Chapter 2
Collection of Multispectral Biometric Data for Cross-spectral Identification Applications

J.M. Dawson, S.C. Leffel, C. Whitelam and T. Bourlai

Abstract The ultimate goal of cross-spectral biometric recognition applications involves matching probe images, captured in one spectral band, against a gallery of images captured in a different band or multiple bands (neither of which is the same band in which the probe images were captured). Both the probe and the gallery images may have been captured in either controlled or uncontrolled environments, i.e., with varying standoff distances, lighting conditions, poses. Development of effective cross-spectral matching algorithms involves, first, the process of collecting a cohort of research sample data under controlled conditions with fixed or varying parameters such as pose, lighting, obstructions, and illumination wavelengths. This chapter details "best practice" collection methodologies developed to compile large-scale datasets of both visible and SWIR face images, as well as gait images and videos. All aspects of data collection, from IRB preparation, through data post-processing, are provided, along with instrumentation layouts for indoor and outdoor live capture setups. Specifications of video and still-imaging cameras used in collections are listed. Controlled collection of 5-pose, ANSI/NIST mugshot images is described, along with multiple SWIR data collections performed both indoors (under controlled illumination) and outdoors. Details of past collections performed at West Virginia University (WVU) to compile multispectral biometric datasets, such as age, gender, and ethnicity of the subject populations, are included. Insight is given on the impact of collection parameters on the general quality of images collected, as well as on how these parameters impact design decisions at the algorithm level. Finally, where applicable, a brief description of how these databases have been used in multispectral biometrics research is included.

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2.1 Multispectral Face Imagery—Background

One of the key aspects to facial recognition (FR) technology is the proper development of algorithms, which are able to successfully and consistently identify subjects. Many challenges exist within this realm, ranging from image quality to subject pose angle. These challenges are impacted by not just the camera system, but also by the scenario in which the data are collected. These scenarios impact the strategy of the algorithms that need to be designed, to mitigate the scenario-specific challenges. For example, in defense or law enforcement surveillance applications, it is often necessary to covertly (but non-intrusively) or opportunistically collect facial biometric data. This data, in turn, must be used to match subjects against a gallery or watch list to identify an unaware or uncooperative subject. This operational scenario poses a set of challenges to FR systems in that a myriad of non-idealities must then be considered to achieve high-confidence match scores. Some of these challenges, as also discussed above, are face acquisition at variable or long distances, facial occlusions, poor lighting, and otherwise obscured faces.

Currently, the majority of facial recognition systems employ the use of visible images captured under controlled conditions as probes to match against galleries of visible data. This poses several challenges which, due to the physical limitations of the visible spectrum, in nighttime or non-uniform lighting scenarios, yield poorer quality images. Further work is required to successfully incorporate FR in challenging environments.

To overcome the issues associated with poor lighting, researchers have explored other, non-visible wavelengths as a means of capturing face images. In particular, the infrared (IR) spectrum has been investigated as a means of possibly extending the facial recognition technology. The IR spectrum can be divided into *two primary divisions*: *thermal* and *reflective*. The lower reflective bands resolve images with well-resolved facial features, closely resembling those captured at visible wavelengths. The lower bands can further be divided into NIR (near infrared) (750–1100 nm) and SWIR (short-wave infrared) (900–1900 nm) [1–3]. These bands have a particular advantage over traditional visible imaging as they do not suffer from illumination-based color shifting. Algorithms have trouble distinguishing the difference between an object change and the illumination of the object changing [4].

On the opposite end of the infrared spectrum exists what is referred to as thermal infrared. These bands are commonly classified as MWIR (mid-wave infrared) (3–5 μm) and LWIR (long-wave infrared) (7–14 μm) [5–7]. Research in the LWIR bands has incorporated polarimetric thermal imaging as a means of enhancing cross-spectral face recognition; this notably improved face detection performance by combining polarimetric and traditional thermal facial features [8]. Extended polarimetric thermal imaging research also allows for the geometric and textural facial detail recognition [9]. Progress has also been made with the employment of partial least-square-based face recognition and more specifically thermal to visible face matching [10]. While the resolved images do not yield the same level of detail, the associated wavelengths are able to show recognizable facial details. The advantage to this side of the spectrum is

that it does not require an illumination source, as the detection is that of the emitted radiation from the subject rather than the reflected light.

When approaching the issue of matching visible galleries to infrared probe images, the shorter wavelengths promote a more natural transition from the visible gallery. Both the visible band and the shorter IR wavelengths have their advantages when applied to facial recognition, and thus, different applications have been developed. For instance, in 2009, a research group from the West Virginia High Technology Consortium Foundation (WVHTCF) developed an active-SWIR system, dubbed TINDERS, for detecting facial features at distances up to 400 m [11]. The group also demonstrated the ability to actively track human subjects at distances up to 3 km. Working on a part of the TINDERS face dataset, the authors in [1] worked on developing a heterogeneous FR matcher and demonstrated its capability and limitations at short as well as at long ranges. In 2010, the WVHTCF group was able to improve the TINDERS system to yield clearer, sharper images [12]. Since SWIR was chosen, an active illumination source was required. An advantage of that source is that it is considered eye safe for wavelengths greater than 1400 nm [11]. The SWIR spectrum also has the added benefit of being able to produce clear images in adverse weather conditions, such as heavy rain [13].

Different research groups have developed algorithmic approaches that allow matching of face images irrespective of their spectral view [1, 3]. The suggested approaches seem to preserve the facial structures and, thus, lending toward successful cross-spectral matches [3]. Similar approaches also lend promise toward the ultraviolet band [14], as well as the MWIR and LWIR bands making face detection, eye detection, and face recognition possible across the majority of the IR spectrum [6]. Lower IR (NIR) wavelengths can be eye safe and their biometric systems are mostly used in law enforcement applications [15]. However, NIR-based detectors suffer from issues of being detectable by silicon-based image sensors or in some case even the human eye [13].

