Hyperspectral imaging and association phenomenology of pedestrians in a cluttered urban environment

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Hyperspectral Imaging and Association Phenomenology of Pedestrians in a Cluttered Urban Environment

by

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A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Chester F. Carlson Center for Imaging Science Rochester Institute of Technology

August 17, 2012

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Hyperspectral Imaging and Association Phenomenology of Pedestrians in a Cluttered Urban Environment

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Jared A. Herweg

Submitted to the Chester F. Carlson Center for Imaging Science in partial fulfillment of the requirements for the Doctor of Philosophy Degree at the Rochester Institute of Technology

Abstract

Remote hyperspectral imaging (HSI) has shown promise in several applications such as object detection and tracking. Typically research has focused on large objects, such as vehicles, for tracking due to the spatial resolution of current operational HSI systems. This research seeks to extend the utility of applying HSI to human pedestrian detection using the reflective solar spectral range between 400 - 2500 nm. A phenomenological investigation of a novel scheme to differentiate between pedestrians is studied. By applying the basics of detection theory, this research focuses on being able to differentiate between pedestrians, as well as background materials. Specifically, this research explores the likelihood of detecting and differentiating pedestrians based on four defined subregions comprised of the exposed hair, skin, and the fabrics used for shirts and trousers.

The scope of this work encompassed detecting a pedestrian of interest outdoors among other pedestrians in an urban environment consisting of a mixture of asphalt, concrete, grass, and trees. Two unique datasets were created during the course of this effort. One dataset was a collection of fully ground-truthed hyperspectral images of pedestrians in an urban environment. A second dataset was a synthetic rendering of the real-world ground truthed pedestrian scene developed using the Digital Imaging and Remote Sensing Image Generation (DIRSIG) model. Subregion separability analysis results, using spectral reflectance data, provided strong evidence that combining the observable spectral features of detectable subregions is a viable means of distinguishing...
between pedestrians. Further analysis using real-world HSI data demonstrated that the detection and classification of the pedestrian subregions when changes in illumination, location, and background occur within the field of view of a hyperspectral sensor is achievable with a greater than 60% accuracy. In addition to the direct detection and association analysis using the full spectral range, trade-offs in using spectral subsets of the reflectance spectrum were explored for their utility in detecting and classifying each of the pedestrian subregions. The results suggested that the clothing worn on a pedestrian’s torso is the dominant feature for classification and either using a full spectral range (400 - 2500 nm) with 152 spectral bands or the visible to near-infrared spectral range (400 - 1000 nm) with 39 bands provides similar capability to the full spectral range for distinguishing among pedestrians with similar skin and clothing types.
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As I sit and ponder the work performed under my doctoral research, I am humbled by the selfless efforts of those who have made this journey with me and contributed along the way. I would like to take the space here to express my sincerest gratitude to those individuals and organizations that made this work possible.

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Dedicated to those who told me I could, and made sure I did.
Contents

1 Introduction

1.1 Research Motivation ........................................ 26
1.2 Scene and Subject: The Detection Paradigm ................. 27
  1.2.1 Scene Example ......................................... 28
  1.2.2 Detection Paradigm .................................. 29
  1.2.3 Feature Taxonomy ................................. 31
1.3 Previous Pedestrian Imaging and Tracking Methodologies ......... 34
1.4 Hyperspectral Imaging for Pedestrian Detection and Track Association .... 35
1.5 Research Question, Objectives, and Scope ...................... 35
  1.5.1 Research Objectives .................................. 36
  1.5.2 Context and Scope .................................. 36
1.6 Scientific Impacts From This Research ....................... 38
1.7 Organization of Dissertation ................................ 38

2 Background

2.1 Anatomy of a Pedestrians as a Multi-Region Target ............... 40
2.2 Sources of Observed Spectral Radiance Variability ............. 47
  2.2.1 Illumination Variation ............................... 47
  2.2.2 Adjacency Effects ................................. 48
  2.2.3 Observation Orientations ........................... 49
3 Previous Work

3.1 Human Detection and Tracking with Segmentation
3.2 Hair Detection and Classification
3.3 Skin Detection and Classification
3.4 Clothing Detection and Classification

4 Methodologies

4.1 Field Collected Data Sets
   4.1.1 Hyperspectral Measurements of Natural Signatures from Pedestrians (HYMNS-P)
   4.1.2 Ground Level Pedestrian High Resolution HSI Data Set
4.2 Synthetically Generated Imagery
4.3 Measuring Spectral Separability Among Subregions
   4.3.1 The Pedestrian Two-Class Discriminant
   4.3.2 Assessing Pedestrian Separability in the Presence of Noise
   4.3.3 Separability For Single Subregions vs. Combining Subregions
   4.3.4 Reflectance Sample Separability using Spectrum Subsets
   4.3.5 Assessing Pedestrian Separability in Remotely Sensed Imagery
4.4 Unsupervised Subregion Segmentation
4.5 Detecting Pedestrian Subregions in Remotely Sensed Imagery
4.6 Subregion Detection after Changes in Illumination

5 Results

5.1 Probability of Error for POI Subregions versus SNR
5.2 Probability of Error for POI Subregions in Remotely Sensed Data
5.3 Binary Classification Error When Combining Subregions in HYMNS-P Imagery
5.4 Binary Classification Error for POI Subregions After Illumination Changes .... 113
5.5 Unsupervised Subregion Segmentation ............................................. 117
5.6 Assessing Spectral Distance Measures for Pedestrian Subregion Detectability ... 121
5.7 Subregion Detection after changes in Illumination .......................... 133

6 Conclusions and Future Work .......................................................... 135
6.1 Conclusions .............................................................................. 135
6.2 Future Work ............................................................................. 140
  6.2.1 Additional Pedestrian HSI Data Gathering .............................. 140
  6.2.2 Pedestrian BRDF Effects .......................................................... 140
  6.2.3 HSI Spectral Resolution Requirements ................................. 141
  6.2.4 HSI Spatial Resolution Requirements .................................... 141
  6.2.5 Classification Error Versus Solar Illumination Angle .............. 141
  6.2.6 Spectral Variations of Moist Skin ........................................... 142
  6.2.7 Data processing for POI Classification from Remotely Sensed Imagery . 143

A HYMNS-P Data Collection ............................................................... 144
 A.1 Overview .............................................................................. 144
 A.2 Methodology .......................................................................... 145
   A.2.1 Institute Review Board Approvals ........................................ 145
   A.2.2 Scenes ............................................................................ 145
   A.2.3 Instrumentation ................................................................. 154
   A.2.4 Ground Truth ................................................................. 157
A.3 Characterization of HYMNS-P Bad Bands List .......................... 168
   A.3.1 Selecting Pixels ................................................................. 168
   A.3.2 Calculating the SNR .......................................................... 169
   A.3.3 Selecting Bad Bands .......................................................... 169
   A.3.4 Assessing Noisy/Bad Pixels ............................................... 169
CONTENTS

B Contact Probe for DHR Measurements 175
  B.1 Overview ......................................................... 175
  B.2 DHR Instrument .................................................. 175
    B.2.1 Method ....................................................... 176
    B.2.2 Comparison of Results and Discussion ......................... 177

C Synthetic Scene Generation 179
  C.1 Overview ......................................................... 179
  C.2 Modeling Atmosphere with MODTRAN .............................. 180
  C.3 Synthetic Scene Generation using DIRSIG .......................... 181
  C.4 Adding Noise to DIRSIG Imagery ................................. 182
    C.4.1 Approaches to Adding Noise ................................. 183
    C.4.2 Calculating Noise from Real-World Data ...................... 186
    C.4.3 Comparing Resulting Imagery of Additive Noise Methods .... 190

D Pedestrian BRDF 191
  D.1 Overview ......................................................... 191
  D.2 General BRDF Model ............................................. 191
  D.3 BRDF of Pedestrian ............................................. 194
    D.3.1 Skin BRDF ................................................ 194
    D.3.2 Fabric BRDF ............................................... 196
    D.3.3 Hair BRDF ............................................... 198
  D.4 Next Steps in Pedestrian Subregion BRDF Modeling .............. 200

E Subregion Probability of Error per pedestrian 201
  E.1 Overview ......................................................... 201
  E.2 Source Data for Table 5.2 ....................................... 201
  E.3 Source Data for Table 5.3 ....................................... 205
  E.4 Source Data for Table 5.4 ....................................... 209
  E.5 Source Data for Table 5.5 ....................................... 213
E.6 Source Data for Table 5.6 ................................................. 217
E.7 Source Data for Table 5.8 ................................................. 221
E.8 Source Data for Table 5.9 ................................................. 225
E.9 Source Data for Table 5.10 ................................................. 231
E.10 Source Data for Table 5.11 ............................................ 237
E.11 Source Data for Table 5.12 ............................................ 243
E.12 Source Data for Table 5.13 ............................................ 247
E.13 Source Data for Table 5.14 ............................................ 251

F Subregion Detection ROC Results ........................................ 255
F.1 Overview ........................................................................ 255
F.2 Detectability with Full Spectral Range ................................ 255
F.3 Detectability in Tricolor Imagery ....................................... 261
F.4 Detectability in 22-Band Visible Imagery ............................ 266
F.5 Detectability in 39-Band VNIR Imagery .............................. 271
F.6 Detectability in SWIR Imagery ......................................... 276
F.7 Detectability Under Differing Illumination Conditions ............ 281
List of Figures

1.1  Context scenes for pedestrian detection .......................... 29
1.2  Pedestrian Detection Paradigm ........................................ 30
1.3  Taxonomy of Observable Pedestrian Features ....................... 32

2.1  Illustration of pedestrian as multi-class target .................... 41
2.2  Cross section of human hair follicle .................................... 43
2.3  Comparing spectral reflectance of hair from several pedestrians .... 44
2.4  Differences in skin reflectance from the same pedestrian .......... 45
2.5  Differences in skin reflectance from the same pedestrian .......... 46
2.6  Solar irradiance spectrum .................................................. 48
2.7  Solar illumination geometries onto a pedestrian .................... 49
2.8  BRDF Geometry Illustration .............................................. 50
2.9  Illustration of BRDF from skin ........................................... 51
2.10 Processing workflow for pedestrian detection and classification .... 54

3.1  Blob model for segmenting pedestrians ............................... 57

4.1  Example true color image from HYMNS-P dataset .................... 63
4.2  Example true color image from skin detection dataset ............... 64
4.3  Illustration of high fidelity synthetic image rendering using DIRSIG .... 66
4.4  Example of shirt spectral reflectance with noise added ............... 69
LIST OF FIGURES

4.5 Example of distance distributions for one versus many .......................... 71
4.6 Example illustration of two distribution likelihood ratio .......................... 72
4.7 Example discrete PMF for the remote sensed imagery .............................. 75
4.8 Context and sky image of HYMNS-P imagery for POI Detection, Scene 1 .... 80
4.9 Context and sky image of pedestrian B as POI after movement in HYMNS-P imagery 81
4.10 Context image for detection in Ground level HSI, Scene 1 ...................... 82
4.11 Context image for detection in Ground level HSI, Scene 2 ...................... 82
4.12 Context image for detection in Ground level HSI, Scene 3 ...................... 83
4.13 Example subregion truth mask for HSI image ..................................... 84
4.14 Example ensemble of ROC curves for subregion pixel detection ................. 85
4.15 DIRSIG scenes for detection under varying illumination ......................... 87

5.1 Plots of $P(\text{error}|\omega_{POI})$ versus SNR for subregion reflectance data, full spectral range 90
5.2 Family of curves for $P(\text{error}|\omega_{POI})$ versus SNR for subregion reflectance data, FR 91
5.3 Plots of $P(\text{error}|\omega_{POI})$ versus SNR for subregion reflectance data, RGB .......... 92
5.4 Family of curves for $P(\text{error}|\omega_{POI})$ versus SNR for subregion reflectance data, RGB 93
5.5 Plots of $P(\text{error}|\omega_{POI})$ versus SNR for subregion reflectance data, Vis ............ 94
5.6 Family of curves for $P(\text{error}|\omega_{POI})$ versus SNR for subregion reflectance data, Vis 95
5.7 Plots of $P(\text{error}|\omega_{POI})$ versus SNR for subregion reflectance data, VNIR .......... 96
5.8 Family of curves for $P(\text{error}|\omega_{POI})$ versus SNR for subregion reflectance data, VNIR 97
5.9 Plots of $P(\text{error}|\omega_{POI})$ versus SNR for subregion reflectance data, SWIR1 ........ 98
5.10 Family of curves for $P(\text{error}|\omega_{POI})$ versus SNR for subregion reflectance data, SWIR1 99
5.11 Plots of $P(\text{error}|\omega_{POI})$ versus SNR for subregion reflectance data, SWIR2 .......... 100
5.12 Family of curves for $P(\text{error}|\omega_{POI})$ versus SNR for subregion reflectance data, SWIR2101
5.13 HYMNS-P scene 1, pose 1, with pedestrians labeled ............................. 104
5.14 HYMNS-P scene 3, pose 1, with pedestrians labeled ............................. 105
5.15 First GLHR HSI scene with pedestrians labeled .................................. 106
5.16 Second GLHR HSI scene with pedestrians labeled ............................. 107
5.17 Third GLHR HSI scene with pedestrians labeled ............................. 108
### LIST OF FIGURES

5.18 Probability of error plot for pedestrians in the HYMNS-P scene 1, pose 1, FR . . . 109
5.19 Comparison of mean spectral radiance for HYMNS-P images . . . . . . . . . 111
5.20 Synthetic pedestrian scene with pedestrians labeled . . . . . . . . . . . . . . . 116
5.21 Results of \textit{k-Means} clustering using euclidean distance metric . . . . 118
5.22 Results of \textit{k-Means} clustering using spectral angle distance metric . . . 119
5.23 Results of \textit{k-Means} clustering using correlation distance metric . . . . 120
5.24 Summary scatter plot for subregion detection using full spectral range . . . 127
5.25 Summary scatter plot for subregion detection using 3-band color imagery . . . 128
5.26 Summary scatter plot for subregion detection using 22-bands in the visible . . . 129
5.27 Summary scatter plot for subregion detection using 39-bands in the VNIR . . . 130
5.28 Summary scatter plot for subregion detection using 114-bands in the SWIR . . . 131

