bands (i.e., 1450, 1550 and 1650nm) in iris recognition and to determine if the texture can be reliably extracted.

4.4.2 Definitions

Intra spectral genuine scores are obtained when two samples from the same spectral band of the same eye of a subject are matched. Cross spectral genuine scores are obtained when an image from one spectral band is matched against an image from different spectral band, where both the images correspond to the same eye of the same subject. Intra spectral impostor scores are obtained when an image of, say, the left eye of a subject from a particular spectral band is matched against an image of the left eye of a different subject from the same spectral band.

4.4.3 Fusion

Since 5 images corresponding to multiple spectral bands are available for each (probe) eye, the match scores generated by comparing these individual images against their counterparts (of each eye) in the database (gallery) can be fused. Fusion is expected to benefit the recognition process in the following ways: (a) when images pertaining to a subset of the spectral bands are not of good quality, then images from the other bands could be used to perform matching; (b) if all the images are corrupted by noise, then fusion at the score level

can help reduce the variance associated with the noise. In this work, fusion is accomplished using the simple sum rule.

In the current acquisition system, the multispectral images of a single iris are not acquired simultaneously due to the fundamental limitation of the configuration of the system. However, future advances in optics and imaging can make this possible thereby exploiting the benefits of parallel fusion.

4.4.4 Histogram plots

A total of 2500 intra spectral genuine scores (10 scores for each spectral band per subject per each eye, left and right eyes for each subject, 25 subjects and 5 spectral bands in all); 25000 cross spectral genuine scores ($5 \times 5 = 25$ scores for each pair of spectral bands per each eye of a subject, 4 pairs for each spectral band under consideration, 5 spectral bands, left and right eye of 25 subjects); and 75000 intra spectral impostor scores ($5 \times 5 = 25$ scores for each pair of impostors in each spectral band, 5 spectral bands in all, impostor combinations, for left and right eyes) are generated. The normalized histogram plots of distance scores for each spectrum band (for 25 subjects, the plot shows combined scores for both left and right eyes of a subject), along with the normalized histogram plot of the scores from all the bands, are shown in Fig. 4.9. The histogram plot of fused scores is shown in Fig. 4.10.

The intra spectral impostor scores are observed to be fairly well separated from the intra spectral genuine scores. Cross spectral genuine scores, on the other hand, are spread over a wide range of scores. In some cases, the cross spectral genuine scores overlap with the intra spectral impostor scores. This is expected because of the varying textural information across the spectral bands of a single eye. Most of the overlap is due to images taken at 1350nm because of their low textural quality. However, the experiments confirm the possibility of performing cross-spectral matching beyond 900 nm. Also, some outliers for genuine intra spectral scores can be observed in the histogram plot for 950nm, as shown in Fig. 4.10(a). This may be due to improper manual segmentation as the limbic boundary was blurred in some eye images making it difficult for the operator to accurately segment the image. It is clearly evident that fusion is beneficial and that the fused genuine and impostor scores are

better separated than the scores before fusion.

4.4.5 Box Plots

Fig. 4.11 shows the box plots for genuine intra-spectral and genuine cross-spectral scores. It is observed that genuine intra-spectral scores have the least median value and are mostly spread around this value. Another observation is that the distribution of genuine intra-spectral scores is almost similar across all the spectral bands, as can be visualized in the box plots along the main diagonal. Also, when comparing images of the same iris at two spectral bands that are farther apart, the distance scores tend to be higher (i.e., worse) as can be observed from the first row of plots in Fig. 4.11. The distribution of scores tends to move up in the box plots when traversing from left to right in this row.

4.5 Summary and Conclusions

The purpose of this work was to explore the feasibility of conducting iris recognition beyond 900nm. It represents the first attempt in the literature to do so. Such an analysis is required to understand the structure of the iris that is revealed at longer wavelengths. Further, in tactical environments, the use of detectors/sensors beyond the visible range would necessitate the processing of biometric images acquired at longer wavelengths. An acquisition system using an InGaAs focal plane array camera is designed in this work to acquire a small data set of images in the 900nm - 1600nm range. Initial experiments suggest the possibility of cross-spectral matching in the 900 to 1400nm range. However, more detailed experiments are necessary to confirm this possibility for irides corresponding to different eye colors.