As previously mentioned, the face images (probes) used in cross-spectral matching scenarios must be comparable to visible gallery photographs in some manner. This requires the development and implementation of cross-spectral face-matching algorithms. Allowing for accurate recognition and identification matching of non-visible probe images to visible galleries aides image matching from an ideal image (such as a photograph ID) to security footage, as recorded by an infrared camera in variable environmental conditions. In particular, SWIR has the added advantage of being able to operate in low-light scenarios, such as twilight or low illumination [11]. When natural or existing illumination is not sufficient, truly non-visible illumination sources are able to covertly illuminate a darkened area. SWIR band illumination can also be disguised from being detected by only illuminating selected wavelengths, e.g., 1550 nm, which will otherwise appear dark even in other SWIR wavelengths [5]. This capability enhances the covert nature of facial recognition in dark environments (where visible-based FR becomes very challenging) and has been shown to resolve better matching scores than visible data [16].

The SWIR spectrum also extends the viability of non-visible facial recognition by its wide applicability to both urban and rural environments. Urban environmental

obstacles such as reflective and tinted glass become transparent [17]. Additionally, common urban particulates, such as pollution and smog, are eliminated when operating in the SWIR band [17]. In rural settings, particulates such as dust, fog, and haze can be removed from SWIR images [18]. This lends SWIR tactical imagers to be highly desirable for operating in extraordinarily obstructed visible environments. As discussed, the NIR band can also be used in tactical imagery systems with success [17, 19], the disadvantage being easy detection of active NIR illumination sources.

Other Challenges in the SWIR Band

Though the non-visible SWIR band has many advantages, there are many issues that negatively impact facial recognition. A notable issue is that, above 1450 nm, the moisture found in skin begins to absorb the infrared wavelengths. This causes the skin to appear black or dark [17]. In darkened settings, the issue becomes further complicated when eye-safe illumination is necessary. As mentioned above, eye-safe illumination is above 1400 nm; the resulting images, however, will result in darkened skin on subjects [11]. This poses a challenge to many facial recognition algorithms currently in place, commercial or in-house (academic). Similarly, membrane tissues, such as the eye, become darker as the wavelength increases, and thus, the efficiency of automated eye-detection methods can be negatively affected. This issue is driven by the fact that the pupil becomes obscured in these wavelengths. Certain oils produced by the skin reflect infrared light as well. This causes saturation effects in images with high-intensity sources, such as infrared-emitting lamps (e.g., tungsten bulbs) and direct sunlight. Many of these effects can, however, be mitigated through hardware filtering to specific SWIR bands.

Contributions

The advantages of multispectral imagery outweigh the current associated issues found therein. Through its involvement with the NSF-funded Center for Identification Technology Research (CITeR), a cooperative agreement as lead academic partner of the FBI CJIS Division Biometric Center of Excellence, and funding from other federal agencies, West Virginia University, has conducted numerous data collection projects to build repositories of multimodal biometric data that can be used to mitigate different challenges identified within the field of human identification. To overcome these issues, particularly those associated with infrared-focused or cross-spectral-based face imaging, several of these data collection activities have included wavelength-specific SWIR face image capture (highlighting specific bands across the SWIR spectrum) and the generation of multi-wavelength SWIR face image datasets. Together, with a database of visible face images (a visible gallery), algorithmic development tends toward cross-spectral face-matching systems. Table 2.1 presents a selection of available infrared databases featuring human subjects. The use of such datasets allows for the development of better and more universally viable face-matching algorithms.

This chapter will outline the methods and procedures used to collect and build the aforementioned WVU SWIR databases, as well as provide a summary of cross-spectral matching results for the respective datasets. Lastly, if a SWIR imager lacks the optical system needed to capture high-resolution face images at a distance,

Table 2.1 Databases containing infrared images of human features

Authors	Spectral band	Application	Environment conditions
Pan et al. [27]	Infrared in range 700–1000 nm	Hyperspectral face recognition using liquid crystal tunable filter (LCTF) wheel	Outdoor
Multispectral Imagery Lab (WVU) [1, 5, 6, 15, 28–30]	Infrared in range 900–1550 nm as well as Thermal IR	Multispectral eye and pupil detection, multispectral face recognition, and cross-spectral face-matching algorithms	Indoors and outdoors
Kang et al. [31]	Illumination source of 940 nm wavelength	Face recognition using principal component analysis (PCA) and linear discriminant analysis (LDA)	Indoor
Ngo et al. [32]	Infrared in range from 450 to 1550 nm	Multispectral iris acquisition system	Indoor
Steiner et al. [33]	Infrared in range from 900 to 1700 nm	Multispectral face verification using spectral signatures	Indoor
Pavlidis et al. [34]	Infrared in range from 1400 to 2400 nm	Automatic detection based on a fusion scheme	Indoor
Jacquez et al. [35]	Infrared in range from 700 to 2600 nm	Spectral reflectance from human skin	Indoor
Bertozzi et al. [36]	Infrared in range from 900 to 1700 nm	Pedestrian detection	Outdoor
Lemoff et al. [37]	Infrared in range from 900 to 1700 nm	Face matching using fusion scheme	Indoor/outdoor
Qianting et al. [38]	Infrared in range from 1000 to 1700 nm	Image mosaicing using global thresholding	Indoor

gait information may be used to perform identification. Thus, gait-based recognition will also be discussed as a means to supplement face image data acquired at long distances (i.e., more than 50 m).