6.1 Comparing impacts of moisture on skin . . . . . . . . . . . . . . . . . . . . . . . 142

A.1 IRB Approval . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 146
A.2 HYMNS-P Scenarios . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 148
A.3 True color HSI image of HYMNS-P Scene 1, Pose 1 . . . . . . . . . . . . . . . . 148
A.4 True color HSI image of HYMNS-P Scene 1, Pose 2 . . . . . . . . . . . . . . . . 148
A.5 True color HSI image of HYMNS-P Scene 1, Pose 3 . . . . . . . . . . . . . . . . 149
A.6 True color HSI image of HYMNS-P Scene 2, Pose 1 . . . . . . . . . . . . . . . . 149
A.7 True color HSI image of HYMNS-P Scene 2, Pose 2 . . . . . . . . . . . . . . . . 149
A.8 True color HSI image of HYMNS-P Scene 2, Pose 3 . . . . . . . . . . . . . . . . 150
A.9 True color HSI image of HYMNS-P Scene 3, Pose 1 . . . . . . . . . . . . . . . . 150
A.10 True color HSI image of HYMNS-P Scene 3, Pose 2 . . . . . . . . . . . . . . . . 150
A.11 True color HSI image of HYMNS-P Scene 3, Pose 3 . . . . . . . . . . . . . . . . 150
A.12 True color HSI image of HYMNS-P Scene 4, Pose 1 . . . . . . . . . . . . . . . . 151
A.13 True color HSI image of HYMNS-P Scene 4, Pose 2 . . . . . . . . . . . . . . . . 151
A.14 True color HSI image of HYMNS-P Scene 4, Pose 3 . . . . . . . . . . . . . . . . 151
A.15 True color HSI image of HYMNS-P Scene 5, Pose 1 . . . . . . . . . . . . . . . . 151
A.16 True color HSI image of HYMNS-P Scene 5, Pose 2 . . . . . . . . . . . . . . . . 152
A.17 True color HSI image of HYMNS-P Scene 5, Pose 3 .................................. 152
A.18 True color HSI image of HYMNS-P Scene 6, Pose 1 .................................. 152
A.19 True color HSI image of HYMNS-P Scene 6, Pose 2 .................................. 152
A.20 True color HSI image of HYMNS-P Scene 6, Pose 3 .................................. 153
A.21 HST3 Hyperspectral Imaging Sensor .................................................. 154
A.22 HST3 Hyperspectral Imaging Sensor on roof of building. ......................... 155
A.23 RIT Contact Probe Illustration ......................................................... 157
A.24 Spectral reflectance measurements of pedestrian hair. .......................... 158
A.25 Spectral reflectance measurements of pedestrian facial skin. .................. 159
A.26 Spectral reflectance measurements of pedestrian arm skin. .................... 160
A.27 Spectral reflectance measurements of pedestrian shirts. ......................... 161
A.28 Spectral reflectance measurements of pedestrian trousers. ...................... 162
A.29 Example pedestrian self-assessment survey ........................................... 163
A.30 Sky conditions on day of HYMNS-P Data Collect ................................. 164
A.31 Selection of calibration panel used for in-scene bad band selection ............ 168
A.32 Illustrating the radiance profiles for the pixels selected in Figure A.31. .... 170
A.33 Selected bad band regions overlaid with gray bars. ............................... 171
A.34 Example bad pixel map for the HST-3 hyperspectral sensor .................... 172
A.35 Family of distributions for possible bad pixels .................................... 173

B.1 DataColor SpectraFlash 600 Instrument with Sample. ............................ 176
B.2 Fabric samples used for DHR measurement comparison. .......................... 177
B.3 Spectral Plots for DHR Comparison .................................................... 178

C.1 Annotated scene used for radiance matching ......................................... 180
C.2 Spectral reflectance curves of asphalt and concrete from HYMNS-P Dataset .... 181
C.3 Comparing real-world and estimated spectral radiance curves of asphalt and concrete 183
C.4 DIRSIG Scenes for different times ...................................................... 184
C.5 Example false color image of raw HSI data as captured by HST3 sensor .... 186
C.6 Spectral plots of dark and white calibration samples from HST3 sensor ....... 188
C.7 Spectral SNR Plots for HST3 HSI sensor ............................................. 189
C.8 Illustration of sample area for computing difference image .................... 189
C.9 Comparing Resulting Imagery of Additive Noise Methods ...................... 190
D.1 BRDF Geometry Illustration .................................................................. 192
D.2 Fabric Plain Weave Geometry Illustration .............................................. 196
E.1 Probability of error plot for pedestrians in the HYMNS-P scene 1, pose 1, FR . 202
E.2 Probability of error plot for pedestrians in the HYMNS-P scene 1, pose 1, RGB . 202
E.3 Probability of error plot for pedestrians in the HYMNS-P scene 1, pose 1, VIS . 203
E.4 Probability of error plot for pedestrians in the HYMNS-P scene 1, pose 1, VNIR . 203
E.5 Probability of error plot for pedestrians in the HYMNS-P scene 1, pose 1, SWIR 1  204
E.6 Probability of error plot for pedestrians in the HYMNS-P scene 1, pose 1, SWIR 2  204
E.7 Probability of error plot for pedestrians in the HYMNS-P scene 3, pose 1, FR . 205
E.8 Probability of error plot for pedestrians in the HYMNS-P scene 3, pose 1, RGB . 206
E.9 Probability of error plot for pedestrians in the HYMNS-P scene 3, pose 1, Vis . 206
E.10 Probability of error plot for pedestrians in the HYMNS-P scene 3, pose 1, VNIR . 207
E.11 Probability of error plot for pedestrians in the HYMNS-P scene 3, pose 1, SWIR 1 . 207
E.12 Probability of error plot for pedestrians in the HYMNS-P scene 3, pose 1, SWIR 2 . 208
E.13 Probability of error plot for pedestrians in the GLHR Scene 1, FR ............ 209
E.14 Probability of error plot for pedestrians in the GLHR Scene 1, RGB .......... 210
E.15 Probability of error plot for pedestrians in the GLHR Scene 1, Vis ............ 210
E.16 Probability of error plot for pedestrians in the GLHR Scene 1, VNIR ........ 211
E.17 Probability of error plot for pedestrians in the GLHR Scene 1, SWIR 1 .... 211
E.18 Probability of error plot for pedestrians in the GLHR Scene 1, SWIR 2 .... 211
E.19 Probability of error plot for pedestrians in the GLHR Scene 2, FR ............ 212
E.20 Probability of error plot for pedestrians in the GLHR Scene 2, RGB .......... 213
E.21 Probability of error plot for pedestrians in the GLHR Scene 2, Vis ............ 214
E.22 Probability of error plot for pedestrians in the GLHR Scene 2, VNIR ........ 214
E.23 Probability of error plot for pedestrians in the GLHR Scene 2, SWIR 1 .... 215
LIST OF FIGURES

E.24 Probability of error plot for pedestrians in the GLHR Scene 2, SWIR 2 . . . . . . . 216
E.25 Probability of error plot for pedestrians in the GLHR Scene 3, FR . . . . . . . . . 217
E.26 Probability of error plot for pedestrians in the GLHR Scene 3, RGB . . . . . . . . 218
E.27 Probability of error plot for pedestrians in the GLHR Scene 3, Vis . . . . . . . . . 218
E.28 Probability of error plot for pedestrians in the GLHR Scene 3, VNIR . . . . . . . . 219
E.29 Probability of error plot for pedestrians in the GLHR Scene 3, SWIR 1 . . . . . . . 219
E.30 Probability of error plot for pedestrians in the GLHR Scene 3, SWIR 2 . . . . . . . 220
E.31 Probability of error plot for pedestrians in the HYMNS-P scene 3, pose 1, FR . . . 221
E.32 Probability of error plot for pedestrians in the HYMNS-P scene 3, pose 1, RGB . . 222
E.33 Probability of error plot for pedestrians in the HYMNS-P scene 3, pose 1, VIS . . 222
E.34 Probability of error plot for pedestrians in the HYMNS-P scene 3, pose 1, VNIR . 223
E.35 Probability of error plot for pedestrians in the HYMNS-P scene 3, pose 1, SWIR 1 223
E.36 Probability of error plot for pedestrians in the HYMNS-P scene 3, pose 1, SWIR 2 224
E.37 Probability of error plot for pedestrians in the HYMNS-P scene 1, pose 1, FR . . 225
E.38 Probability of error plot for pedestrians in the HYMNS-P scene 1, pose 1, RGB . . 226
E.39 Probability of error plot for pedestrians in the HYMNS-P scene 1, pose 1, Vis . . . 227
E.40 Probability of error plot for pedestrians in the HYMNS-P scene 1, pose 1, VNIR . 228
E.41 Probability of error plot for pedestrians in the HYMNS-P scene 1, pose 1, SWIR 1 229
E.42 Probability of error plot for pedestrians in the HYMNS-P scene 1, pose 1, SWIR 2 230
E.43 Probability of error plot for HYMNS-P scene 1, pose 1, Hair-Skin Combination . . 231
E.44 Probability of error plot for HYMNS-P scene 1, pose 1, Hair-Torso Combination . 232
E.45 Probability of error plot for HYMNS-P scene 1, pose 1, Hair-Trousers Combination 232
E.46 Probability of error plot for HYMNS-P scene 1, pose 1, Skin-Torso Combination . 233
E.47 Probability of error plot for HYMNS-P scene 1, pose 1, Skin-Trousers Combination 233
E.48 Probability of error plot for HYMNS-P scene 1, pose 1, Torso-Trousers Combination 234
E.49 Probability of error plot for HYMNS-P scene 1, pose 1, Hair-Skin-Torso Combination 234
E.50 Probability of error plot for HYMNS-P scene 1, pose 1, Hair-Skin-Trousers Combi-

nation . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 235
LIST OF FIGURES

E.51 Probability of error plot for HYMNS-P scene 1, pose 1, Hair-Torso-Trousers Combination ................................................................. 235
E.52 Probability of error plot for HYMNS-P scene 1, pose 1, Skin-Torso-Trousers Combination ................................................................. 236
E.53 Probability of error plot for HYMNS-P scene 1, pose 1, Hair-Skin-Torso-Trousers Combination ................................................................. 236
E.54 Probability of error plot for HYMNS-P scene 3, pose 1, Hair-Skin Combination ................................................................. 237
E.55 Probability of error plot for HYMNS-P scene 3, pose 1, Hair-Torso Combination ................................................................. 238
E.56 Probability of error plot for HYMNS-P scene 3, pose 1, Hair-Trousers Combination ................................................................. 238
E.57 Probability of error plot for HYMNS-P scene 3, pose 1, Skin-Torso Combination ................................................................. 239
E.58 Probability of error plot for HYMNS-P scene 3, pose 1, Skin-Trousers Combination ................................................................. 239
E.59 Probability of error plot for HYMNS-P scene 3, pose 1, Torso-Trousers Combination ................................................................. 240
E.60 Probability of error plot for HYMNS-P scene 3, pose 1, Hair-Skin-Torso Combination ................................................................. 240
E.61 Probability of error plot for HYMNS-P scene 3, pose 1, Hair-Skin-Trousers Combination ................................................................. 241
E.62 Probability of error plot for HYMNS-P scene 3, pose 1, Hair-Torso-Trousers Combination ................................................................. 241
E.63 Probability of error plot for HYMNS-P scene 3, pose 1, Skin-Torso-Trousers Combination ................................................................. 242
E.64 Probability of error plot for HYMNS-P scene 3, pose 1, Hair-Skin-Torso-Trousers Combination ................................................................. 242
E.65 Probability of error plot for pedestrians in the synthetic scene 1, FR ................................................................. 243
E.66 Probability of error plot for pedestrians in the synthetic scene 1, RGB ................................................................. 244
E.67 Probability of error plot for pedestrians in the synthetic scene 1, Vis ................................................................. 244
E.68 Probability of error plot for pedestrians in the synthetic scene 1, VNIR ................................................................. 245
E.69 Probability of error plot for pedestrians in the synthetic scene 1, SWIR 1 ................................................................. 245
E.70 Probability of error plot for pedestrians in the synthetic scene 1, SWIR 2 ................................................................. 246
E.71 Probability of error plot for pedestrians in the synthetic scene 2, FR ................................................................. 247
E.72 Probability of error plot for pedestrians in the synthetic scene 2, RGB ................................................................. 248
LIST OF FIGURES

E.73 Probability of error plot for pedestrians in the synthetic scene 2, Vis . . . . . . . 248
E.74 Probability of error plot for pedestrians in the synthetic scene 2, VNIR . . . . . . 249
E.75 Probability of error plot for pedestrians in the synthetic scene 2, SWIR 1 . . . . . 249
E.76 Probability of error plot for pedestrians in the synthetic scene 2, SWIR 2 . . . . . 250
E.77 Probability of error plot for pedestrians in the synthetic scene 3, FR . . . . . . . . 251
E.78 Probability of error plot for pedestrians in the synthetic scene 3, RGB . . . . . . . 252
E.79 Probability of error plot for pedestrians in the synthetic scene 3, Vis . . . . . . . . 252
E.80 Probability of error plot for pedestrians in the synthetic scene 3, VNIR . . . . . . . 253
E.81 Probability of error plot for pedestrians in the synthetic scene 3, SWIR 1 . . . . . 253
E.82 Probability of error plot for pedestrians in the synthetic scene 3, SWIR 2 . . . . . 254

F.1 Detection ROC curves for HYMNS-P Pedestrian B in Scene 1, Pose 1, FR . . . . . 256
F.2 Detection ROC curves for HYMNS-P Pedestrian B in Scene 3, Pose 1, FR . . . . . 257
F.3 Detection ROC curves for POI in ground level HSI data, Scene 1, FR . . . . . . . 258
F.4 Detection ROC curves for POI in ground level HSI data, Scene 2, FR . . . . . . . 259
F.5 Detection ROC curves for POI in ground level HSI data, Scene 3, FR . . . . . . . 260
F.6 Detection ROC curves for HYMNS-P Pedestrian B in Scene 1, Pose 1, RGB . . . . 261
F.7 Detection ROC curves for HYMNS-P Pedestrian B in Scene 3, Pose 1, RGB . . . . 262
F.8 Detection ROC curves for Pedestrian in Ground Level HSI data, Scene 1, RGB . . 263
F.9 Detection ROC curves for Pedestrian in Ground Level HSI data, Scene 2, RGB . . 264
F.10 Detection ROC curves for Pedestrian in Ground Level HSI data, Scene 3, RGB . . 265
F.11 Detection ROC curves for HYMNS-P Pedestrian B in Scene 1, Pose 1, Vis . . . . 266
F.12 Detection ROC curves for HYMNS-P Pedestrian B in Scene 3, Pose 1, Vis . . . . 267
F.13 Detection ROC curves for Pedestrian in Ground Level HSI data, Scene 1, Vis . . 268
F.14 Detection ROC curves for Pedestrian in Ground Level HSI data, Scene 2, Vis . . 269
F.15 Detection ROC curves for Pedestrian in Ground Level HSI data, Scene 3, Vis . . 270
F.16 Detection ROC curves for HYMNS-P Pedestrian B in Scene 1, Pose 1, VNIR . . . 271
F.17 Detection ROC curves for HYMNS-P Pedestrian B in Scene 3, Pose 1, VNIR . . . 272
F.18 Detection ROC curves for Pedestrian in Ground Level HSI data, Scene 1, VNIR . 273
F.19 Detection ROC curves for Pedestrian in Ground Level HSI data, Scene 2, VNIR . 274
F.20 Detection ROC curves for Pedestrian in Ground Level HSI data, Scene 3, VNIR . 275
F.21 Detection ROC curves for HYMNS-P Pedestrian B in Scene 1, Pose 1, SWIR . . . 276
F.22 Detection ROC curves for HYMNS-P Pedestrian B in Scene 3, Pose 1, SWIR . . . 277
F.23 Detection ROC curves for Pedestrian in Ground Level HSI data, Scene 1, SWIR . 278
F.24 Detection ROC curves for Pedestrian in Ground Level HSI data, Scene 2, SWIR . 279
F.25 Detection ROC curves for Pedestrian in Ground Level HSI data, Scene 3, SWIR . 280
F.26 Detection ROC curves for POI in DIRSIG imagery, indirect illumination . . . . . 281
F.27 Detection ROC curves for POI in DIRSIG imagery, PD illumination . . . . . . . 282
F.28 Detection ROC curves for POI in DIRSIG imagery, FD illumination . . . . . . . 283
F.29 Detection ROC curves for POI in DIRSIG imagery using FD to PD . . . . . . . . 284
F.30 Detection ROC curves for POI in DIRSIG imagery using FD to indirect . . . . . 285
## List of Tables