From a computer vision perspective, the difference in iris texture across spectral bands is an intricate function of the physical characteristics of the detector (i.e., sensor), optical characteristics of the camera lens, bandpass filters and the anatomical differences in the iris structure revealed in these bands. This justifies the use of a fusion scheme to enhance recognition accuracy. Better enhancement techniques for photometric normalization and geometric registration may be required to improve the performance of multi spectral matching

in large data sets.

Figure 4.4: Image histogram plots of images taken at (a) 950nm, (b) 1050nm, (c) 1150, (d) 1250nm, (e) 1350nm, (f) 1450nm, (g) 1550nm, and (h) 1650nm.

Figure 4.5: Images taken at wavelengths (a) 950nm and (b) 1350nm. The color of eyelashes is black at 950nm where as they turn white at 1350nm and beyond. Also note the sharp limbic boundary at 1350nm.

Figure 4.6: Adaptive histogram equalized images taken at (a) 1350nm, (b) 1450nm, (c) 1550nm and (d) 1650nm wavelengths. No distinct texture available at these wavelengths and also whitened eyelashes can be observed.

Figure 4.7: (a) Manually segmented iris image, obtained at 950nm, showing the masked pixels as black, (b) Unwrapped iris (c) Adaptive histogram equalized image of image in (b), and (d) Mask array showing whitened regions corresponding to noise.

Figure 4.8: Image histogram plots of images taken at (a) 950nm, (b) 1050nm, (c) 1150, (d) 1250nm and (e) 1350nm, before and after adaptive histogram equalization is applied. Contrast variation, spread in the horizontal direction, is improved after adaptive histogram equalization.

Figure 4.9: Normalized histogram plots of genuine cross spectral (blue dotted line), genuine intra spectral (black line) and impostor intra spectral (red line with markers) distance scores for (a) 950nm, (b) 1050nm, (c) 1150nm, (d) 1250nm, (e) 1350nm and (f) all the wavelengths combined.

Figure 4.10: Normalized histogram plots of genuine intra spectral and impostor intra spectral distance scores for (a) 950nm, (b) 1050nm, (c) 1150nm, (d) 1250nm, (e) 1350nm and (f) fused case. Simple fusion of scores results in good separation between genuine scores and impostor scores.

Figure 4.11: Box plots of genuine intra-spectral and genuine cross-spectral scores. Each boxplot shows the distribution of genuine scores when image pairs obtained at the spectral bands indicated in the row and column labels are matched.

Chapter 5

Conclusions and Future work

In this thesis, iris matching was performed at different wavelengths corresponding to the visible, NIR and SWIR spectrum. Experiments were carried out on UBIRIS and UPOL databases (for visible spectrum), WVU multispectral and ‘FaceIris’ dataset (for NIR spectrum) and ‘WVU SWIR multispectral dataset’ (for SWIR spectrum).

In the visible spectrum, the red channel was observed to elicit maximum textural response even for dark irides as the effect of color inducing pigment, called Melanin, decreases towards the red wavelength. Cross-spectral and intra-spectral matching was performed on red, green and blue channels of a RGB image. Correlation matching was used as the baseline performance against which other matching methods were compared. Other matching methods included traditional ‘IrisCode’ method and SIFT-based matching method. A novel blob-based matching method that generates a match score based on similarity between blob like structures in the iris images was presented. The new blob-based matching achieves a reasonable matching performance on the ideal UPOL database for Red versus Red matching. The ‘IrisCode’ method yielded the best performance on both the UPOL and the UBIRIS databases even for the red vs blue channel matching scenario. Very low EER of 0.26% on UPOL database and 0.7% on UBIRIS database for red vs red channel matching suggests that the ‘IrisCode’ method can be successfully used to match iris images obtained in visible spectrum with high confidence. It was also observed that greater the difference in wavelengths of the two iris images to be matched, the poorer was the performance of cross-spectral matching. This is borne out by a larger equal error rate for red vs blue chan-

nel matching compared to red vs green matching. The future work in this domain may be directed towards iris matching on non-ideal datasets.