2.2 Institutional Review Board (IRB) Preparation

Projects that involve human research, including biometric data collection, require an approved Institutional Review Board (IRB) protocol. An institutional review board is a committee of individuals that reviews project details relating to human subjects research to ensure that investigators comply with all federal, state, and institutional requirements and policies relating to the appropriate protections for

human subjects. These protections include adequate provisions for minimizing subjects risk, documentation of subjects' consent forms, and, finally, protection of subjects' privacy and maintaining data confidentiality. For the research efforts described in this chapter, the IRB of the WVU Office of Research Integrity and Compliance provided reviews of all aspects of the data collection protocol, including participant recruitment, collection activities, remuneration, and biometric data privacy and storage. For the WVU IRB, the following two requirements are central to IRB approval:

1. *Training of personnel*: Any person affiliated with WVU (faculty, student, or staff) that is involved in the data collection or data processing is required to take a series of online courses to educate them on the ethics associated with human research related to social and behavioral studies (which WVU biometric collections fall under). At WVU, these courses are currently offered by the Collaborative Institutional Training Initiative at the University of Miami (citiprogram.org). There are online tests associated with these courses that train personnel in proper human subject research ethics. All collection staff members must pass these tests in order for the proposed IRB protocol to be approved.
2. *Protocol Statement Description*: This form is submitted electronically to the WVU Institutional Review Board (IRB) by the Principal Investigator. The Protocol Statement form contains information about:

   - Research teams: Principal Investigator, affiliated and non-affiliated team members, primary study contact, etc.
   - Funding sources.
   - Research studies and activities location.
   - Exemption determination.
   - Design of the research, including the category of research, procedures, subjects, sample size, potential risks and discomforts, potential benefits, confidentiality, subjects' costs, payments to subjects, etc.
   - Consent procedures, which involves a *Consent and Information* form. This document informs the subject (research study participant) about the project and confirms the voluntarily participation of the subject in the project.
   - Advertisements—any email text, newspaper ads, or flyers used to recruit participants must be included along with the data collection protocol.

If a prototype device is not used, or if biological samples are not collected, biometric collection projects may be eligible for *Expedited Review* (ER). Within the expedited review process, the protocol may be reviewed by an individual, member of the IRB panel and that is not involved in full-board meetings. Please note that this process may vary from institution to institution. The ER process may allow the protocol to be approved within a period of one or two weeks rather than one month or more. After the submission of the IRB protocol to the appropriate office, an IRB panel reviews the submitted documents. One of the potential outcomes of the assessment is the request for further revisions, and/or

the recommendation for the personnel to complete the appropriate course on human subject research (in case they did not). Next, required revisions are applied to the *Protocol Statement* form. Then, the form is resubmitted to the Office of Research Integrity and Compliance. Finally, the office approves the submitted IRB protocol under the conditions that human subject research is appropriate and conforms to federal regulations.
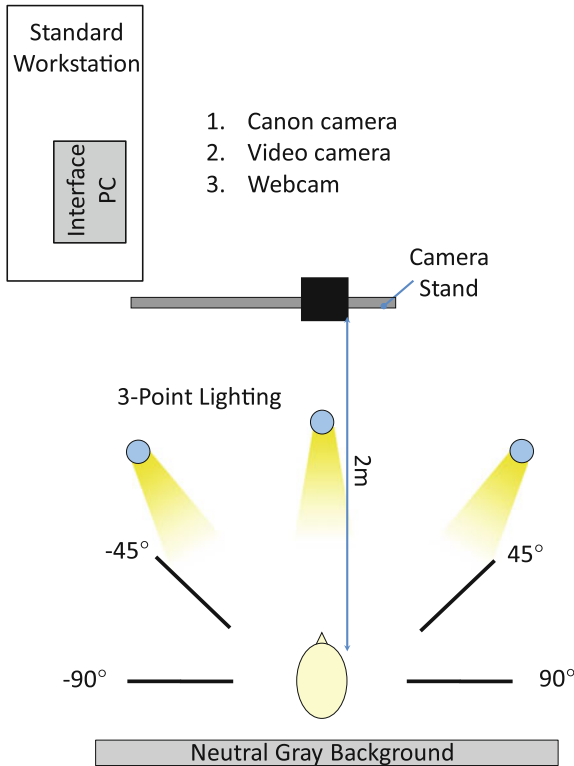
During the period for which the project is active, it is necessary that the project is annually reviewed, and thus, a *Continuing Protocol Review* (CR) needs to be completed. For a CR, statistical information pertaining to the study is gathered, including the number, gender, and race of the subjects enrolled in the study; the number of subjects from the special categories such as pregnant women and children, adverse events, number of subjects removed from the project, and grievances or complaints received about the study. All changes to the project, including added or removed researchers, new locations, new procedures or changes in procedures, new forms of advertisement, must be documented and submitted to the Office of Research Integrity and Compliance using as an amendment to the latest IRB protocol approved.

2.3 Standard Visible Mugshot Capture

In order to generate a baseline dataset of good-quality face images, a live subject-capture setup was used. It involves the necessary hardware (cameras, lenses, etc.) as well as a data collection protocol to be followed that uses the hardware under a specific scenario. In this work, the hardware typically employed for high-resolution ground truth capture of visible face images was a conventional DSLR camera, such as a Canon 5D Mark II or equivalent, with a telephoto zoom lens (such as a Canon EF 800 mm f/5.6L IS USM). This camera was used to capture 5 different poses: −90°, −45°, 0°, 45°, and 90°. A schematic view of the indoor photograph collection is shown in Fig. 2.1.

Three-point lighting is used to meet the standards outlined in ANSI/NIST–ITL 1-2007 *Best Practice Recommendation for the Capture of Mugshots* [20]. The lighting is comprised of one 250-W fixture and dual 500-W fixtures. The positioning of these light sources, with respect to the participant, is slightly asymmetric. There is also sufficient distance between the backdrop (neutral gray) and the participant in order to avoid background shadows. In addition, plastic diffusers in front of the reflector-mounted light bulbs are utilized to avoid "hot spots" that may appear on face images. The following camera settings typically result in the best focal depth and image quality under the 3-point tungsten lighting, i.e., (i) White Balance: Tungsten, (ii) ISO: 1000, (iii) F/2.6: 1/10, and (iv) exposure set to 1/60.