4.1 Differences between HYMNS-P and GLHR HSI datasets ........................................ 64

4.2 Noted weather differences between HYMNS-P and GLHR HSI datasets ................. 65

5.1 Summary table of $P(error|\omega_{POI})$ for pedestrian subregion spectral reflectance combinations at SNR = 5. ................................................................. 102

5.2 Summary table of $P(error|\omega_{POI})$ for subregions of HYMNS-P Image 1 .......... 105

5.3 Summary table of $P(error|\omega_{POI})$ per subregions of HYMNS-P Image 2 ........ 106

5.4 Summary table of $P(error|\omega_{POI})$ per subregions of GLHR HSI Image 1 ........ 107

5.5 Summary table of $P(error|\omega_{POI})$ per subregions of GLHR HSI Image 2 ........ 108

5.6 Summary table of $P(error|\omega_{POI})$ per subregions of GLHR HSI Image 3 ........ 110

5.7 Comparing spectral distance of three clothing types ............................................. 110

5.8 Summary table of $P(error|\omega_{POI})$ for subregions of HYMNS-P Image 3 ........ 111

5.9 Summary table of $P(error|\omega_{POI})$ per subregions of HYMNS-P Image 1 ........ 112

5.10 Summary table for $P(error|POI)$ when combining subregion information from HYMNS-P Imagery ................................................................. 114

5.11 Summary table for $P(error|POI)$ when combining subregion information from HYMNS-P Imagery ................................................................. 115

5.12 Summary table of $P(error|\omega_{POI})$ per subregions of DIRSIG Image 1 .......... 115

5.13 Summary table of $P(error|\omega_{POI})$ per subregions of DIRSIG Image 2 .......... 116

5.14 Summary table of $P(error|\omega_{POI})$ per subregions of DIRSIG Image 3 .......... 116


**LIST OF TABLES**

5.15 Summary AUC detection metrics for full spectral range ................. 122  
5.16 Summary AUC detection metrics for tricolor imagery .................. 123  
5.17 Summary AUC detection metrics for 22-band visible imagery ............ 124  
5.18 Summary AUC detection metrics for 39-band VNIR imagery .............. 125  
5.19 Summary AUC detection metrics for 114-band SWIR imagery .......... ... 126  
5.20 Summary table of the AUC for full spectral range imagery .............. 132  
5.21 Comparing AUC detection metrics for real-world vs. DIRSIG data .... 134  
5.22 AUC detection metrics for Illumination Differences .................... 134  
A.1 List of ground truth collected for HYMNS-P dataset .................... 165  
A.2 Metadata provided by pedestrian volunteers in HYMNS-P dataset ........ 166  
A.3 Metadata provided by pedestrian volunteers in HYMNS-P dataset (continued) ... 167  
A.4 Bad bands list for HYMNS-P dataset ........................................ 174  
C.1 MODTRAN settings for atmospheric modeling in DIRSIG .................. 182
Chapter 1

Introduction

1.1 Research Motivation

Detecting and tracking human pedestrians (sometimes referred to as dismounts) in imagery is an area of research which is approached from many different contexts [14]. The physical size of humans and their likeness or dissimilarity to their environment are the dominant aspects that make this research particularly profound. Many in the remote sensing and image processing community have tried to devise ways to efficiently detect and identify humans in imagery and then try to track them while they move. Due to the nature of remote sensing imaging systems and the resulting two dimensional images, the only information available to accomplish this task are the reflective characteristics, and to some extent, the geometric qualities of an object [5]. Herein lies the challenge. There are several outside factors that affect how the object will appear in the imagery. These factors include the characteristics of the illumination source, the illumination-target-sensor geometry, and the spatial and spectral resolution of the sensor. Each of these factors will be discussed in depth later in this dissertation. For now, suffice it to say that there is a need to consider each area independently within the context of the target, which in this case is a human. For simplicity, lets refer to the human pedestrian as just the pedestrian.

The unique aspects of the pedestrian must be assessed to identify the dominant features that
will be available for observation to the remote sensing system in order to accomplish the task of
detecting and identifying the target of interest. While this seems like a straightforward and benign
goal on the surface, an additional complication is presented when the imagery is used for a more
complex task such as tracking over time as the pedestrian moves. Most simply, this complication
has to do with how the subject’s features change with respect to the background. These features
may be spatial (geometric profile change), kinematic (how the subject moves), or spectral (the
sensor reaching reflected radiance of the subject). For this reason, it is proposed that the subject
is an integral part of the background which is both influencing as well as being influenced by the
background. So the question is, how can the subject’s features be separated from the background
adequately such that they can be successfully detected, uniquely labeled among other pedestrians,
and then sufficiently distinguished from other pedestrians as they move within a scene?

Technologies in hyperspectral imaging (HSI) have shown promise for accomplishing the tasks
related to pedestrian detection, labeling, and tracking by increasing the information content of the
two-dimensional images from the three-dimensional world [6, 7]. HSI involves capturing images
with hundreds of narrow contiguous co-registered spectral bands. This research effort will explore
spectral features inherent to the subject that will further enhance the detection and tracking of
pedestrians from an HSI standpoint.

1.2 Scene and Subject: The Detection Paradigm

It can be reasonably assumed that there are many contexts in which the task of pedestrian detection
can be utilized. Therefore, it behooves us to first consider a particular context in which human
detection is most likely to occur, without loss of generality. The reader is cautioned that this in no
way limits our problem of finding suitable features unique to an individual. However, it provides
a logical thought exercise for the context of the environment in which the research presented here
could be applied.
1.2.1 Scene Example

In the city of Prague, Czech Republic, there is a famous square called the Staroměstské Náměstí or Old Town Square. Figure 1.1 contains several images from this town square from varied vantage points. The square is mostly cement and stone, however there is some vegetation present in the square around the central monument, known as the Jan Hus Memorial [8], as well as in front of one of the buildings as can be seen in Figures 1.1(a) and 1.1(b). The square is a popular tourist destination and draws many people. At times there may be shelters and displays present as can be seen in Figures 1.1(a). Other times, the square may seem quiet, but still draws several people as shown in Figure 1.1(b). Figure 1.1(c) shows The Old Town Hall Tower as well as one of the narrow streets that feed into the square. The view in Figure 1.1(d) shows a closer view of some of the shelters in front of a few buildings across from the Old Town Hall Tower.

While this square is only one example of the type of environment to encounter a pedestrian, the Staroměstské Náměstí, with its surrounding buildings and convenient vantage points from which to observe the square, provides an example of a complex scene wherein a pedestrian may be detected. It contains many of the elements that illustrate the inherent challenges to the detection problem. If a pedestrian of interest (POI) were to visit the square, they may be first observed from a vantage point such as shown in Figure 1.1(c). Then they could be detected and monitored by a sensor located on the Old Town Hall Tower. The view may be as shown in Figure 1.1(a). Once the subject crossed the square, a third sensor may be tasked with surveying the subject, but limited to steep view angles as shown in Figure 1.1(d). The inherent challenges illustrated are where several people are within close proximity or even surrounding each other. Also, given the high buildings as well as the time of the day, pedestrians may be shadowed by the buildings, which creates a complicated spectral radiance pattern that is likely to change as the pedestrian moves through the scene. Note that the geometric profile of the pedestrian as observed is also very dependent on the vantage point as illustrated by comparing the views in Figure 1.1.
Figure 1.1: Images of the Staroměstské Náměstí (Old Town Square) in Prague, Czech Republic. The views in (a) and (b) were taken from the clock tower [9]. The view in (c) shows the clock tower and illustrates a vantage point looking into the square from a side street [10]. The view in (d) illustrates surveillance over the town square from a steep view angle [11].

1.2.2 Detection Paradigm

The task of detecting a pedestrian in a complex urban environment could be approached using the paradigm shown in Figure 1.2. In the figure, there are five hierarchical questions that could be asked:

1. What is a pedestrian?
2. What is not a pedestrian?
3. What separates one pedestrian from another pedestrian?
4. How do I define my pedestrian of interest?

5. What did I know about my person just before now?

In order to answer these questions, a tool must be used to observe and measure the pedestrian and the scene in which they exist. There are many different ways to consider how a pedestrian looks and may be uniquely defined. Some of the observable aspects of a pedestrian are presented in Section 1.2.3. Not all observables are feasible or practical to measure, depending on the requirements associated with detecting and tracking the pedestrian. Therefore, a subset of the observables must be chosen by which the POI would be uniquely defined. Once the set of observables are chosen, then the modality required to capture these observables may be defined and subsequently the tool may be chosen to measure these observables and select unique features. In this context, the pedestrian detection problem is very much a pattern recognition problem as outlined in [12].

In order to select features from the set of observables, data associated with the pedestrian within their environment must be made available to test against. The data may be actual or synthetic measurements, but it must represent the pedestrian accurately with a sufficient understanding of the context in which the data was collected/generated such that the pedestrian’s observables may be processed as features. Finally, the manner in which the data is processed must be chosen or developed in order to extract the unique features from the observables. This final step is what allows for testing the validity of how the pedestrian is defined.
1.2.3 Feature Taxonomy

Taking the visual cues from the scene shown in Figure 1.1 as well as the responses to the questions in the detection paradigm, a taxonomy for the impacts on the features related to the subject’s dynamic signature can be formalized. Figure 1.3 illustrates this taxonomy.

The taxonomy is broken into three supertypes: Scene, Sensor, and Processing. The end goal is to detect and label a pedestrian with the intent to detect in later imagery. To aid in making the taxonomy, we can use the assumptions outlined in Section 1.5.2 to simplify the context under which this taxonomy would apply. The supertypes can be further broken down as described in the following paragraphs.

The scene supertype has three subtypes relating the target to its illumination source(s) and the background environment. The source and type of illumination on the pedestrian will dominate the incident spectrum. An example might be a fluorescent source with spectral radiance constrained mainly to the visible spectrum. The atmospheric conditions at the time of capture give a wavelength dependent scattering and absorption of the illumination, both on the pedestrian and into the sensor. Secondary sources include those highly reflective and possibly specular sources directing additional background light onto the scene. The spectral characteristics of the secondary sources can have a large effect on the pedestrian as described in [13].

The location of the pedestrian will affect the feature set as well. If the pedestrian is in the open, fairly distant from other objects, there is little impact from the background and the pedestrian feature set can be easily isolated. As the scene becomes more and more cluttered to include people and obscurants, isolating the pedestrian specific spectral feature set will be more difficult. This is important for cases where the pedestrian is identified initially and then tracked or re-acquired later using a different sensor. This could be accomplished using algorithms that key on the spatial relationships of the spectral pixels. The one draw-back of pixel association relates to the possibility for mixed pixels around the edges of the pedestrian.

Finally, under the scene supertype, let’s consider the actual pedestrian. The pedestrian itself is the source of the features used for unique detection. From an overall view, the pedestrian will have three primary sources of surface reflection. This includes the hair, skin, and clothing. Except in
Figure 1.3: Taxonomy showing the physical as well as system effects on the spectral features on a person.
cases of warm weather and the pedestrian chooses to dress lightly, the dominant spectral features will be related to clothing. The clothing may be limited to a single layer or exist up to many layers and as such there may or may not be any skin reflection from underneath. Additionally, clothing may be changed due to time of day, activity, and season. This makes maintaining a feature set based strictly on clothing very difficult. Bringing the skin into account will allow for additional distinction between pedestrians as the melanin and oxygen level of the skin affect its reflectivity [7]. A potential confuser to the feature set includes any type of topical agents such as makeup, skin creams/lotions, or artificial colorant (i.e. sunless tanning products). Finally, the hair provides the last feature source. The hair can be colored artificially or naturally, and may have additional products applied for styling. The hair may also be left in its primary natural state which shifts due to season and exposure. These conditions will influence the visible appearance of the hair, but often will not change the physical structure of the hair [14].

Moving to the next supertype brings us to the imaging sensor. The sensor is the interface to the world and must be able to acquire sufficient information to detect the features related to the pedestrian. As such, the spectral range, spectral resolution, detectivity, and spatial resolution are key parameters required. Given the simple scenario presented in Section 1.2.1, a pedestrian may be acquired on one sensor and then handed off to another sensor or series of sensors for possible tracking. Thus there may be multi-sensor distortion or calibration errors among the sensors that reduce the distinguishability of the discrete features. Additionally, there are the random variations in the sensor signal level due to Johnson, shot, temperature, or generation-recombination noise sources [15].

Finally, the last supertype is the processing. The processing has two subtypes for the computational and analytical processing that will be done to detect and identify the pedestrian. Aspects related to the computational type are related to the digital nature of the output from the sensor. If images are combined from one sensor with another sensor to manage the pedestrian feature profile, mis-registration and resampling errors are prone to occur. The type of coding used to compress the data and the digital resolution also play a factor in data reusability. However, the computational aspects will not be handled in depth here. Of more interest are the aspects related to the analytical processing of the data. First, consider the training sets derived from the pedestrian features and
used in the classifiers applied to the pedestrian in subsequent instances. All subsequent attempts at detection will be dependent on the data in the training sets. Also, any assumptions about the pedestrian, its environment, or the system used to acquire the unique feature set will affect the utility of certain analytical approaches. Finally, physical models may be employed for trade studies in fleshing out automated algorithms utilizing the pedestrian’s feature set.