In the NIR domain, the analysis was restricted to matching NIR iris images against iris images obtained in the visible spectrum. The cross-spectral matching results on WVU multispectral dataset containing co-registered NIR, red, green and blue channel images indicate that NIR iris images can be successfully matched against visible-wavelength iris images. A novel problem of matching traditionally acquired NIR iris images against iris images extracted from a high resolution face image obtained in the visible spectrum was presented. The eye region was automatically detected and iris regions were extracted from these high resolution face images. As the red channel was most suitable for matching in the visible domain, it was used to match against NIR iris images. Average EER of 25% was achieved on the ‘FaceIris’ dataset for NIR vs visible matching scenario. An EER of around 8% for NIR vs NIR matching indicates that the ‘FaceIris’ dataset is non-ideal and that future work should aim at developing new methods for cross-spectral iris recognition.

In the SWIR domain, an image acquisition setup was designed and iris images were collected from 25 subjects in 100nm spectral bands from 900nm to 1700nm with peak transmission at 950, 1050, 1150, 1250, 1350, 1450, 1550 and 1650nm, respectively. To our knowledge, this was the first attempt to study or analyze the iris at these wavelengths. ‘IrisCode’ method was used to perform iris matching up to 1350nm only as there was no visible textural pattern available from 1450nm onward. The iris images obtained at greater than 1450nm wavelengths presented a problem for manual segmentation of pupillary boundary even after enhancement and, hence, were not used for matching. Though the IrisCode method performs well from 950nm-1350nm, the experiments should be carried out on a larger dataset to adequately claim the use of these spectral bands for iris matching. Fusion of cross-spectral match scores resulted in a better separation between genuine and impostor scores. Safety precautions have to be taken when the subject is exposed to the SWIR wavelengths for longer durations.

Appendix A

Integration times for SWIR iris dataset

The XEVA-818 camera used for iris image acquisition was operated with default values using the X-Control software. The only parameter that was varied is the *integration time*. Integration time is the duration upto which the the captured frames are integrated to improve luminous intensity of the image. This parameter is varied between 0-10000 μs and a suitable value based on perceived image contrast is selected. This selection was done subjectively by the operator collecting the data. The integration values for the 25 subjects in the SWIR database along with their eye color information in presented in Table A.1.

	Wavelength (nm)								
	950	1050	1150	1250	1350	1450	1550	1650	
	Integration time (0-10000 μs)								Eye Color
Subject 1	7724	3496	5854	10000	10000	10000	10000	1000	brown
Subject 2	8699	3902	4408	5528	6829	10000	10000	10000	brown
Subject 3	10000	7886	10000	10000	10000	10000	10000	10000	blue
Subject 4	5935	4878	7317	8780	10000	10000	10000	10000	hazel
Subject 5	9431	4390	5285	5285	8455	10000	10000	10000	brown
Subject 6	10000	9187	10000	10000	10000	10000	10000	10000	green
Subject 7	7000	4878	4878	4878	10000	10000	10000	10000	brown
Subject 8	7000	4500	5500	5500	10000	10000	10000	10000	brown
Subject 9	7561	4634	5772	5772	10000	10000	10000	10000	dark brown
Subject 10	10000	6341	10000	10000	10000	10000	10000	10000	brown
Subject 11	8049	10000	10000	10000	10000	10000	10000	10000	brown
Subject 12	10000	10000	10000	10000	10000	10000	10000	10000	black
Subject 13	10000	4634	6229	5285	10000	10000	10000	10000	-
Subject 14	10000	4472	5366	5366	10000	10000	10000	10000	black
Subject 15	10000	5691	5691	8005	10000	10000	10000	10000	brown
Subject 16	4263	2764	2764	4263	6179	10000	10000	10000	brown
Subject 17	5935	3984	6016	4553	8374	10000	10000	10000	brown
Subject 18	8130	-	4390	5203	6423	10000	10000	10000	brown
Subject 19	8211	5122	5041	7317	10000	10000	10000	10000	brown
Subject 20	4959	3659	4309	3902	8374	10000	10000	10000	brown
Subject 21	7236	4228	4065	4309	8455	10000	10000	10000	brown
Subject 22	7724	5203	5772	10000	10000	10000	10000	10000	brown
Subject 23	-	4065	5122	5610	6992	10000	10000	10000	brown
Subject 24	3821	2195	3252	4634	6504	10000	10000	10000	hazel
Subject 25	3821	3008	3984	5122	10000	10000	10000	10000	brown