Fig. 2.1 Photograph station layout

1. Canon camera
2. Video camera
3. Webcam

2.4   SWIR Face Data Collection Activities

SWIR face data collection activities were undertaken to create a challenging dataset comprised of obstructed views of participants' faces under varying lighting conditions. Obstruction in this case consisted of various types of tinted glass and sunglasses. In order to assess the extent to which these materials or conditions affected the capture, characterization of the semi-transparent materials was first conducted in order to down-sample the number of materials used in data collection efforts, as well as establish a collection scheme for an *indoor data collection* (*Phase I*). An *outdoor collection* was then performed (*Phase II*) in order to establish more effective recognition algorithms under uncontrolled lighting conditions. The *Phase I* and *Phase II SWIR face image capture activities* were performed at a standoff distance of two (2) meters.

West Virginia University (WVU) partnered with the WVHTCF to extend the original SWIR face image collection by performing a long-distance, nighttime SWIR face image collection. By utilizing a specialized SWIR hardware setup, designed for day- or nighttime face image acquisition at long standoff distances, the

partnership resulted in an original face dataset that includes face images of 104 subjects captured at different standoff distances ranging from 100 to 350 m at night. At each distance, the following data were captured: neutral expression of participant looking directly at camera, participant rotating 360°, and neutral expression looking directly at camera through tinted glass. The following sections of this chapter will describe the SWIR data collections performed at WVU. First, characterization of tinted materials at different temperatures will be presented to illustrate the spectral transmission as a function of temperature. Next, indoor and outdoor data collection of face images will be discussed, highlighting the challenges of collecting SWIR face images through tinted materials in varying lighting conditions and standoff distances. Finally, a discussion of gait recognition based on SWIR video is provided as a complimentary means of recognition if facial features cannot be resolved in long-distance imagery.

2.4.1   Tinted Material Characterization

Prior to the initiation of cross-spectral face matching using images captured under challenging conditions (i.e., at night and/or through tinted materials), two studies were performed to understand how environmental factors, such as temperature and lighting, may impact the ability to see through tinted materials. The *first study* was aimed at understanding how changes in temperature may alter the spectral transmission properties of different materials. The *second study* explored how tint type/level coupled with internal and external lighting conditions affected the ability to image faces through glass. The material samples used in this study represent common architectural and automotive tinted glass with tint embedded in the material (all provided by Pittsburgh Plate Glass (PPG); Two (2) architectural samples include mirror coating), clear plate glass covered with tinted plastic film (Johnson Window Film), and various types of plastic lenses in eyewear (i.e., sunglasses) from several manufacturers. A detailed discussion of the results from this study is published in [21]. In summary, temperature change does not have a significant impact on the ability to see through tinted materials. Instead, different interior and exterior lighting conditions have the largest impact on the ability to acquire images though tinted materials. Contrast quality measures were applied to sample images taken under varying lighting conditions through materials of varying tint levels in order to rank materials according to transparency and image quality [21]. The tint transparency ranking was used to down-select the number of glass materials that were used in data collection efforts described in this chapter. Three samples were chosen representing low, medium, and dark tint.

2.4.2   SWIR Face Image Collections

Data collections were performed to provide operationally relevant data samples with which to develop eye and face detection techniques as well as SWIR face recognition algorithms that perform well under challenging conditions. Initial studies were performed on a dataset that was collected indoors under controlled lighting conditions (Phase I), with glass and sunglass types and lighting levels determined during the glass characterization experiments. After the completion of the Phase I data collection, a second collection (Phase II) was performed outdoors under varying daytime and nighttime lighting conditions to test the performance of and optimize recognition tools. This section summarizes the collection protocols and results of these two data collection efforts, with a brief description of other SWIR datasets that were developed in partnership with the WVHTCF.

2.4.2.1   Phase I—Indoor Collection Under Controlled Lighting Conditions

An InGaAs-based Goodrich SU640HSX-1.7RT SWIR camera was used for image acquisition based on previous work in this area [22, 23]. The solid-state InGaAs imaging array possesses high sensitivity in the 900–1700 nm spectrum and is capable of capturing images at 640 × 512 pixel resolution. The photograph booth and lighting setup shown in Fig. 2.2 was utilized to independently control interior and exterior light levels. The booth was designed with a removable front panel to which tinted materials with varying transparency would be affixed. The details of these materials are included in [21]. Due to interfering/obstructing reflections on the glass seen during initial testing using high exterior light levels at a short imaging

Fig. 2.2 Indoor data collection setup and lighting arrangement

distance (2 m), the camera setup was slightly angled ($\sim 12°$) to reduce the impact of reflections on images captured under these lighting conditions. In addition, a neutral gray background was placed in the reflection path to provide a constant background, further reducing the impact of image reflection.

An image collection protocol was designed to capture images for different materials under variable lighting conditions at wavelengths ranging from 1150 to 1550 nm. The wavelength filters were assembled in a wheel, which spun five (5) times in the process of collecting. Thus, we manage to acquire five (5) images per filter per participant.