1.3 Previous Pedestrian Imaging and Tracking Methodologies

One technology area which can be enhanced by robust pedestrian detection is tracking systems. From the several observables outlined in Figure 1.3, many approaches to extracting features from the observables have been devised. In many cases, the pedestrian tracking problem has centered around the kinematics (i.e., the way a person moves) and pose estimation of individuals within a scene [2, 4, 16]. Other methods, strive for facial recognition as in [6]. These methods utilize physical profile aspects of the person in the imagery and strive to correlate physical characteristics of the pedestrian projected into the imager as they move through the scene. While these techniques have varying levels of demonstrated success, these methods require fairly high spatial resolution with facial recognition being the most demanding [17]. Additionally, they lack the ability to distinguish between pedestrians with similar physical characteristics, but vastly different spectral characteristics. Having the spectral reflectance feature set of a person would aid in further distinguishing pedestrians from each other.

Empirical data collected during this project, and reported on in Appendix A, illustrate the spectral differences which can be measured among materials on a pedestrian. Utilizing these spectral differences can enhance distinguishing between pedestrians and ensuring the same pedestrian is being tracked, frame-to-frame.
1.4 Hyperspectral Imaging for Pedestrian Detection and Track Association

For several years hyperspectral imaging systems have been used to remotely sense and characterize the Earth from spaceborne and airborne systems [13]. More recently, research has been looking at the utility of utilizing hyperspectral imaging systems for tracking objects such as automobiles and buses as shown in [18] and [19]. In order to track transient objects like automobiles, a HSI system needs to be over an area for a long enough period of time to capture several frames of imagery which is typically not possible with a spaceborne system. Airborne HSI systems could provide this ability, but resolutions of such systems are typically on the order of 0.5 to 1 meter ground sample distance (GSD) [20]. Given a pedestrian is less than 1m$^2$ when viewed nadir from a typical airborne system [21], they will typically be captured as a sub pixel target. This poses a unique challenge as it was shown in Figure 1.3 that the pedestrian would likely be composed of several unique materials. Therefore, in order to study the phenomenology of pedestrian spectral signatures in HSI, a ground mounted sensor is necessary, which could see the whole side profile of a pedestrian with a pixel size less than 0.5 m. This would allow for full view of the pedestrian and allow for more sample pixels of the pedestrian constituents and better develop a pedestrian spectral profile. It would also allow for the follow-on work to study the impacts of having the sensor mounted with a more nadir viewpoint and a lower resolution and possibly with some materials removed from the feature set.

1.5 Research Question, Objectives, and Scope

The primary research question studied within these pages is, “Can a pedestrian of interest be uniquely associated in hyperspectral imagery using a spectral feature vector derived from four constituent subregions?” This research effort looks at the phenomenology associated with the imaging of pedestrians in HSI. This dissertation contributes to the fundamental knowledge of and processing requirements associated with the spectral profile characteristics of a pedestrian in an urban environment. Aspects of understanding this question were explored through analytical
development as well as simulation tools and generation of real-world data.

1.5.1 Research Objectives

The main objectives of this research looked at the following basic areas of research:

1. Establish an empirical database of pedestrian signatures under controlled and natural illumination.

2. Investigate spectral range requirements for imaging a pedestrian for unique detection and labeling in a cluttered urban environment.

3. Investigate utility of using a multi-region feature vector derived from in situ spectral measurements from hair, skin, torso clothing, and trouser clothing while posed in a cluttered urban environment.

4. Explore appropriate metrics for separating a POI from background and other pedestrians using HSI.

5. Investigate impacts of losing one subregion feature set through obscuration, illumination change, or background changes.

Each of these objectives were studied independently for identifying direct impacts of environmental or sensor characteristics to pedestrian detection based on spectral radiance.

1.5.2 Context and Scope

By simple observation it can be concluded that pedestrians can be viewed in almost all environments, and almost all locations. Within the context and objectives previously outlined, this research effort can be treated as a detection and classification problem. This work was not intended to develop an optimal tracking algorithm. For the purposes of scientific discovery, it would be impossible to envision and interrogate all such possibilities. As such, for this research it was of decided value that the case of a pedestrian walking through an urban area under natural sunlight
be studied. To mitigate unintended complications, the following assumptions were made at the outset of this research effort regarding the scene and pedestrian.

1. Assume that the pedestrian is only viewed by a single imager over a finite period of time.
2. Assume the sensor is a low angle close-in sensor such as a building mounted sensor.
3. Assume there are enough pixels on target that regions for the hair, face, neck, torso, hands, legs, and footwear are resolved.
4. Assume that the pedestrian will be the same when they enter and exit the imager’s field of view.
5. Assume that the pedestrian’s feature set can be established at the first instance of detection for future reference (e.g., the pedestrian’s feature set is not explicitly known a priori to the time of initial detection).

With the above assumptions, the research was limited to studying the phenomenology of a single pedestrian as they traverse a city scene which may, or may not have additional pedestrians present. The POI was assessed in a one-versus-many context. The desired end state of this research effort was to have a working understanding of the spectral features which could be used to identify a pedestrian uniquely from the background and other pedestrians. This included considering the pedestrian in several locations within the scene.

The first three assumptions above establish the geometry and sensing environment in which the pedestrian could be imaged. This limits the considerations regarding a pedestrian changing clothes while walking and registration errors when associating pedestrians across different imaging systems. Note that frame-to-frame registration would still be a concern for a single imager. By taking these assumptions into consideration, the questions related to understanding the phenomenology associated with illumination sources, background materials, and scene geometries can be decisively chosen. The last two assumptions establish how the pedestrian could behave and how they could be uniquely labeled.

In addition to the assumptions above, this work does not seek to establish an automated approach to detecting and segmenting pedestrians. It relies heavily on supervised detection and
manual labeling of data for verification purposes. That is not to say the techniques pursued within this research could not be used for automated processing; it simply was not a goal of this research.

Finally, this research focuses on the the spectral features in the visible, near infra-red, and short-wave infra-red (450 - 2500 nm) portions of the electromagnetic spectrum. Additional portions of the spectrum may be of utility for feature aided tracking of pedestrians in an urban environment, but those are left for future work.

1.6 Scientific Impacts From This Research

Much of the previous work done in the areas of pedestrian detection, as outlined in Chapter 3, has focused on tri-color imagery limited to the 400 - 700 nm portion of the electromagnetic spectrum. This work extends these studies by looking at the phenomenology associated with a much higher spectral resolution. Additionally, this work includes more of the electromagnetic spectrum from 450 nm to approximately 2500 nm. By having an understanding of the detectability of the pedestrian materials with the spectral resolutions and in the range of wavelengths pursued, future studies, such as novel tracking algorithms, will be enabled. Also, a better understanding of the trade-space associated with pedestrian detection in remote sensing is realized.

In addition to the phenomenological aspects studied within the scope of this work, an extensive HSI dataset was generated. This dataset includes a fully ground truthed collection of hyperspectral images of pedestrians in an urban scene as viewed from a building mounted sensor. It is the first community accessible data resource of its kind developed with the intent to support future pedestrian detection phenomenology studies.

1.7 Organization of Dissertation

This dissertation is organized such that Chapter 2 provides background on the pedestrian detection within the context of this research. It sets up the problem and defines the pedestrian as a multi-region target. Chapter 3 outlines some of the previous work done in the area of material detection as it relates to the constituent materials, organized as subregions, of the pedestrian. Next, Chapter 4
addresses the methodologies used in assessing the detectability of pedestrians in hyperspectral imagery. The results follow in Chapter 5. Finally, concluding remarks on the research as well as outlined future work is contained in Chapter 6. Several appendices follow the conclusions, which include background on the primary datasets used in this research as well as methods used to characterize those datasets.
Chapter 2

Background

As Figure 1.3 indicates, there are many potential observables associated with characterizing a pedestrian. For the purposes of this dissertation, only the spectral reflectance of hair, skin, and clothing on the pedestrian were studied. Each one of these materials is unique and has different properties with different spectral signatures. As stated in the research question of Section 1.5, it was proposed that a pedestrian of interest (POI) could be uniquely identified (classified) in an urban scene using a spectral feature vector comprised of these four subregions.

This chapter discusses the subregion materials selected for pedestrian spectral detection. A discussion related to the challenges of pedestrian detection due to illumination, noise, and other effects is also included. Additionally, a simple processing approach for frame-to-frame pedestrian detection and classification is presented.

2.1 Anatomy of a Pedestrians as a Multi-Region Target

An example pedestrian is shown in Figure 2.1 with the subregion materials identified. Before getting to the composite spectral representation of the pedestrian as a whole, characteristics of each of the materials are discussed.
Hair

In [22], Sinha and Poggio suggest that hair is a very prominent, if not the most dominant [23], feature for visual recognition of familiar faces. However, very little research has been conducted to extract unique features of hair from people in imagery. One argument is that hair features are unstable for human identification given the ease for an individual to change their style. However, according to a survey reported in [23] most people tend to be fairly consistent and typically do not manipulate their hair. Additionally, for the scope of the research to be conducted within this dissertation, the spectral features of a pedestrian would be based upon the measured reflectance at the time and place of capture and would only be considered over a finite time frame. Therefore, it is expected that attributes of hair provide a valid cue for distinguishing among pedestrians within a short period of time.

At its root, hair is one of the most complex miniorgans of the human body [24]. It consists of two primary parts. The first part is the follicle, which is embedded in the dermis of the skin and contains the hair bulb. The bulb is the root of the hair from which hair grows. The second part
is the hair shaft. This extends from the hair bulb through the follicle and out of the epidermis. The terminal hair shaft (portion beyond the follicle) is what is observable from a remote sensing standpoint. It is the only portion of the hair considered for the this portion of this research. Subsurface processes within the follicle, which may affect attributes of hair such as blood flow, perspiration, and general health indicators of the hair, will not be considered under this study and are therefore omitted. The interested reader can find more information about the anatomy and function of the follicle in [24].

In [24], Krause and Fötzzik explain that the body is estimated to have approximately 5 million hair follicles with approximately 80,000 to 150,000 occurring on the scalp. The hair of the scalp, eyebrows, lashes, and male facial hair (predominantly) consists of terminal hair shafts which are thick, medullated, and pigmented. The rest of the body is covered with short, thin and often unpigmented vellus hairs. Though hair will occur on most of the body, this study is most concerned with the hair occurring around the head region as a source of distinctive information as it relates to pedestrians.

A cross section of the hair follicle is shown in Figure 2.2. The terminal hair shaft is comprised of the inner three sections, namely the medulla, cortex and the cuticle. The cuticle is comprised of thin, overlapping scales and is the interface from the air to the hair shaft. The remaining layers shown in Figure 2.2 are the parts of the inner and outer sheath of the hair follicle and generate the terminal hair shaft and will not be considered further in this research.

As demonstrated by Marschner, et al., in [26], the color of hair visible to human perception is due to the pigments of the cortex and medulla as well as the light interactions within the structure of the hair. When using a white source, a portion of the incident light scatters off the scales of the cuticle layer as white light and the remaining light enters the hair shaft. Of the light that enters the shaft, a portion of it is scattered or absorbed and any reflected light is due to the pigments, or melanin [24], present in the terminal hair shaft. What is then perceivable to the human observer is a combination of this white and colored light reflecting from the hair shaft [26].

The description thus far has dealt with the single hair shaft. When hair is taken as a bundle, there is a myriad of interactions occurring within the fiber bundle. For the purposes of this research, this interaction and the aggregated effect will be dependent on the density of hair as well as the
spatial resolution of the hyperspectral imager; topics thus far only researched within the computer animation community for the purposes of rendering life-like hair within the visible spectrum.

Figure 2.3 shows spectral measurements of hair measured on the head from four unique subjects taken from the data set described in Section 4.1.1 and Appendix A. It should be pointed out that Subjects E, F, and J identified their hair as brown, while Subject H identified their hair as dark brown. Inspection of the four curves indicates that hair is more reflective above 1000 nm with many features readily observable between 1000 and 2200 nm. What is not readily apparent is how the density of hair, as well as the skin tone under the hair, affects the measured reflectance and unique spectral signature.

**Skin**

Human skin is a complex organ comprised of several layers of tissue, namely the epidermis, dermis, and subcutaneous tissue [7]. These layers are each constructed from various combinations of water, collagen, blood, melanosomes, and other chromophores. While each of these substances contribute
to the skin color, the melanosomes in the epidermis account for the primary difference in skin color [27]. Due to the high water content of skin, it has very low reflectance and variability among skin types at wavelengths beyond 1400 nm [28]. Nunez, in [7], showed how the melanin level could be estimated for unique detection of skin tone. This melanin estimation provides for a unique signature of the skin.

Due to differing amounts of exposure, mainly due to wardrobe choice, it should be pointed out that the skin of a person may not all be of the same tone as shown in Figure 2.4. Figure 2.4 shows the reflectance spectra from skin of the face and arm from the subject in Figure 2.1 as taken from the data set discussed in Section 4.1. In Figure 2.4 it is readily apparent that the skin spectra from different parts of the same person has slight variation, but is correlated. The hair spectra from the same subject is included for comparison. The absorption just below 1200 nm can be seen in the hair spectra as well.

Figure 2.3: Spectral measurement curves of hair from several pedestrian subjects with hair identified as brown from the data set described in Section 4.1.1.
Figure 2.4: Skin reflectance spectra taken from a pedestrian in the HYMNS-P data set discussed in Section 4.1 showing the slight variation between the two areas of exposed skin.

Clothing

In many cultures, pedestrians wear two piece outfits consisting of a shirt covering the torso and trousers or shorts covering the waist and legs. Some cultures wear more and others wear less, which may also be driven by the environment, but for this dissertation only the case of two piece clothing was considered. For convenience in analysis, the clothing signatures were broken down into two subregions so the shirt and trouser subregions could be treated separately. This was due to a common observation that shirts and trousers are colored differently and often of different fabrics.

Around the world, clothing materials can vary by region and culture. Cotton continues to be one of the most common materials used for clothing materials worldwide [29]. Some other materials include polyester, spandex, bamboo, or a mixture of materials. Each of these materials exhibit a different spectral characteristic as illustrated in Figure 2.5. The 100% cotton material
was a reddish brown t-shirt, the 67/33 cotton-polyester blend was a yellow t-shirt, and the 100% polyester was a blue shirt. It is clear that there are spectral differences in the visible region (450 - 700 nm) and in the short-wave infrared (SWIR) region around 1550 nm and 1900 - 2250 nm among the spectral reflectance profiles. Additionally, research by Haran [30] on the reflectance properties of cotton and polyester in the SWIR spectrum (1000 - 2500 nm) showed the major absorption bands for cotton are centered at approximately 1196 nm, 1492 nm, 1930 nm, 2106 nm, and 2328 nm. For polyester, the absorption features are centered at approximately 1122 nm, 1395 nm, 1656 nm, 1900 nm, 2132 nm, 2254 nm, and 2328 nm. Certainly the features at 1500 nm, 1930 nm, and 2106 nm for cotton and 1656 nm for polyester are seen in Figure 2.5. These features could be used to distinguish between 100% cotton and 100% polyester materials. However, the 67/33 cotton/poly blended fabric exhibits features from both materials. Additionally, there are significant water absorption bands at approximately 1400 nm and 1900 nm (see Figure 2.6) which would mask the spectral features near those wavelengths.