Table A.1: Integration values and eye color information for the 25 subjects in the SWIR dataset

References

- [1] <http://www.nextgenid.com/>.
- [2] <http://www.bio-guard.net/index.php/homeguard-white-paper/>.
- [3] <http://www.integratedbiometrics.com/>.
- [4] Y. Adini, Y. Moses, and S. Ullman. Face recognition: The problem of compensating for changes in illumination direction. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 19(7):721–732, 2002.
- [5] S. Baker, K. Bowyer, and P. Flynn. Empirical evidence for correct iris match score degradation with increased time-lapse between gallery and probe matches. *Advances in Biometrics*, pages 1170–1179, 2009.
- [6] C. Belcher and Y. Du. Region-based sift approach to iris recognition. *Optics and Lasers in Engineering*, 47(1):139–147, 2009.
- [7] I. Biederman. Human image understanding: Recent research and a theory. *Computer Vision, Graphics, and Image Processing*, 32(1):29–73, 1985.
- [8] WW Boles and B. Boashash. A human identification technique using images of the iris and wavelet transform. *IEEE Transactions on Signal Processing*, 46(4):1185–1188, 2002.
- [9] T. Bourlai, N. Kalka, A. Ross, B. Cukic, and L. Hornak. Cross-Spectral Face Verification in the Short Wave Infrared (SWIR) Band. In *International Conference on Pattern Recognition (ICPR)*, pages 1343–1347. IEEE, 2010.
- [10] K.W. Bowyer, K. Hollingsworth, and P.J. Flynn. Image understanding for iris biometrics: A survey. *Computer Vision and Image Understanding*, 110(2):281–307, 2008.
- [11] C. Boyce, A. Ross, M. Monaco, L. Hornak, and X. Li. Multispectral iris analysis: A preliminary study. In *CVPR workshop on Biometrics*, 2006.
- [12] L. Chenhong and L. Zhaoyang. Efficient iris recognition by computing discriminable textons. In *International Conference on Neural Networks and Brain*, volume 2, pages 1164–1167. IEEE, 2006.

- [13] J.A. Curcio and C.C. Petty. The near infrared absorption spectrum of liquid water. *Journal of the Optical Society of America*, 41(5):302, 1951.
- [14] J. Daugman. How iris recognition works. *IEEE Transactions on Circuits and Systems for Video Technology*, 14(1):21–30, 2004.
- [15] J.G. Daugman. Two-dimensional spectral analysis of cortical receptive field profiles. *Vision research*, 20(10):847–856, 1980.
- [16] J.G. Daugman. Uncertainty relation for resolution in space, spatial frequency, and orientation optimized by two-dimensional visual cortical filters. *Journal of the Optical Society of America A*, 2(7):1160–1169, 1985.
- [17] J.G. Daugman. High confidence visual recognition of persons by a test of statistical independence. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 15(11):1148–1161, 2002.
- [18] M. Dobes and L. Machala. UPOL iris image database. <http://www.inf.upol.cz/iris/>.
- [19] H. Ellis. *Aspects of face processing*. Springer, 1986.
- [20] J. Fairfield. Toboggan contrast enhancement. In *Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series*, volume 1708, pages 282–292, 1992.
- [21] S.P. Fenker and K.W. Bowyer. Experimental evidence of a template aging effect in iris biometrics. In *IEEE Workshop on Applications of Computer Vision (WACV)*, pages 232–239. IEEE, 2011.
- [22] L. Flom and A. Safir. Iris recognition system, February 3 1987. US Patent 4,641,349.
- [23] Y. Hao, Z. Sun, T. Tan, and C. Ren. Multispectral palm image fusion for accurate contact-free palmprint recognition. In *International Conference on Image Processing (ICIP)*, pages 281–284. IEEE, 2008.
- [24] J. Heo, S.G. Kong, B.R. Abidi, and M.A. Abidi. Fusion of visual and thermal signatures with eyeglass removal for robust face recognition. *Computer Vision and Pattern Recognition Workshop*, 2004.
- [25] M. Jahangiri and M. Petrou. An attention model for extracting components that merit identification. In *International Conference on Image Processing (ICIP)*, pages 965–968. IEEE, 2009.
- [26] A.K. Jain, P.J. Flynn, and A.A. Ross. *Handbook of biometrics*. Springer, 2007.
- [27] A.K. Jain, A. Ross, and S. Prabhakar. An introduction to biometric recognition. *IEEE Transactions on Circuits and Systems for Video Technology*, 14(1):4–20, 2004.
- [28] Helga Kolb. Webvision. <http://webvision.med.utah.edu/imageswv/draweye.jpeg>.