Facial images were collected under the following scenarios, with all illuminance (lux) measurements taken at the interior booth seating location:

(A) External lighting eliminated, the only illumination source is the interior lighting at full intensity
(B) External lighting eliminated, the only illumination source is the interior lighting dimmed to ~ 60 lux
(C) External 3-point lighting only (~ 2 m distance; providing ~ 350 lux to booth interior), interior lighting eliminated
(D) Single external exterior light source only (~ 4 m distance, providing ~ 5 lux to booth interior)
(E) 1550 nm wavelength fiber couple laser operating at 500 mW; diffused to provide uniform face illumination (only applicable for 1550 nm SWIR filter)

Booth Panel ON:

1. *Clear w/0 % Film Tint* **Glass Panel**

  (A) Full interior (~ 2600 lux), 0 lux exterior
  (B) Minimum interior (~ 60 lux), 0 lux exterior
  (C) 0 lux interior, 3-point exterior (~ 350 lux)
  (D) Single external source (~ 5 lux)
  (E) 500 mW 1550 nm active illumination

2. *Clear w/85 % Film Tint* **Glass Panel**

  (A) Full interior (~ 2600 lux), 0 lux exterior
  (B) Minimum interior (~ 60 lux), 0 lux exterior
  (C) 0 lux interior, 3-point exterior (~ 350 lux)
  (D) Single external source (~ 5 lux)
  (E) 500 mW 1550 nm active illumination

3. *Solarcool (2) Graylite* **Glass Panel**

  (A) Full interior (~ 2600 lux), 0 lux exterior
  (B) Minimum interior (~ 60 lux), 0 lux exterior
  (C) 0 lux interior, 3-point exterior (~ 350 lux)
  (D) Single external source (~ 5 lux)
  (E) 500 mW 1550 nm active illumination

Booth Panel OFF:

4. *Ground Truth (**No Glass Panel**)*

  (A) Full interior ($\sim$2600 lux), 0 lux exterior
  (B) 0 lux interior, 3-Point exterior ($\sim$350 lux)

5. *Oakley Flak Jacket **Sunglasses***

  (A) 0 lux interior, 3-point exterior ($\sim$350 lux)
  (B) Single external source ($\sim$5 lux)
  (C) 500 mW 1550 nm active illumination

6. *Oakley Straight Jacket **Sunglasses***

  (A) 0 lux interior, 3-point exterior ($\sim$350 lux)
  (B) Single external source ($\sim$5 lux)
  (C) 500 mW 1550 nm active illumination

7. *RB3449 59 **Sunglasses***

  (A) 0 lux interior, 3-point exterior ($\sim$350 lux)
  (B) Single external source ($\sim$5 lux)
  (C) 500 mW 1550 nm active illumination

8. *RB3025 58 **Sunglasses***

  (A) 0 lux interior, 3-point exterior ($\sim$350 lux)
  (B) Single external source ($\sim$5 lux)
  (C) 500 mW 1550 nm active illumination

Visible images were acquired for each case using a standard Canon DSLR camera (5D Mark II with kit lens). A custom software SWIR camera interface was created for the purpose of simplifying the data collection process of SWIR and visible photographs when various materials and lighting conditions were used. The complexity of constant adjustments of the Goodrich SWIR and Canon cameras (as well as other equipment/devices) necessitated the development of an easy-to-use interface for collection personnel. This allowed for a quicker collection process and had the added benefit of limiting errors and/or poor data capture.

Sample images for ground truth, tinted glass, and sunglasses are included in Tables 2.2, 2.3, and 2.4, along with optimal OPR and ENH values (user-defined

Table 2.2 Sample ground truth images from Phase I data collection

Visible	SWIR (OPR 5, ENH OFF)				
	1150	1250	1350	1450	1150

Table 2.3 Sample tinted glass images from Phase I data collection

Variable Lightning – Clear glass with 85% Tint					
	Full Internal, No External	**Minimal Interior, No Exterior**	**No Internal, Full External**	**Single-Source External**	**Active Illumination**
Visible					
OPR	6	8	7	9	9
ENH	OFF	OFF	ON	ON	OFF
1150 nm					
1250 nm					
1350 nm					
1450 nm					
1550 nm					

SWIR camera settings) for each condition (lighting and filter wavelength). Table 2.2 shows sample ground truth images collected in visible and 1150-1550 SWIR bands. These images were used to establish a base comparison of ideal (i.e., constant illumination, no facial obstruction) verses operational data (i.e., through tinted glass and with sunglasses, both with varying lighting conditions).

For the SWIR images, a notable darkening of the skin can be seen in wavelengths longer than 1350 nm. Also, the entire eye (sclera and pupil) becomes black, posing challenges to eye-finding algorithms. Table 2.3 provides sample images collected with the 85 % tint glass panel in place under varying lighting conditions. These images show how high levels of external lighting combined with low levels of internal lighting can lead to reflections that obscure facial features in SWIR imagery. Table 2.4 provides sample images of an individual-wearing Oakley Flak Jacket sunglass under varying lighting conditions. The SWIR imager allows the periocular region to be seen clearly, but the effects of blackening of the eye still

Table 2.4 Sample sunglasses images from Phase I data collection

Variable Lightning – Oakley Flak Jacket			
	No Internal, Full External	**Single-Source External**	**Active Illumination**
Visible			
OPR	6	9	7
ENH	OFF	OFF	OFF
1150 nm			
1250 nm			
1350 nm			
1450 nm			
1550 nm			

remain. It should be noted that none of the glasses chosen for this study possessed polarizing lenses. Polarization coatings can greatly reduce or even eliminate the ability to see through the tinted glass or polymer used to make sunglass lenses. This effect can be seen in both natural lighting and active illuminators, and is highly dependent on the polarization state of the light emitted by the source.

The OPR (Operational Setting) value listed in these tables is an integer value corresponding to settings associated with the camera hardware; specifically, a combination of optimally associated digital camera gain and integration time settings. While sensor gain and integration time of this particular camera can be altered individually, the camera manufacturer did not guarantee optimal imaging

conditions at settings other than those associated with a fixed OPR value. The camera used in this collection has OPR values ranging from 0 to 11. The ENH (Enhancement) is a Boolean value and reflects image enhancement performed by the camera. The ENH setting ("OFF" or "ON") optimizes the 16-bit image to dynamically scale the image intensity. This allows oversaturated images or excessively dark images to appear more balanced, effectively normalizing pixel intensities within the image.