Figure 2.5: Textile reflectance spectra taken from pedestrian clothing in the HYMNS-P data set discussed in Section 4.1. The the spectral differences between the three material types are apparent.
In many cultures it is common to wear some type of head covering. This usually conceals most of the hair on top of a pedestrian’s head and portions of the pedestrian’s skin. While the result may lead to interesting effects of a person’s spectral characteristics, this was not considered in depth within the scope of this dissertation.

**Spectral Reflectance Mixing Within Subregions**

Noting that hair may be different thicknesses or bulk, clothing may be porous and skin may be somewhat transmissive from the surface to the lower layers, there is likely to be a certain amount of mixing among the spectral reflectance characteristics of the subregions [31]. This intimate mixture poses a challenge to developing the unique pedestrian spectral feature set. However, it was proposed that despite this mixing, the spectral feature set of the pedestrian of interest will be separable from background and other pedestrians in the scene. Investigations into mixing levels and mixed signature separability was not pursued within the scope of this research.

### 2.2 Sources of Observed Spectral Radiance Variability

As a pedestrian moves through the scene, there are many extraneous influences on the pedestrian’s spectral profile which cause it to have a temporal nature. This includes the illumination on the pedestrian, the pedestrian’s bidirectional reflectance over the body, light scattered off the background onto the pedestrian, and various types of skin coatings. All of these induce variability within each material subregion on the pedestrian and create unique challenges on the pedestrian.

#### 2.2.1 Illumination Variation

For the scope of this research, only sunlight as the illumination source was considered. Figure 2.6 shows the solar radiation spectrum [32] illustrating the spectral irradiance above the atmosphere and at sea level. The presence of the water absorption bands as well as other atmospheric constituents can be seen in the curve. These must be considered when calculating the separability of spectral feature sets of the sub-class materials.
Figure 2.6: Illustration of the solar spectral irradiance exoatmospherically (yellow) and at sea level (red). Note the theoretical blackbody spectrum is overlaid as the gray band. Image courtesy of the Global Warming Art Project [32].

Another area of consideration is when a pedestrian goes from direct sunlight to shadow. The indirect illumination onto a pedestrian is predominantly due to Rayleigh scattering and there is a disproportionate reduction in the radiation power between the visible and the infra-red portions of the spectrum [31].

2.2.2 Adjacency Effects

A stationary pedestrian is shown in Figure 2.7(a). Due to the geometry of the sun onto the pedestrian, the top of the head and shoulders as well as parts of the left leg are in direct illumination while most of the surfaces facing the sensor are in indirect illumination. This creates a challenge when identifying unique signatures for a pedestrian. A simplified illustration of the source-target-sensor geometry of Figure 2.7(a) is shown in Figure 2.7(b). Due to the extreme difficulty characterizing the adjacency within a scene, this phenomenon is merely pointed out at this point and was not extensively characterized within the scope of this research. However, there was ground truth reflectance measurements collected for the scene with the pedestrian shown in Figure 2.7(a) so this
CHAPTER 2  BACKGROUND

analysis could be performed in future work.

Figure 2.7: (a) True color image of a pedestrian being directly and indirectly illuminated. The sun is slightly behind the pedestrian causing the front side to be indirectly illuminated. (b) Simplified illustration of direct illumination and background radiance for subject in (a)

2.2.3 Observation Orientations

As a pedestrian moves through a scene, it should be noted that their appearance will vary. Part of this variance is due to the bidirectional reflectance distribution function (BRDF) of the surface materials on the pedestrian. The BRDF describes the collection of reflectance values for all incident and reflected geometric angle combinations. The reflectance can be defined as the ratio of the reflected radiance to the incident irradiance with respect to the reflected and incident geometry such that [13]

\[ \rho(\theta_i, \phi_i; \theta_r, \phi_r | \lambda) = \frac{L(\theta_r, \phi_r | \lambda)}{E(\theta_i, \phi_i | \lambda)} [sr^{-1}] \]  

(2.1)
where $L(\theta_r, \phi_r|\lambda)$ is the spectral reflected radiance per wavelength, $\lambda$, and $E(\theta_i, \phi_i|\lambda)$ is the incident spectral irradiance. Note that the angles have a range of $0 \leq \theta_i, \theta_r \leq \pi/2$ and $0 \leq \phi_i, \phi_r \leq 2\pi$. The normalized total sum of combinations for all reflectance angles in Equation 2.1 is referred to as the BRDF. Figure 2.8 illustrates the geometry of the BRDF for a surface.

\[
\rho_{\text{ward}}(\theta_i, \phi_i; \theta_r, \phi_r|\lambda) = \frac{\rho_d(\lambda)}{\pi} + \frac{\rho_s(\lambda)}{4\pi \alpha_x \alpha_y \sqrt{\cos(\theta_i) \cos(\theta_r)}} \exp[-\tan^2 \theta_h (\cos^2(\phi_h)/\alpha_x^2 + \sin^2(\phi_h)/\alpha_y^2)]
\]  

(2.2)

where $\alpha_{x,y}$ is the standard deviation of the surface slope in the $x$ or $y$ direction and $\phi_h = \phi_r/2$ per the geometry depicted in Figure 2.8. For Equation 2.2, the factor $1/(4\pi \alpha_x \alpha_y)$ is a normalization factor replacing the geometric attenuation and Fresnel reflection coefficients. Ward points out that it is valid for surfaces where $\alpha$ is not much greater than 0.2. Note that the width of the specular
lobe is governed by $\alpha_x$ and $\alpha_y$. A special case occurs when $\alpha_x = \alpha_y$ and the specular lobe becomes isotropic.

Previous research has shown that the color of non-metallic materials is primarily due to the light interaction with the sub-surface materials [34]. When the viewing geometry is within the specular lobe, the first surface reflection dominates and materials appear to be almost white and therefore spectrally constant over all wavelengths if white light is used as the source. With this in mind, $\rho_s$ in Equation 2.2 can be approximated as unitary for all wavelengths when no other data exists.

The contours of the human body contribute to an overall BRDF of the pedestrian. This is illustrated in the synthetic image of a human head in Figure 2.9 where the skin has a varying sheen as seen [35]. The skin is a common material but the appearance at each pixel location is different due to the BRDF of the skin and the way it lays over the contour of the skull.

![Figure 2.9: Illustration of a synthetically generated human head showing BRDF effects. Notice the sheen off portions of the skin around the face and forehead while other portions of the scalp do not appear as bright. Image courtesy of Marschner, et al. [35].](image)

Note that the BRDF can exist on several levels which go from the microscale, to a milliscale and finally to an object scale [36]. In the case of the sub-class materials, there exists a localized BRDF due to the hair shaft, clothing fibers, or skin texture as well as the absorption and scattering phenomenon inherent in each material (microscale). Then there is the aggregate of the localized micro BRDFs which make up an area BRDF such as that associated with a portion of cloth (milliscale). Finally, there is the whole person BRDF (object scale). In traditional remote sensing applications, this would be akin to the BRDF of a forest where there are BRDF’s of the individual
leaves, then the BRDF of the individual trees, and finally the BRDF of the whole forest. The measurement of the BRDF is then limited to the resolution of the imaging system for a given application. Work has been conducted looking at bridging the BRDF to the sensor resolution which lead to the bidirectional reflectance variance function (BRVF) [37].

In considering the BRDF of a pedestrian, several models exist which characterize the subregions of the pedestrian. During the course of this research, it was determined that these models need additional development and validation to extend these models from just the visible spectrum to the infra-red spectrum. Additional reading on these models can be found in Appendix D.

2.2.4 Spectral Reflectance Variability

It should be noted that there are a variety of items that can be present on skin and hair which are both naturally and artificially applied. These include sweat, sunscreen, lotions, make-up, and several different types of hair products. While these pose an interesting aspect of the phenomenology associated with the pedestrian detection, there are simply too many possible combinations and scenarios of conditions to consider in this research. Much of the phenomenology associated with skin and hair products is left to future work. However, it should be kept in mind that a primary assumption of this research is that the spectral characterization of a pedestrian is done with respect to imaging and detecting at a given point in time. No a priori knowledge was considered.

2.2.5 Noise Effects

As pointed out in [13] and [15], all imaging systems exhibit some type of noise. Noise can be the result of the random occurrence of photons (shot noise), thermal variations of the detector (Johnson noise), thermal interactions with the surrounding environment (temperature noise), or simply the random variations of electron movement in the detector electronics (generation-recombination noise). These noise sources affect the mean input signal level when imaging. The signal-to-noise ratio (SNR) is the measure of mean signal level to the noise which can be calculated such that

\[
SNR = \frac{\bar{x}}{\sigma_x} \tag{2.3}
\]
where $\bar{x}$ represents the mean spectral vector of a digital image and $\sigma_x$ is the standard deviation about the mean. It should be pointed out that imaging systems typically have SNR levels of many hundred to preserve image quality. However, any noise present does affect detection. One way to overcome the effect of noise is to take many samples and average; however it only improves noise as the inverse of the square root of the number of samples such that

$$n_n = \frac{N}{\sqrt{n}} \quad (2.4)$$

where $n_n$ is the noise after averaging $n$ samples, assuming the noise is independent.

### 2.3 Simple Processing Scheme

Within the context and objectives previously outlined, this research effort focused primarily on detection and characterization of the pedestrian. However, a simple tracking workflow framework could be envisioned as shown in Figure 2.10.

The first step in the process after acquiring the image would be to detect the pedestrians. This could be done in one of two ways, thus the two parallel paths. If the pedestrians are detected using another system, then their locations are known and the pedestrians could be segmented into subregions with the POI labeled as such. Alternately, a material map could be generated and pedestrians detected based on spectral features associated with their subregions. This, in effect, pre-segments the pedestrians. Once the pedestrians are segmented into labeled subregions, features which distinguish the POI from other pedestrians could be generated from the first imagery frame. Subsequent images would rely on these pre-defined features to distinguish pedestrians as the POI or not. The labeled pedestrian locations could be passed to a tracking algorithm which might use additional information about the image or the pedestrian to further enable tracking the pedestrian.

There were three primary tasks in this workflow which were focused on during the course of this research. These tasks are highlighted by the boxes enclosed with the dashed lines. Each of these tasks are described in detail in Chapter 4.
Figure 2.10: Illustration of a simple processing scheme to glean features from the POI and properly classify the POI frame to frame. The boxes enclosed by dashed lines were focused on during the course of this research.
Chapter 3

Previous Work

This chapter will present previous work performed in the areas of pedestrian detection and classification within the context of this research. Research related to human and the subregion materials will also be discussed.

3.1 Human Detection and Tracking with Segmentation

Work performed by the computer vision research community has looked at pedestrian tracking using various segmentation approaches [1, 3, 17]. Most of the work conducted so far worked with tricolor imaging systems whereas this dissertation is concerned with hyperspectral imaging systems and the available spectral features unique to pedestrians.

Work performed by Vaquero, et al., [17] looked at identifying attributes of individuals for improved people search in archival video and still imagery. The work sought to identify a universal framework of salient features that would be applicable over a variety of spatial resolutions and environmental conditions. Most of the features were drawn from the head area such as the presence of hair, balding, eye-wear, and/or facial hair. Additionally, the feature space included the dominant colors of the torso and legs. The processing was such that first faces were detected using the wavelet based Haar transform and then features were extracted related to the detected face using nine trained detectors based on work in [38]. The torso and the legs were detected using expected
spatial locations based on the location of the detected face. The authors were not concerned with explicit torso or leg shape and extent as they were only seeking the dominant visible color of the clothing present.

The results presented by Vaquero, et al., showed a classification accuracy for individual attributes ranging from 50% to near perfect depending on the attribute being classified, with a bald crown having the highest classification rate. Classifying images with eye wear (e.g., sunglasses, eyeglasses, etc.) performed much lower. The authors hypothesized that shadows and spatial resolution caused problems for the eye wear detector. Results for the shirt and pants color detector also scored very high (> 90%) for selecting dominant color within the regions. Despite these favorable results, this work was limited to the information of the tri-color imagery and could not capitalize on the additional classification performance afforded with the plethora of bands in hyperspectral imaging data. Additionally, they did not look at ways to resolve lighting and shadowing limitations to their classification algorithms.

Research performed by Zhao, Nevatia, and Wu in [1] looked at segmenting and tracking of multiple pedestrians in a crowded urban environment. In their work, humans were segmented from each other using a human blob model, as shown in Figure 3.1. The blob model captures the gross shape of a human body in imagery and artificially limits the spatial extent of the person being tracked. This aided tracking for the case when people pass close to or behind one another. The pixels corresponding to respective individuals were maintained thus reducing motion confusion for the tracker. The algorithm first identified heads of pedestrians in the imagery and then applied the blob model to segment humans from each other.

The results from the multi-human tracking offered a 62% success rate in tracked humans (i.e., maintained track against a previously known trajectory). The tracker had problems when pedestrians became completely occluded and also when they had clothing that appeared similar to the background. Proposed solutions to these problems included implementing a process that could detect when a pedestrian approached a full occlusion and anticipated where the pedestrian would reappear. Some particle filtering techniques attempt to overcome the limitations of tracking when targets are occluded [39].

Given that the resolution of hyperspectral imagery may lead to mixed pixels along transition
regions, such as the neck line and torso to trousers, it is of interest to estimate the projected area of human body shape. One such study that looked at the problem of body area projection onto the focal plane was reported by Kubaha, Fiala, and Lomas in [40]. In this study, a process was developed for projecting body sections onto focal plane areas for a given viewing range. Validation consisted of using physically accurate synthetic wire mesh human body models and measuring projected area factors onto synthetic focal planes. Their results were compared to earlier results published by other authors and referenced in [40].

Other work in the computer vision community, such as that by Zhao, Fu, and Liu in [2] and Li, et al., in [3] looked at human segmentation for performing pose estimation. These approaches were applied to estimating human movement to aid in tracking performance. However, these approaches are beyond the scope of this work. They require higher spatial resolutions than what this dissertation was concerned with and they did not consider the spectral reflectance functions of the body parts to aid in the segmentation.