- [29] N. Kollias. The spectroscopy of human melanin pigmentation. *Melanin: Its Role in Human Photoprotection*, pages 31–38, 1995.
- [30] WK Kong and D. Zhang. Accurate iris segmentation based on novel reflection and eyelash detection model. In *Proceedings of International Symposium on Intelligent Multimedia, Video and Speech Processing*, pages 263–266. IEEE, 2001.
- [31] T. Lindeberg. *Scale-space theory in computer vision*. Springer, 1993.
- [32] Y. Liu, S. Yuan, X. Zhu, and Q. Cui. A practical iris acquisition system and a fast edges locating algorithm in iris recognition. In *Proceedings of Instrumentation and Measurement Technology Conference*, volume 1, pages 166–169. IEEE, 2003.
- [33] D.G. Lowe. Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision (IJCV)*, 60(2):91–110, 2004.
- [34] L. Ma, T. Tan, Y. Wang, and D. Zhang. Efficient iris recognition by characterizing key local variations. *IEEE Transactions on Image Processing*, 13(6):739–750, 2004.
- [35] L. Ma, Y. Wang, and T. Tan. Iris recognition using circular symmetric filters. In *Proceedings of the 16th International Conference on Pattern Recognition (ICPR)*, volume 2, pages 414–417, 2002.
- [36] L. Masek. MATLAB source code for a Biometric Identification System Based on Iris Patterns. *The School of Computer Science and Software Engineering, The University of Western Australia*, 2003.
- [37] G. Neethirajan, S.R. Krishnadas, P. Vijayalakshmi, S. Shashikant, and P. Sundaresan. PAX 6 gene variations associated with aniridia in south India. *BMC Medical Genetics*, 5(1):9, 2004.
- [38] H.T. Ngo, R.W. Ives, J.R. Matey, J. Dormo, M. Rhoads, and D. Choi. Design and implementation of a multispectral iris capture system. In *Conference Record of the Forty-Third Asilomar Conference on Signals, Systems and Computers*, pages 380–384. IEEE, 2009.
- [39] K.A. Nixon and R.K. Rowe. Multispectral fingerprint imaging for spoof detection. In *Proceedings of SPIE*, volume 5779, page 214, 2005.
- [40] M. Petrou and C. Petrou. *Image processing: the fundamentals*. Wiley, 2010.
- [41] H. Proença and L. Alexandre. UBIRIS: A noisy iris image database. *Image Analysis and Processing-ICIAP 2005*, pages 970–977, 2005.
- [42] H. Proença and LA Alexandre. Iris segmentation methodology for non-cooperative recognition. In *IEEE Proceedings on Vision, Image and Signal Processing*, volume 153, pages 199–205, 2006.
- [43] G. Rhodes, S. Brennan, and S. Carey. Identification and ratings of caricatures: Implications for mental representations of faces. *Cognitive Psychology*, 19(4):473–497, 1987.