A total of 138 participants provided data between September 26, 2011, and December 4, 2011.

Figure 2.3 provides a breakdown of participant demographics by age, ethnicity, and gender, as well as a cumulative measurement of participation as a function of time.

Figure 2.3a indicates an average of ∼ 14 participants per week throughout the 10-week collection period, with highest participation during the week of 10/31. The week of 11/21 lacks participation due to West Virginia University being on Thanksgiving Break during that time. Figure 2.3b indicates that the majority of participants (67 %) were between 20 and 29 years of age, followed by 18–19, and 30–39 of age ranges. This is primarily due to student and staff participation in the data collection, conducted on the WVU campus. Only 6 % of participants were 50 or older. Figure 2.3c indicates that approximately half of the participants were Caucasian, followed by Asian Indian (18 %) and Asian (17 %) ethnicities. This demographic distribution is consistent with the student/staff population of WVU.
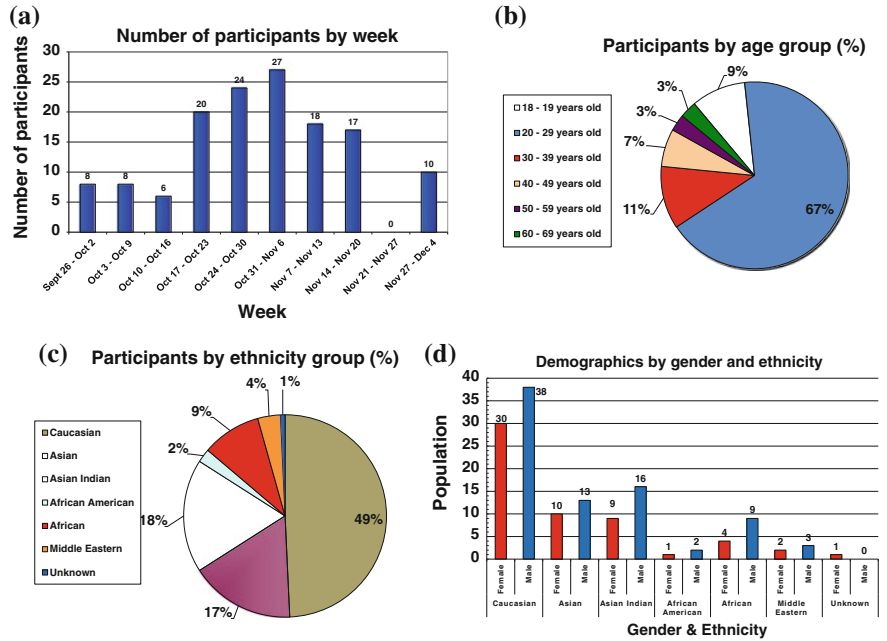

Fig. 2.3 Participant demographics for Phase I study

Figure 2.3d indicates that there was consistently higher male participation than female for all identified ethnic groups.

2.4.2.2 Phase II—Outdoor Collection Under Uncontrolled Lighting Conditions

Facial images were collected under the following scenarios, with all lux measurements taken at the interior booth seating location:

(A) External lighting was the ambient available light during collection, the only controlled illumination source is the interior lighting at full intensity
(B) Ambient external light sources, the only controlled illumination source is the interior lighting dimmed to ∼60 lux
(C) External ambient light only, all controlled light sources eliminated
(D) External ambient lighting, utilization of a 500 mW 1550 nm active illumination diffused laser light source was the only controlled light source.

Glass Panels:

1. *Clear w/0 % Film Tint* **Glass Panel**

 (A) Full interior (∼2600 lux), natural exterior
 (B) Minimum interior (∼60 lux), natural exterior
 (C) 0 lux interior, natural exterior
 (D) Natural exterior and 500 mW 1550 nm active illumination

2. *Solarcool (2) Graylite* **Glass Panel**

 (A) Full interior (∼2600 lux), natural exterior
 (B) Minimum interior (∼60 lux), natural exterior
 (C) 0 lux interior, natural exterior
 (D) Natural exterior and 500 mW 1550 nm active illumination

Sunglasses:

3. *Ground Truth (**No Sunglasses/Glass Panel**)*

 (A) Full interior (∼2600 lux), natural exterior
 (B) 0 lux interior, natural exterior
 (C) Natural exterior and 500 mW 1550 nm active illumination

4. *RB3025 58* **Sunglasses**

 (A) Full interior (∼2600 lux), natural exterior
 (B) 0 lux interior

   (i) Natural exterior only
   (ii) Natural exterior and 500 mW 1550 nm active illumination

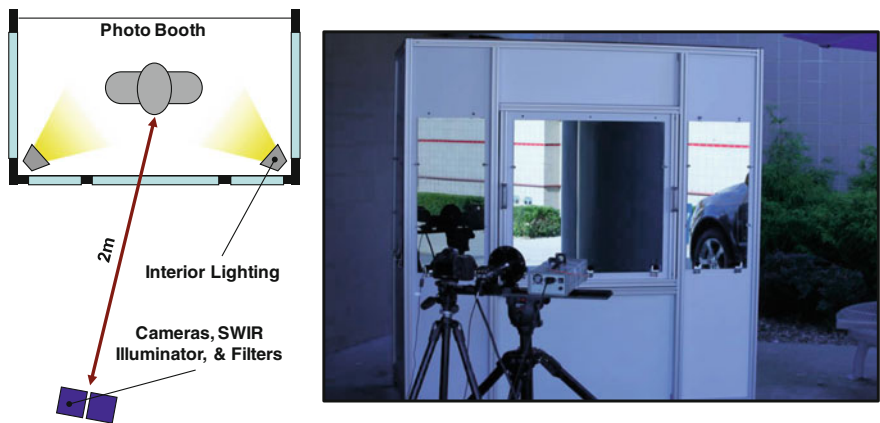An image of the outdoor data collection setup is shown in Fig. 2.4.