### 3.2 Hair Detection and Classification

As alluded to in Section 2.1, it appears that until recently very little research has been conducted looking specifically at using hair attributes to distinguish between people. Work conducted by Yacoob and Davis [41] looked at establishing a multidimensional representation of hair appearance for automatic recognition of people in color pictures. In this work, the attributes of hairline, texture,
length, surface area, symmetry, volume, color, and split location were used as cues. High resolution true color photographs of 524 unique subjects were used to study the similarity among individuals based on individual hair attributes. Additionally, a data set of 3,100 unique photographs from 126 subjects was used to assess person-identification using single and multiple attribute combinations. The photos were taken in salons and barber shops near the college where the study was being conducted using a three-color (red, blue, green) hand held camera. Each subject was photographed in several poses and without any other people present in the background. Also, the locations of the subjects varied and, though the pictures were all taken indoors, the lighting was not controlled during many of the captures.

The hair detection approach in [41] utilized the color difference between the temples and likely pixel locations for detecting presence of hair in the pixel. An automated process was implemented which located the temples based on eye location and bridge of the nose; the details of which the reader is referred to the source paper.

The results of the hair detection had a reported 71 percent success rate. Visual inspection of photographs was performed on the remaining 29 percent of photos to outline the hair regions. The most difficult cases for their approach included receding hair lines, hair similar in color to background and hair with multiple hair colors (i.e., highlights).

Once the hair was detected, each of the eight attributes was tested in isolation to select the best match of a person taken from among the data set. Texture proved as the most valuable though it only had a 19.6% accuracy for selecting the best match when only considering the top ranked photo match. The attributes of volume, surface area, symmetry, split, and length were not as useful for properly associating individuals between photographs with high confidence.

The authors also looked at combining the best three attributes and using them together to properly associate a person across images. This approach demonstrated a 20-30% improvement in pattern matching across the image data sets. Thus, the idea that keying on several attributes of an individual yields better image association, but the result still barely yielded 50% proper classification at best.

In [41] several attributes about hair were studied, however the authors were limited in the spectral resolution of their camera. Additionally, the authors admitted there were likely factors
regarding the environment in which the images were taken that limited the ability of the hair
detection algorithm to work. Further work in the areas of spectral reflectance beyond the visible
spectrum would shed light on additional features and thus allow for spectral pattern matching
between images.

3.3 Skin Detection and Classification

Skin detection in hyper- and multi-spectral imagery has been looked at for various applications
such as search and rescue [42, 43], face recognition [6, 44], and automatic vehicle occupancy [28].

Research performed by Nunez in [7] developed the Normalized Skin Difference Index (NSDI)
for detecting the presence of skin in a pixel. Patterned after the Normalized Difference Vegetation
Index (NDVI), this technique allowed for quickly and specifically detecting skin pixels in hyper-
spectral imagery. Once a skin pixel was detected, then the melanosome content of the epidermis
could be regressively estimated and a skin type assigned according to the Fitzpatrick Skin Type
Scale [45].

Results of using the NSDI on field collected HSI imagery had a reported probability of detection
success of 95%. There were still challenges with detecting pixels of low illumination, such as
under the chin, but the NDSI proved a viable solution for skin detection in real-world imagery.
Additionally, the estimated skin type from the estimated melanin levels provided favorable results,
though it was assessed qualitatively and not quantitatively. It is suspected that since live human
subjects were used in the field collected HSI data, truth skin samples were not collected from the
participants.

3.4 Clothing Detection and Classification

Clothing detection specifically in hyperspectral imagery appears to be an emerging area of research
as very little is directly published on this area. As mentioned in Section 3.1, work has been done
that looks at estimating clothing color in visible imagery. Additionally, the textile industry is very
concerned with the appearance of fabrics in the visible spectrum [46].
The remote sensing community has looked at fabric detection in a broad sense when calibration targets of known fabric are placed in a scene during a data collection [31] and subsequently the imagery is segmented or classified. Also, there has been some work for developing specialized fabrics, such as those worn by military members, to reduce the fabric reflectance signature in the visible and near infra-red as reported in [47, 48]. Additionally, work reported in [49] looked at feature selection in hyperspectral data and used 850 - 2450 nm reflectance data of 12 fabric materials to test the classification performance of the proposed algorithm.

The work performed in this dissertation represents a novel extension to these other studies with respect to clothing detection and classification in the context of pedestrian worn clothing. This work goes beyond material reflectance studies, such as work reported by Haran in [30]. In that study, Haran collected several diffuse reflectance measurements of cotton and polyester textile fabrics and characterized the spectral features in the visible to short-wave infrared spectrum (400 - 2500 nm). Some of these features were mentioned in Section 2.1.
Chapter 4

Methodologies and Data

To accomplish the goals of this research, several aspects of detectability were investigated. These areas included the separability of spectral reflectance samples in the presence of noise, natural clusterings of the spectral radiance imagery, pedestrian subregion detection between images, illumination effects, and detectability using spectral subsets. First, a description of the data used in this work is presented and then each of the areas of detectability studied is discussed.

4.1 Field Collected Data Sets

For this research effort, two field collected datasets and one synthetic dataset were used. The field collected data used were from the Hyperspectral Measurements of Natural Signatures for Pedestrians (HYMNS-P) experiment [50] and HSI data collected in conjunction with the skin detection research performed in [7]. The second dataset will be referred to as the Ground Level High Resolution Pedestrian HSI (GLHR HSI) data. Each of these datasets are described in this section.
4.1.1 Hyperspectral Measurements of Natural Signatures from Pedestrians (HYMNS-P)

One of the primary contributions of this work was the creation of the Hyperspectral Measurements of Natural Signatures - Pedestrian (HYMNS-P) dataset. It is a collection of fully ground truthed hyperspectral images of an urban scene as viewed from a building rooftop mounted sensor. It also contains a spectral reflectance database of several pedestrians that participated in the study. A brief synopsis of this dataset is described here, but a more extensive overview is included in Appendix A.

Figure 4.1 shows an example of one of the hyperspectral images with pedestrians present in the scene. For this dataset, there were 16 pedestrians that were positioned in known locations around an urban scene within the field of view of the imager. A total of 18 unique scene images were captured with the pedestrians placed in different poses for each image. Regarding the pedestrians, there were both male and female as well as a range of heights, weights, and ethnicities to provide a variety within the scene. Given this was an outdoor field data collect, there are certain spectral absorption bands which were of little use in the data analysis. Appendix A, Section A.3, describes the characterization of bands that were counted among the bad bands set.

The hyperspectral images were collected on 21 June 2011 and were captured using the Hyper-SpecTIR 3 (HST3) airborne imaging instrument [51] positioned on the roof of a building. The instrument is a pushbroom sensor with scan mirror oriented in the cross track direction. It had 256 spatial pixels along track with a 1 miliradian resolution. It has 227 unique spectral bands covering 450 - 2450 nm with 8 - 12 nm spectral resolution. It was originally designed to be flown in aircraft, but was mounted in a pelican shipping case for easy transport and set-up for taking side-looking hyperspectral images from the ground.

An extensive ground truth effort was conducted during the data collection. Table A.1 in Appendix A outlines the items that were ground truthed during the data collect. Pedestrian reflectance measurements and downwelling measurements were taken using an Analytical Spectral Devices (ASD), Inc., Field Spec Pro Spectroradiometer which captured spectra from 400 to 2500 nm. The reflectance measurements above 2250 nm were excessively noisy, so the analysis was lim-
CHAPTER 4. METHODOLOGIES

Figure 4.1: True color image of the scene with pedestrians from the HYMNS-P experiment.

itted to measurements between 400 to 2250 nm. Note that there were two ASD spectroradiometers used to capture downwelling measurements during image collection. The scene material reflectance measurements were taken using a Spectra Vista Corporation (SVC) 1024 Spectroradiometer. High resolution color photos were taken using a Nikon D50 SLR camera. Several aspects of the ground truth information were used to aid in understanding the phenomenology of pedestrian detection. Additionally, the ground truth supports many aspects of pedestrian detection and association phenomenology that transcend the collection of work included in this dissertation.

4.1.2 Ground Level Pedestrian High Resolution HSI Data Set

In [7], Nunez describes a dataset collected in support of research that led to the development of a first principles based model of human skin. For convenience, this dataset will be referred to as the Ground Level Pedestrian High Resolution HSI (GLHR HSI) dataset. An example of the imagery collected is shown in Figure 4.2.

For this dataset, the imagery was collected using the HST3 [51] sensor, which was also used for the HYMNS-P dataset (see above and also Appendix A). Table 4.1 outlines some of the differences
between this dataset and the HYMNS-P dataset. The primary difference from the HYMNS-P imagery though was the position of the sensor during the collection. This dataset was collected on an overcast day and the sensor was on the ground at the same level as the pedestrians, so imaging was a straight side-looking shot with much higher resolution. Metadata was not gathered related to the pedestrians or ground truth taken such as downwelling nor pedestrian position. Additionally, there were also weather related differences as outlined in Table 4.2. However, the GLHR HSI dataset contained a range of skin and body types, as well as pedestrians in different positions between images.

Table 4.1: Table outlining the differences between the HYMNS-P and ground level high resolution HST3 collected datasets.

<table>
<thead>
<tr>
<th></th>
<th>HYMNS-P Imagery</th>
<th>GLHR HSI Imagery</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time of year</td>
<td>June 21</td>
<td>March 9</td>
</tr>
<tr>
<td>Sky Conditions</td>
<td>Direct sunlight, passing clouds</td>
<td>Full sky cover</td>
</tr>
<tr>
<td>Sensor Position</td>
<td>Elevated on a building 4 stories up, approximately 42 feet high</td>
<td>Ground level</td>
</tr>
<tr>
<td>Approximate resolution</td>
<td>2.5 cm (1 inch)</td>
<td>0.5 cm (1/4 inch)</td>
</tr>
<tr>
<td>Scene Backing</td>
<td>Urban scene with parking lot and vegetation</td>
<td>Residential area</td>
</tr>
<tr>
<td>Pedestrian Positions</td>
<td>On asphalt or cement sidewalk and under full sky or under shade canopy</td>
<td>under tree branches or partial sky and tree branches.</td>
</tr>
</tbody>
</table>
Table 4.2: Table outlining the weather differences between the HYMNS-P and the ground level HSI datasets. Note the arrows indicate if the parameter was rising or falling.

<table>
<thead>
<tr>
<th></th>
<th>HYMNS-P Imagery</th>
<th>GLHR HSI Imagery</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Location</strong></td>
<td>Dayton, OH</td>
<td>Dayton, OH</td>
</tr>
<tr>
<td><strong>Date Captured</strong></td>
<td>21 June 2011</td>
<td>9 March 2009</td>
</tr>
<tr>
<td><strong>Time of Capture</strong></td>
<td>Late Morning (1000 - 1130)</td>
<td>Afternoon/evening</td>
</tr>
<tr>
<td><strong>Temperature (°F)</strong></td>
<td>78 - 83 (↑)</td>
<td>55 - 50 (↓)</td>
</tr>
<tr>
<td><strong>Humidity (%)</strong></td>
<td>82 - 72 (↓)</td>
<td>50 - 60 (fluctuating)</td>
</tr>
<tr>
<td><strong>Heat Index</strong></td>
<td>87 - 95 after 1000</td>
<td>N/A after 1400</td>
</tr>
<tr>
<td><strong>Pressure (in)</strong></td>
<td>29.85</td>
<td>30.2</td>
</tr>
<tr>
<td><strong>Visibility (mi)</strong></td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td><strong>Wind speed (mph)</strong></td>
<td>6 - 13</td>
<td>3 - 7</td>
</tr>
<tr>
<td><strong>Conditions</strong></td>
<td>Partly cloudy - scattered clouds</td>
<td>Mostly cloudy - overcast</td>
</tr>
</tbody>
</table>

4.2 Synthetically Generated Imagery

As noted in [52], humans do not do well with sitting still for long periods of time. Additionally, it is difficult to control and fully characterize the environment during an outdoor field collect. Therefore, synthetic imagery was generated using the Digital Imaging and Remote Sensing Image Generation (DIRSIG) tool. DIRSIG is a first principles physics based synthetic image generation tool developed and maintained by the Digital Imaging and Remote Sensing Laboratory at Rochester Institute of Technology [53]. DIRSIG works in conjunction with the MODerate resolution atmospheric TRANsmission (MODTRAN) to model both the atmospheric scattering into the sensor and onto the target as well as primary and secondary reflections of surfaces within the scene. Figure 4.3 illustrates the potential fidelity of the synthetic image generation afforded through the DIRSIG tool [54]. Figure 4.3(a) is an actual photograph of a military vehicle shaded under a radar netting. Figure 4.3(b) shows the synthetic image produced by DIRSIG which used a computer aided design (CAD) model of the military vehicle, the netting, and the radiometric attributes of the materials within the scene. As the synthetic image illustrates, DIRSIG accurately models much of the first and secondary surface reflections, but begins to break down when modeling the reflections out of cavities such as the cab of the truck (i.e., areas with significant multiple photon bounces).

As part of this work, the scene shown in Figure 4.1 was simulated using DIRSIG. The several spectral reflectance measurements collected for the pedestrians as well as in-scene materials were
used for the synthetic scene. The DIRSIG dataset was generated to assess the impacts to sub-region pixel detection due to direct vs. indirect illumination changes. Each simulated pedestrian was attributed with the spectral reflectance data from a corresponding individual in the real-world imagery. Thus there was not any exchanging of subregions among the pedestrians. A single atmosphere was maintained during the image simulations with only the sun angle being changed. Uncorrelated noise was added to the synthetic imagery prior to pedestrian detection and separability analysis using the fixed signal-to-noise ratio (SNR) as described in Appendix C. The SNR level was based on the HST3 sensor noise. Images were created for 9:00 AM, 11:00 AM, 1:00 PM, 3:00 PM, and 5:00 PM EDT. Note that the images were not oversampled so there was not spectral mixing at material edge pixels. Additional information about this dataset is contained in Appendix C. The simulated data were used primarily for analysis when changes of illumination occur.
4.3 Measuring Spectral Separability Among Subregions

4.3.1 The Pedestrian Two-Class Discriminant

For the purposes of this work, the classification of the pedestrian was to be treated as a two-class binary classification problem. The classes were designated as POI and Background where the background consisted of other non-POIs with and without non-pedestrian materials. This was further broken down according to subregions on the POI; thus the POI class was defined by the constituent subregions of a specific POI. It was assumed that the subregions were mutually exclusive to one another and could be detected independently of one another. While this may not be the case for subregion edge pixels where mixed pixels are likely to occur, pixel mixing was not considered within the scope of this dissertation. As such, pixel samples from a particular pedestrian's subregion were treated as being from the POI's subregion class and all other pixels were treated as background (i.e., pixels of other subregions on the POI were also treated as part of the background class). In this way, the separability between POI subregions, subregions from other pedestrians, and non-pedestrian materials was assessed.