- [44] N. Ritter, R. Owens, J. Cooper, and P.P. Van Saarloos. Location of the pupil-iris border in slit-lamp images of the cornea. In *Proceedings of International Conference on Image Analysis and Processing*, pages 740–745. IEEE, 1999.
- [45] A. Ross. Iris Recognition: The Path Forward. *IEEE Computer*, 43(2):30–35, 2010.
- [46] A. Ross, R. Pasula, and L. Hornak. Exploring multispectral Iris recognition beyond 900nm. In *International Conference on Biometrics: Theory, Applications, and Systems (BTAS)*, pages 1–8. IEEE, 2009.
- [47] A. Ross and S. Shah. Segmenting non-ideal irises using geodesic active contours. In *Biometrics Symposium: Special Session on Research at the Biometric Consortium Conference*, pages 1–6, 2006.
- [48] T.D. Rossing and C.J. Chiaverina. *Light science: physics and the visual arts*. Springer Verlag, 1999.
- [49] R.K. Rowe and K.A. Nixon. Fingerprint enhancement using a multispectral sensor. In *Proceedings of SPIE*, volume 5779, page 81, 2005.
- [50] R.K. Rowe, U. Uludag, M. Demirkus, S. Parthasaradhi, and A.K. Jain. A multispectral whole-hand biometric authentication system. In *Biometrics Symposium*, pages 1–6. IEEE, 2007.
- [51] W.J. Ryan, D.L. Woodard, A.T. Duchowski, and S.T. Birchfield. Adapting starburst for elliptical iris segmentation. In *International Conference on Biometrics: Theory, Applications and Systems (BTAS)*, pages 1–7. IEEE, 2008.
- [52] W. Sankowski, K. Grabowski, M. Zubert, and M. Napieralska. Iris Finder—Program For Reliable Iris Localization In Images Taken Under Visible Light, 2006.
- [53] D.A. Socolinsky and A. Selinger. A comparative analysis of face recognition performance with visible and thermal infrared imagery. In *International Conference on Pattern Recognition (ICPR)*, volume 16, pages 217–222, 2002.
- [54] M.B. Stegmann and D.D. Gomez. A brief introduction to statistical shape analysis. *Informatics and Mathematical Modelling, Technical University of Denmark, DTU*, page 15, 2002.
- [55] WS Stiles and G. Wyszecki. *Color science: concepts and methods, quantitative data and formulae*. John Wiley & Sons, New York, NY, 1982.
- [56] N. Sudha, NB Puhon, H. Xia, and X. Jiang. Iris recognition on edge maps. *Computer Vision, IET*, 3(1):1–7, 2009.
- [57] Z. Sun, T. Tan, and X. Qiu. Graph matching iris image blocks with local binary pattern. *Advances in Biometrics*, pages 366–372, 2005.
- [58] Z. Sun, T. Tan, and Y. Wang. Robust encoding of local ordinal measures: A general framework of iris recognition. *Biometric Authentication*, pages 270–282, 2004.

- [59] M.S. Sunder and A. Ross. Iris Image Retrieval Based on Macro-features. *International Conference on Pattern recognition (ICPR)*, 2010.
- [60] J. Wilder, PJ Phillips, C. Jiang, and S. Wiener. Comparison of visible and infra-red imagery for face recognition. In *Proceedings of the Second International Conference on Automatic Face and Gesture Recognition*, pages 182–187. IEEE, 1996.
- [61] R.P. Wildes. Iris recognition: an emerging biometric technology. *Proceedings of the IEEE*, 85(9):1348–1363, 2002.
- [62] L.B. Wolff, D.A. Socolinsky, and C.K. Eveland. Quantitative measurement of illumination invariance for face recognition using thermal infrared imagery. In *Proceedings of SPIE*, volume 4820, page 140, 2003.
- [63] W. Zhao, R. Chellappa, PJ Phillips, and A. Rosenfeld. Face recognition: A literature survey. *ACM Computing Surveys (CSUR)*, 35(4):399–458, 2003.
- [64] R. Zhu, J. Yang, and R. Wu. Iris Recognition Based on Local Feature Point Matching. In *International Symposium on Communications and Information Technologies (ISCIT)*, pages 451–454. IEEE, 2006.
- [65] K. Zuiderveld. Contrast limited adaptive histogram equalization. In *Graphics gems IV*, pages 474–485. Academic Press Professional, Inc., 1994.