Fig. 2.4 Outdoor data collection setup

Sunglass images were taken outside of the booth with the participant facing toward and away from the sun to determine the effects of spurious reflections on eye-finding. A polarization filter was used in all cases (both sunglasses and glass panels) to reduce these reflections, but they were not completely eliminated. The collection location was varied and recorded from day to day (shade, full sun, etc.) to provide a variety of lighting conditions. Collections performed during the day with overcast sky or at night did not include "sunglasses toward sun," and added the active-SWIR illuminator to the "sunglasses away from sun" scenario. Table 2.5

Table 2.5 Sample daytime images for Phase II data collection

	Ray Ban Sunglasses		Tinted Glass Panel On		Tinted Glass Panel Off	
	Participant facing sun	Participant facing sway From Sun	Interior booth lights On	Interior booth lights Off	Interior booth lights On	Interior booth lights Off
1150nm						
1350nm						
1550nm						
SWIR Illuminator						

shows sample images of data at different wavelengths using the three (3) band-pass filters.

Table 2.6 provides sample images indicating the imaging differences for differing sky/lighting conditions. This table is not meant to include examples of all scenarios considered, but serves to provide a qualitative indication of how uncontrolled conditions introduce a high degree of variability in image quality.

A total of 200 participants provided data between July 9, 2012, and September 14, 2012, with participation split evenly between day and night collection times (100 participants each).

Figure 2.5 provides a breakdown of participant demographics by age, ethnicity, and gender, as well as cumulative measured of participation as a function of time.

Figure 2.5a indicates an average of 19 participants per week throughout the 10-week collection period, with peak participation between July 23rd and August 3rd. Low participation rates during the periods from 7/9 through 7/13 and 8/6 through 8/17 were due to closure of the university for anational holiday and the beginning of the fall semester respectively. Figure 2.5b indicates the majority of participants (52 %) were between 20 and 29 years of age, followed by 30–39, and 50–59 age ranges. This is primarily due to student and staff participation in the data collection, conducted on the WVU campus. Minor age ranges were 18–19 (1 %) and 70–79 (2 %). Figure 2.5c indicates that slightly more than half of the participants were Caucasian, followed by African American (13 %), then Middle Eastern and Asian Indian (10 % each) ethnicities. This demographic distribution is consistent with the student/staff population of WVU. Figure 2.5d indicates Caucasian and Hispanic gender participation was nearly equal, while Middle Eastern, Asian, and African males participated more than females. The contrary is true for African Americans.

The images collected in both the indoor and the outdoor data collection efforts have been used to develop cross-spectral facial identification algorithms with automated face and eye detection and photometric normalization. A total 1020 face

Table 2.6 Variations in image quality with variable sky conditions (taken at 1550 nm)

	Glass On, Interior Lights Off, SWIR Illuminator On	Glass On, Interior Lights Off, No SWIR Illuminator	Ray Ban Sunglasses, Facing Away From Sun	Ray Ban Sunglasses, Facing Toward Sun	Ray Ban Sunglasses, No SWIR Illuminator	Ray Ban Sunglasses, SWIR Illuminator
Day						
Overcast						
Night (street lamp illumination)						

(a)

Number of participants by week

(b)

Participants by age group (%)

(c)

Participants by ethnicity(%)

(d)

Demographics by gender and ethnicity

Fig. 2.5 Participant demographics for the Phase II study

images, including 980 SWIR face images (140 subjects × 7 scenarios) and 140 visible (ground truth) face images, were evaluated. Results indicate an eye-detection rate of greater than 96 % in the majority of the scenarios and a rank-1 identification rate of 94.26 %when using the ground truth data acquired in this collection [17].

2.4.3 Long-Range Face Image Collections

Our group collaborated with the WVHTCF to obtain long-range SWIR data collected both indoors and outdoors using the TINDERS camera system. An *indoor collection* was performed by WVHTCF personnel in their high-bay area, with images collected under active illumination at 50 and 106 m. A second, *outdoor collection* was performed with the assistance of WVU staff. This data collection took place at night on the WVU Evansdale campus, with images captured at 100, 200, and 350 m. Faces were unobscured/obscured by glass at each distance. Sample images for each of these datasets are shown in Figs. 2.6 and 2.7.

Fig. 2.6 Indoor TINDERS data collected at 50 m (*left*) and 100 m (*right*)

Outdoor: 100m   100m glass   200m   200m glass   350m   350m glass

Fig. 2.7 Outdoor TINDERS data collected from 100 to 350 m with and without glass

While not apparent in the indoor data, atmospheric effects, primarily thermal distortion caused by the warm asphalt surface, can be observed in the data captured at 350 m. It should also be noted that reflections from the illuminator are not an issue when imaging through tinted glass due to the separation distance between the imager and the participant.

Please note that the WVHTCF group has performed matching analysis of the long-range outdoor SWIR face data collected with their imager [12]. For the data collected indoors, custom academic algorithms [24, 25] were used to achieve matching results as high as 90 % rank 1 for 50 subjects' images captured at 50 m and 80 % for the 106 m distance. Matching experiments were performed on a subset of 42 images captured outdoors at night at 100 m (no glass obstruction), with 63 % matched to the correct gallery image at rank-1 and 90 % of the correct gallery image within rank-7 using a commercial (provided by MorphoTrust) face matcher plugin developed specifically for the TINDERS imager. It should also be noted that the average inter-pupillary distance for all long-distance images is approximately 60–70 pixels wide. This is a result of the zoom capabilities of the long-range SWIR camera used in this collection, which was designed to maintain inter-pupillary distance at all zoom levels.