4.3.2 Assessing Pedestrian Separability in the Presence of Noise

The high dimensionality of hyperspectral data allows for improved separability between dissimilar materials [13]. However, rarely are pure reflectance samples available. With this in mind, one aspect of this research looked at the classification error of reflectance samples in the POI class while in the presence of noise [55]. During this research several spectral reflectance samples were collected from volunteers as described in Section 4.1 and also in Appendix A. Noise was added to each of these samples and the pair-wise spectral distance was computed as described in the sections below. The noise level was varied in order to gain an understanding of the noise tolerance of the separability between subregion samples. Note that for this portion of the study, only spectral reflectance samples of the following pedestrian subregions were assessed: hair, facial skin, torso clothing, and trousers. There were skin samples available from arms and legs if the pedestrians were wearing shorts. However, for convenience in managing samples, only the facial skin spectral
reflectance samples were used. Also, the separability of pedestrian subregion materials from other in-scene materials was not assessed.

Adding Noise to Reflectance Samples

Several simulated noisy samples were generated for each subregion of each pedestrian from the measured reflectance samples by adding noise to each band such that [56]

\[
\tilde{x} = \bar{x} + \sigma \mathcal{N}(\bar{0}, I) \tag{4.1}
\]

where \(\bar{x}\) is the \(p\)-dimensional spectral reflectance vector as measured by the ASD, \(\sigma\) is the standard deviation, and \(\mathcal{N}(\bar{0}, I)\) is a \(p\)-dimensional vector of random variables taken from the Standard Normal distribution. From Equation C.1, the SNR is the ratio of the spectral sample mean divided by the spectral sample standard deviation. Solving Equation C.1 for the standard deviation and substituting into Equation 4.1, we have

\[
\tilde{x} = \bar{x} + \frac{\bar{x}}{SNR} * \mathcal{N}(\bar{0}, I) \tag{4.2}
\]

where \(\bar{x}\) served as its own local mean. The \(*\) represented an element-by-element multiplication operation. The result of Equation 4.2 was a noise modulated sample with a spectral mean of the original reflectance sample, and variance which followed a Gaussian distribution with a magnitude dictated by the SNR level. To preserve generality and avoid comparisons with specific system spectral response functions, a flat SNR was applied across all bands. There were a total of 100,000 samples generated for each pedestrian's subregion sample to improve the confidence in the separability estimates. An example of a reflectance sample with noise added is shown in Figure 4.4.

The example was from a shirt sample with noise added according to Equation 4.2 and an SNR of 20. The heavy black line is the non-noise added spectral reflectance sample. A lower SNR would increase the spread about the black line and a higher SNR decreases the spread about the black line. Note that there was a significant amount of noise in the field spectrometer measured reflectance data above 2250 nm. Therefore the spectral range was limited from 400 - 2250 nm.
Figure 4.4: Example of a shirt spectral reflectance sample from one pedestrian with noise added according to Equation 4.2 and an SNR of 20. The heavy black line is the non-noise added spectral reflectance sample.

Classification Error versus SNR

The spectral separability between samples was calculated using the adjusted spectral Euclidean distance, which measures the linear distance between two spectral vectors. It is defined as [57]

$$d_e(\vec{x}, \vec{y}) = \sqrt{\frac{1}{p} \sum_{i=1}^{p} (x_i - y_i)^2}$$  \hspace{1cm} (4.3)

where $\vec{x}$ and $\vec{y}$ are two spectral vectors of dimensionality $p$. In order to compute the distance between two vectors, they need to be of the same dimensionality. However, the adjusted spectral Euclidean distance is normalized according to the number of dimensions in order to compare the sample separability when changing the spectral dimensionality. The utility of this will become apparent when we consider combining the spectral information of different pedestrian subregions.

Using the adjusted Euclidean distance, two spectral distance distributions were calculated such
that

\[ d_{e,POI}(\tilde{x}, \tilde{x}_n) = \sqrt{\frac{1}{p} \sum_{i=1}^{p} (x_i - x_{i,n})^2} \]  
(4.4)

and

\[ d_{e,non-POI}(\tilde{x}, \tilde{y}_n) = \sqrt{\frac{1}{p} \sum_{i=1}^{p} (x_i - y_{i,n})^2} \]  
(4.5)

where \( d_{e,POI}(\tilde{x}, \tilde{x}_n) \) represents the distances between the measured subregion reflectance sample of a pedestrian of interest \( n^{th} \) sample of the noise-added samples generated from the source reflectance sample. This was called the POI class. Likewise, \( d_{e,non-POI}(\tilde{x}, \tilde{x}_n) \) represented the distances between the non-noisy POI reflectance sample and all the spectral samples of the other pedestrians, from the same subregion. This was called the \( non-POI \) class. An example of the two class probability density functions generated using equations 4.4 and 4.5 with SNR set to 8 is shown in Figure 4.5. The two distributions in Figure 4.5 were generated using the subject “I” from the HYMNS-P dataset (see Section 4.1.1) as the POI and the other pedestrians constituted the background class. The spectral reflectance sample of the trousers subregion was used. The probability density functions were calculated using the kernel based density estimation with a Gaussian zero mean and unit variance kernel. The kernel based density estimation, also referred to as Parzen window method [12], estimates the continuous probability density function using the discrete histogram of data samples. The kernel used smooths the histogram according to the distribution chosen as the kernel. It is easy to see a slight overlap between the two classes as well as the non-standard distribution of the background class. Some pedestrians were more spectrally similar than others so there was a varying amount of overlap among pedestrians, even at the same SNR level. For the separability, the primary focus was with respect to what point the noise level caused overlap between the POI and background classes. Note that even though the noise added was from a zero mean distribution, the distance calculations are non-zero for any SNR level. This stems from the fact that once noise is added, the spectral reflectance vectors have some amount of dissimilarity. As such, the mean of the POI class distances occurs above zero. As the noise is decreased the mean decreases and the distribution narrows, but it still does not go to zero. Additionally, the means of the background class will slightly shift away and the spread narrows.
Figure 4.5: Example of the POI and Background distribution for Pedestrian “T” vs. all others. The SNR for this example was set to 8.

The Bayes decision rule for minimum error was used to discriminate between the two classes. The threshold for class separability was found using the likelihood ratio test such that [12]

$$L_r(d_e) = \frac{p(d_e|POI)}{p(d_e|\text{non-POI})} \frac{\text{POI}}{\text{non-POI}} \frac{p(\text{non-POI})}{p(POI)}$$

where the a priori probabilities were given based on the number of samples. Pair-wise distances that fall within the region where the likelihood ratio was greater than the threshold were counted as part of the POI class. Conversely, distances where the likelihood ratio falls below the threshold were counted as part of the background class. The likelihood ratio as well as the threshold for the two distributions in Figure 4.5 are shown in Figure 4.6. Note that the graph in Figure 4.6 has been truncated vertically in order to make the threshold more visible. Also note that the values which fell below $10^{-9}$ for both curves in Figure 4.5 were set to $10^{-9}$ in order to avoid divide by zero cases. Intuitively it would seem that the distances which are closest to the origin (i.e., minimum spectral distance) should be considered as part of the POI class. However, it should be pointed out that...
as noise is added and the distributions overlap, there is a probability that the two distributions could completely overlap. This leads to certain spectral reflectance samples from the non-POI class to appear spectrally closer to the origin, or be considered more spectrally similar to the sample spectral mean vector under test.

Per Equation 4.2, the SNR was varied from a level of 1 to 25. It was determined that computing SNR values above 25 were futile and didn’t provide additional insight for this portion of this work. The probability of misclassifying POI samples per SNR for each subregion and each POI, in turn, was calculated such that

\[
p(error|\omega_{POI}) = \frac{1}{n} \sum_{i=1}^{n} \left( d_{e,POI}(\vec{x}, \vec{x}_i) \in \left\{ Lr(d_e) < \frac{p(non-POI)}{p(POI)} \right\} \right)
\]  

(4.7)

where \( n \) are the number of noise-added samples in the POI class and the argument of the sum is a binary operation according to the pair-wise distances that meet the threshold requirements. Given there were many POI’s, the \( p(error|\omega_{POI}) \) for each subregion was averaged over all POI’s per SNR.

Figure 4.6: Example of the likelihood ratio and the class assignment threshold for the POI vs. Background classes when SNR is set to 8. Note the graph has been truncated in the vertical dimension in order to see detail at the lower ratio values.

It should be pointed out that typically in classification problems the total error probability is
reported [12]. However, given there were twenty-eight times more samples in the background class versus the POI class, it was desirable to look only at the conditional probability of error for the POI class rather than total probability. In essence this work is only counting the number of Type I errors (missed detections) and not counting the Type II errors (false alarms). Since the prior probabilities of each class weight the respective error probabilities, the error probability of the non-POI class dominates the total error probability which is lower and does not provide insight into the overlap and probability for missed-detections. A Bayes decision rule for minimum risk could be used to counter the effects of the weighting on the conditional probability of error, but for this research costs were assumed to be equal.

### 4.3.3 Separability For Single Subregions vs. Combining Subregions

In addition to computing the separability for the individual subregions, the separability of the spectral data between pedestrians when the spectral vectors of subregions were combined was assessed. This was accomplished by concatenating the spectral vectors such that

\[
\vec{x}_{a,b} = \begin{bmatrix} \vec{x}_a \\ \vec{x}_b \end{bmatrix}
\]  

where \(a\) and \(b\) represent two different subregions of the same POI and it was assumed \(\vec{x}\) is a column vector with \(p\)-dimensions. Note that \(\vec{x}_{a,b}\) now has dimension \(2p\) which is why the adjusted norm Euclidean distance was used in Equation 4.3. As dimensionality increases, there is an automatic bias in the spectral distance, but normalizing by the dimensionality allows for the separability comparison as dimensionality increases. The same process for computing probability of error versus SNR, as outlined above, was followed for this portion of the study. Note that in addition to the pair-wise combinations, combinations of three and all four subregions together were assessed.

### 4.3.4 Reflectance Sample Separability using Spectrum Subsets

As described in Section 3.1, many current pedestrian detection systems only utilize the visible portion of the spectrum. One of the objectives of this work included looking at how the different
spectral regions of the data affected the separability. The probability of error analysis was performed for the full range (FR, 450 - 2250 nm), the visible region (450 - 700 nm) with only three bands, the visible region with 22 bands, the visible to near infrared region (VNIR, 450 - 1000 nm) with 39 bands, the short-wave infrared 1 region (SWIR1, 1000 - 1700 nm) with 66 bands, and the short-wave infrared 2 region (SWIR2, 1800 - 2250 nm) with 48 bands. It should be pointed out that for the RGB case, the 22-band data from the visible region were spectrally smoothed using three Gaussian kernels centered on 450 nm, 545 nm, and 600 nm. The Gaussian kernel had a standard deviation of 50 nm. The peak wavelengths were chosen to correspond with the wavelength locations of the tristimulus value peaks from the Commission Internationale de l'Eclairage (CIE) 1931 Standard Observer Visual Response model [58].

4.3.5 Assessing Pedestrian Separability in Remotely Sensed Imagery

In addition to computing the separability of the pedestrians spectral reflectance samples, the separability of the pedestrian subregion data from remotely sensed HSI data was assessed. For this portion of the study, two images were used from the HYMNS-P dataset (see Section 4.1) where the pedestrians were in two different locations between images. Each of the pedestrians in the respective images were manually detected and segmented as regions of interest (ROI’s) selected according to the respective subregions. The spectral data was thus labeled according to pedestrian and subregion. This simulated having segmented pedestrians in known locations. The imagery was maintained in sensor reaching radiance and was not atmospherically compensated to convert it to estimated reflectance. However, known bad bands as outlined in Appendix A.3 were removed prior to processing.

Each pedestrian was set as the POI, in turn. For each subregion on the POI, the respective sample mean was calculated. The spectral distances between the POI and their subregion samples were calculated to generate the POI distance class. Likewise, the spectral distances between the POI subregion mean and all the samples of the other pedestrian’s same subregion were calculated. This constituted the background class. For the subregions, there were a limited number of spectral samples. As such, the kernel density estimation that was performed using the spectral reflectance
data was not used in this case. Rather, the discrete probability mass functions were estimated from the normalized discrete histograms. An example normalized histogram from one of the subregions is shown in Figure 4.7. Using the Bayes rule for minimum error and assuming equal costs, the probability of error for the POI class was calculated for each pedestrian.

Figure 4.7: Showing the POI and background class distributions for a pedestrian’s torso subregion pixels.

In order to calculate the optimum threshold, we wanted to find the value of $d_e$ that satisfied the condition $[12]$

$$p(\omega_{POI}|d_e) = p(\omega_{non-POI}|d_e). \quad (4.9)$$

The easiest way to find $d_e$ that makes Equation 4.9 true is to see when the cumulative distributions are equal such that

$$\sum_{i=-\infty}^{D_e} (p(\omega_{POI}|d_e,i)) = \sum_{i=-\infty}^{D_e} (p(\omega_{non-POI}|d_e,i)) \quad (4.10)$$

where $D_e$ is the value of $d_e$ that makes Equation 4.9 true. The *a posteriori* probabilities in Equation 4.10 can be expressed in terms of the *a priori* probabilities using Bayes’ theorem such
CHAPTER 4. METHODOLOGIES

that

\[ \sum_{i=-\infty}^{D_e} \left( \frac{p(d_e, i | \omega_{POI}) p(\omega_{POI})}{p(d_e)} \right) = \sum_{i=-\infty}^{D_e} \left( \frac{p(d_e, i | \omega_{non-POI}) p(\omega_{non-POI})}{p(d_e)} \right) \]  

(4.11)

where \( p(\omega_{POI}) \) and \( p(\omega_{non-POI}) \) are the prior probabilities of the respective POI and background classes and \( p(d_e) \) is the probability of a particular distance occurring. Each of the probabilities in Equation 4.11 can be defined in terms of the discrete data such that

\[ p(d_e | \omega_{POI}) = \frac{H(POI)}{n_{POI}}, \]  

(4.12)

\[ p(\omega_{POI}) = \frac{n_{POI}}{n_{POI} + n_{non-POI}} \]  

(4.13)

where \( H(POI) \) is the histogram of the samples in the POI class, \( n_{POI} \) is the number of samples in the POI class and \( n_{non-POI} \) is the number of samples in the background class. Similar definitions can be defined for the background class. Now Equation 4.11 can be written such that

\[ \sum_{i=-\infty}^{D_e} \left( \frac{H(POI)}{n_{POI}} \frac{n_{POI}}{n_{POI} + n_{non-POI}} \frac{1}{p(d_e)} \right) = \sum_{i=-\infty}^{D_e} \left( \frac{H(non-POI)}{n_{non-POI}} \frac{n_{non-POI}}{n_{POI} + n_{non-POI}} \frac{1}{p(d_e)} \right). \]  

(4.14)

Equation 4.14 can be further simplified such that

\[ \sum_{i=-\infty}^{D_e} (H(POI)) = \sum_{i=-\infty}^{D_e} (H(non-POI)) \]  

\[ \sum_{i=-\infty}^{D_e} (H(POI)) - \sum_{i=-\infty}^{D_e} (H(non-POI)) = 0. \]  

(4.15)

The Bayes decision rule for minimum error, for the two class case, was calculated using the cumulative histograms of the discrete labeled data according to Equation 4.15. When there is a relatively limited number of samples available, as in the case of subregions pixels, it is unlikely there will be an exact value of \( D_e \) to satisfy the final result in Equation 4.15. This lack of exact equality is due to a finite number of available samples and chosen bin size for the discrete histogram. Certain techniques, such as one proposed by He and Meeden [59], attempt to optimize the bin size according to sample size. However, since the projected area of each subregion varied among the pedestrians,
the bin size was not optimized. As such, 300 linearly spaced bins were generated according to the range of $d_e$ values calculated for each subregion. Additionally, the value of $D_e$ that minimized the error in Equation 4.15 was chosen as the threshold.