2.5 SWIR Gait Collection

Although there are limitations associated with capturing faces at a distance, additional modalities may be available in long-distance SWIR imagery that could be exploited for identification purposes. One such modality is gait. To supplement SWIR face image collection, WVU performed an additional data 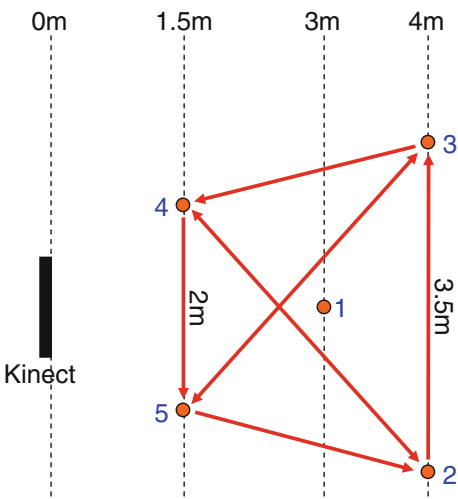collection focused on implementation of SWIR and depth-mapping camera technologies for the acquisition of video from walking individuals to determine the efficacy of soft biometric (body measurement) and gait-based recognition.

Two commercial cameras were used in this study: the Sensors Unlimited Goodrich SU640KTSX-1.7RT High Sensitivity InGaAs SWIR Camera (640 × 512 pixels) with a 50 mm f/1.4 SWIR lens used in face image collection and a Microsoft Kinect depth camera. The Goodrich camera was used to capture gait video at distances ranging from 20–50 m, and the Kinect camera was used to collect video from 1.5 to 4 m. Gait collection with the Goodrich camera was performed outside during daylight hours (natural sunlight illumination), with videos filtered at 1550 nm. Operational settings such as integration time were adjusted to achieve the best image quality based on daily environmental conditions (cloudy, sunny, etc.). The Kinect videos were captured inside under fluorescent illumination. The walking paths used to capture the indoor and outdoor gait cycles are illustrated in Figs. 2.8 and 2.9.

The trapezoidal path for the Kinect camera is required due to its limited field of view at short distances. A calibration pose is performed at an intermediate "center" distance (position "1"). The distances and walking paths chosen for the SWIR collection allowed six or more paces of walking to be collected in a variety of directions with respect to the camera field of view. Example images captured from the indoor and outdoor scenarios are shown in Fig. 2.10.

Fig. 2.8 Indoor Kinect collection layout. Walking paths: location 1 calibration pose, perimeter traversal beginning and ending at location 2, location 2–4 and back, location 3–5 and back

Fig. 2.9 Outdoor SWIR collection layout. Walking paths: location 1–2 and back, location 3–4 and back, location 5–6 and back, location 7–8 and back

Fig. 2.10 Kinect sample image (*left*) and SWIR sample image (*right*)

Data collection was completed on December 4, 2011, with gait and soft biometric data obtained from 157 individuals.

Figure 2.11 provides a breakdown of the participant demographics.

Figure 2.11a indicates an average of ~ 14 participants per week throughout the 11-week collection period, with peak participation between October 24th and October 30th. Thanksgiving break and the corresponding university closure is responsible for the null participation during 11/21 through 11/27. Figure 2.11b indicates the majority of participants (71 %) were between 20 and 29 years of age, followed by 18–19 (12 %) which is consistent with student and faculty populations. Figure 2.11c indicates that approximately half (46 %) of participants were Caucasian, followed by Asian Indian (23 %). This demographic distribution is consistent with the student/staff population of WVU. Figure 2.11d shows a consistent male participation rate over female for all ethnicities with the exclusion of unknown/non-identified ethnicities (in which case was equal participation).

Fig. 2.11 Participant demographics for SWIR gait collection

This dataset was used to developed gait-based approaches to human identification. The results presented in [26] indicate 15–20 % rank 1 identification accuracy and 35–45 % rank 10 identification accuracy for algorithms based on gait energy image (GEI), gait curves, and Frieze pattern matching. Although the performance numbers of all three algorithms are significantly less than the numbers published for existing CASIA gait datasets, these results were obtained from gait data collected in an unconstrained outdoor environment (silhouette quality of WVU is ≈39 % and ≈64 % of the values for the CASIA B and C datasets), and should be viewed as foundational work in the area of SWIR gait recognition under uncontrolled conditions.

2.6 Summary and Conclusions

Face image capture in low-lighting conditions is made possible through SWIR-imaging hardware and novel cross-spectral face recognition algorithms. The development and refinement of cross-spectral face recognition systems is enabled by the collection of both visible and SWIR face images in controlled and operational or difficult conditions. This chapter has provided several examples of data collection efforts for multispectral SWIR face and gait capture, both indoors and

outdoors and at varying standoff distances (2–350 m), along with initial results of matching experiments performed using the collected data.

Introducing non-idealities (e.g.: very low light levels, tinted materials, and long distances) into the data collection process *supplements* facial imagery data collected under ideal conditions, and *allows for* a larger range of operational scenarios to be considered in matching experiments. Gait recognition in the SWIR may also be used in cases where face image quality is not sufficient for confident identification.

While that datasets discussed in this chapter have been used in various academic publications to answer different research questions, there are still challenges that need to be mitigated, especially when related to image restoration efforts and cross-spectral face- and gait-matching activities. These challenges can be overcome through continued use of the existing datasets, supplemented by data acquired in additional collection activities that introduce non-ideal environmental factors. Continued collection of non-ideal face images, leveraged by advances in SWIR sensor technologies (e.g., GA1280JSX High Resolution High Sensitivity InGaAs SWIR Camera by Sensors Unlimited (Goodrich) [18]), is necessary to further mature this emerging area of biometrics research.

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