To assess the results, a plot was generated which showed the probability of error for each subregion per pedestrian. This allowed for comparing the visual characteristics of the pedestrian with their probability of error results. Note that there was not any additional noise added to the pedestrian samples during this analysis. The mean and standard deviation of the probability of error among the pedestrians for each subregion were computed from the results of the pedestrians within the respective image.

The process above was performed using different spectral subsets of the data. The HST3 sensor used to capture the data covered the spectral range of approximately 450 - 2500 nm (see Appendix A). As was the process for the classification error of the spectral reflectance samples, the same spectral subsets were used to assess the separability in the remote sensed data.

Additionally, the pedestrian separability in remotely sensed imagery was performed when combining subregion spectral information. For this portion of the study, the spectral mean for each subregion was computed using the source image. Several combinations were devised using two, three, and all four subregions. The spectral mean vectors were concatenated after the manner shown in Equation 4.8. Then, pixels from the respective subregion combinations were selected and combined according to the available permutations. This generated a distribution of spectral vectors for each pedestrian. Each pedestrian was treated as the POI, in turn, and the binary classification was performed. The spectral subsets outlined above were used in this analysis as well.

4.4 Unsupervised Subregion Segmentation

In addition to the classification error among the subregions, the unsupervised $k$-means clustering algorithm was used [12] to assess the natural spectral groupings of the subregion data along with localized background materials. The $k$-means algorithm seeks to minimize the within-group sum of squares distances while maximizing the between group separation. A user can specify the $k$ number of clusters for the $k$-means algorithm to identify. From there, the $k$-means algorithm will
randomly select $k$ clusters and compute the mean. It will then calculate the distances from each
group mean to all sample points. Points that are above a certain distance from their assigned
group mean are reassigned to the closest group mean. Then the group means are recalculated
according to the updated groupings. This process is repeated until the number of reassigned pixels
or movement in group mean falls below certain thresholds.

The $k$-means algorithm can utilize several different distance metrics for assigning pixels to
clusters. The distance metrics must provide distance data in such a way that the smaller values
represent similarity between pixels. For this study, the Euclidean distance (non-adjusted form),
spectral angle mapper, and correlation metrics were used. Each of these distance metrics are
defined as follows:

Euclidean Distance, non-adjusted. The non-adjusted Euclidean distance is similar to Equation 4.3, except it is not normalized by the spectral vector dimensionality. It is defined as

$$d_e(\vec{x}, \vec{y}) = \sqrt{\sum_{i=1}^{p} (x_i - y_i)^2}. \quad (4.16)$$

Spectral Angle Mapper. Perhaps the simplest and most popular of the distance metrics to be
used in this research is the Spectral Angle Mapper (SAM). The SAM algorithm is basically a
measure of the angle between two multidimensional vectors $\vec{x}$ and $\vec{y}$ such that [13]

$$\theta_{SAM}(\vec{x}, \vec{y}) = \cos^{-1}\left(\frac{\vec{x}}{||\vec{x}||}^T \frac{\vec{y}}{||\vec{y}||}\right) = \cos^{-1}(\vec{x}_u^T \vec{y}_u) \quad (4.17)$$

where the subscript $u$ denotes the unit vector.

The SAM algorithm is easy to compute and operates regardless of the magnitude of the spectral
vectors. Since it only measures the angular separation between vectors, it does not require data
with high dynamic range to be preconditioned prior to computing. Thus it is useful for materials
that may be partially overshadowed. However, this can also be a drawback as the SAM algorithm
does not account for the brightness variation, interaction effects, and within-class variability which
leaves the SAM algorithm as one of the starting algorithms for characterizing separability of the
pedestrians and their constituent material signatures.
Correlation. The normalized correlation distance is similar to the SAM in that it measures how alike two spectral vectors are such that [60]

\[
d_{c}(\vec{x}, \vec{y}) = 1 - \frac{(\vec{x} - \bar{x})^T(\vec{y} - \bar{y})}{\sqrt{(\vec{x} - \bar{x})^T(\vec{x} - \bar{x})}\sqrt{(\vec{y} - \bar{y})^T(\vec{y} - \bar{y})}}
\]  

(4.18)

where \(\bar{x}\) and \(\bar{y}\) are the spectral mean vectors. The correlation metric is another form of spectral template matching. It scores close to one for vectors that are very similar so Equation 4.18 has one minus the normalized correlation in order for materials that are spectrally similar to have lower scores (i.e., spectrally closer together). Conversely, spectrally dissimilar vectors score closer to one.

There are other spectral distance metrics that could be used, but our purposes were to study the phenomenology generally and leave specific details, such as finding the best spectral distance metric, to future work. In order to minimize cluster assignments from the background, image chips of individual pedestrians were extracted which included a small portion of the background around the border of the pedestrian. For the several metrics used, the clustering was assessed by visual inspection for homogeneity among the pedestrian subregions and the background.

For the clusterings, two pedestrians were selected from the first image in the HYMNS-P dataset, described in Section 4.1.1. The clusterings were based on the known good bands which are described more in depth in Appendix A, Section A.3.

### 4.5 Detecting Pedestrian Subregions in Remotely Sensed Imagery

The methods presented so far primarily deal with the case where the pedestrian locations are known and subregions are segmented prior to performing subregion analysis. Next we look at the case where the pedestrians are not known and subregion detection is used to locate the pedestrians. This step corresponds to the first box on the left of the bottom path in Figure 2.10 following image acquisition. The detectability of subregion materials for a single POI against the background across images was assessed. For this assessment, five images were chosen: two from the HYMNS-P and three Ground Truth HSI datasets. The images used are shown in Figures 4.8 through 4.12 where
the single test POI in each case is highlighted. The sky images for the HYMNS-P images are included to gain an understanding of the conditions at the time of image capture. There were not equivalent sky condition data for the Ground Level HSI data. Note that the detection analysis was performed using the radiance images. They were not radiometrically corrected to reflectance.

Figure 4.8: Context image with pedestrian B (enlarged) from the HYMNS-P dataset. The sky image is included to illustrate the conditions at the time of the collect. This particular image was collected at approximately 1044 EDT on the day of the collect.

ROI truth masks of the subregions were created for each of the pedestrians in each image. An example truth mask is shown in Figure 4.13 where the colors represent each of the respective
Figure 4.9: Context image with pedestrian B (enlarged) from the HYMNS-P dataset after movement to a second location. The sky image is included to illustrate the conditions at the time of the collection. This particular image was collected at approximately 1054 EDT on the day of the collection.

subregions for torso (red), skin (green), trousers (blue), and hair (yellow). The truth masks were then used to extract the pixels of a subregion for the POIs highlighted in the context images above. The respective spectral mean of the pixels in each subregion was computed and then the spectral distance for all pixels within the scene was computed against the spectral mean of a particular subregion of a single pedestrian chosen as the POI. This provided a test-on-train case to demonstrate the detectability of the POI's subregion pixels within a source image. Note that the detection
process was only concerned with the subregions of the POI and not of the other pedestrians in the image. They were treated as part of the background for this particular experiment. The process of extracting subregion pixels, computing the mean, and then calculating the spectral distances was repeated for each of the subregions. For this part of the research, the Euclidean distance,
SAM, and Correlation distance metrics were used as defined in Equations 4.16, 4.17, and 4.18, respectively. Additionally, the normalized Spectral Matched Filter (SMF) was used which takes into account the statistics of the background to improve target pixel detection in the presence of noise. The normalized SMF is defined as [13]

$$d_{SMF}(\vec{x}, \vec{y}) = 1 - \frac{\vec{x} - \bar{m}}{(\vec{x} - \bar{m})^T S^{-1} (\vec{x} - \bar{m})} \frac{\vec{y} - \bar{m}}{(\vec{y} - \bar{m})^T S^{-1} (\vec{y} - \bar{m})}$$  \hspace{1cm} (4.19)$$

where $\vec{x}$ is the desired target spectral vector, $\vec{y}$ is the spectral pixel vector under test, $\bar{m}$ is the spectral mean vector of the background, and $S$ is the spectral covariance of the background. Similar to the correlation metric, values close to one (or larger for very bright pixels) indicate a good match, so Equation 4.19 is one minus the normalized SMF to ensure spectrally similar materials have smaller values. The mean and covariance of the background are typically computed using all the pixels from the whole image, which naturally includes the pedestrian or other targets of interest. Other statistical measures could be pursued to overcome this limitation, but it should be pointed out that we are looking at pedestrian detection with the inherent assumption that the detector does not know the pedestrian from the background, prior to detection.
CHAPTER 4. METHODOLOGIES

Figure 4.13: Example truth mask of a pedestrian in one of the HSI images of the HYMNS-P dataset. The colors represent each subregion: torso (red), skin (green), trousers (blue), and hair (yellow).

Using the truth masks, pixels were labeled according to POI subregion or background (again, non-POI pedestrians were treated as background) and a receiver operating characteristic (ROC) curve was generated. A ROC curve maps the probability of detection to the probability of false alarm as a detection statistic threshold is swept from no detections to complete detection [12]. In the case of this research, the detection statistics were the spectral distance metric scores. An example ROC curve with the distance metrics used for the POI torso detection is shown in Figure 4.14. There were ROC curves generated for each subregion. In order to compare the results of each ROC, the area under the curve was computed such that

\[
AUC_{s,d} = \int_{0}^{0.01} P_{d}d P_{f_d} / 0.01
\]

(4.20)

where the subscripts \(s\) and \(d\) refer to a particular subregion and distance metric, respectively. Since the number of pixels within an image can be quite large, the integration was limited to false alarms less than 0.01. Since the area under the curve was computed for only a portion of the total ROC curve, the AUC was normalized by the total area of the portion considered which allowed AUC to range between zero and one.

Following the test-on-train case, the spectral mean of subregions from the first image was used to detect respective subregion pixels in the second and third (for the Ground Level HSI data) images. In this way detectability using a signature in the first image was assessed across images.

As was the case for the reflectance data separability and subregion data separability, comparison
Figure 4.14: Example ensemble of ROC curves for torso subregion pixels. The x-axis is projected on a logarithm scale to accentuate the false alarm rate at low probabilities. Each curve is for a different distance metric used. The solid line with asterisk marker cuts out around $10^{-4}$ because the false alarm rate goes to zero at that point.

of the detection was done for the cases when there is nominally only RGB (400 - 700 nm), visible (Vis, 400 - 700 nm), visible to near infrared (VNIR, 400 - 1000 nm), and SWIR (1000 - 2500) bands available.

4.6 Subregion Detection after Changes in Illumination

In the field collected data, the pedestrians had the sun either above and slightly behind or were under a diffuse sky. Thus none of the subregions were illuminated directly by the sun, aside from shoulders, tops of heads, and certain edge pixels. The DIRSIG data was used to assess the detectability of subregions when they are directly illuminated by the sun. For this assessment, the
three synthetic images in Figures 4.15 were used to assess the changes in detectability as the sun changes angle. In each of these images, the POI was in a static location.

First, pedestrian B as a POI was selected in the 1100 hours image and scene wide pixel detection was performed for each subregion following the test-on-train method outlined in Section 4.3.5. This test-on-train detection analysis with the sun slightly behind the pedestrians was done to compare detection results from the DIRSIG imagery with the real-world imagery. It was referred to as the indirect illumination case. The results were compared with the detection performance of the real-world image shown in Figure 4.8. The subregion reflectance attributes of the POI chosen in the DIRSIG image was similar to the POI from the real-world image thus the detection scenario was similar. Next, the same POI was used to perform subregion detection in the 1300 hours image, also following a test-on-train scheme. In the 1300 hours image, the subregions had direct illumination and self shadowing due to the contours of the CAD modeled pedestrians. This was referred to as partial direct (PD) illumination. The same pedestrian was again selected as the POI in the 1500 hours image and the test-on-train method was followed. In the 1500 hours image, the sun was directly illuminating all subregion pixels visible to the sensor. This case was referred to as the full direct (FD) illumination. This illustrated the change in detectability as the spectral intensity changes.

Following the two test-on-train styled assessments, the spectral mean of each POI subregion in the 1500 hours image was used to detect subregions of the POI in the 1300 and 1100 hours images. This illustrated the detectability at significantly different times and sun angles. Additionally, it illustrated the detectability when the captured spectral profile is based on a brightly light subregion.
Figure 4.15: Illustrating the synthetic scenes generated in DIRSIG used for pedestrians subregion detection when the sun is at different solar zenith angles for (a) 1100, (b) 1300, and (c) 1500 hours local time.
Chapter 5

Results

This chapter contains the results of the several aspects investigated with respect to the phenomenology of pedestrian detection in HSI. First, the classification error as a function of SNR level using the spectral reflectance data is presented. This includes single subregions and when information between subregions is combined. Next, the results of the natural clusterings of the radiance HSI data using the \textit{k-means} algorithm are presented. The results for subregion detection in real-world and synthetic imagery are presented followed by the results of performing detection using subsets of the spectral bands.

5.1 Probability of Error for POI Subregions versus SNR

The average probability of error for the POI class samples as a function of SNR using the full spectral range is shown in Figures 5.1 and 5.2. These graphs were generated following the process outlined in Sections 4.3.2 and 4.3.3. The results for SNR = 5 are summarized in Table 5.1.

As can be seen in Figure 5.1(a), the skin pixels exhibited the highest probability of error for a fixed SNR over other subregions. The hair subregion resulted in the lowest probability of error at a fixed SNR. It is interesting to note for this particular dataset how quickly the probability of error is reduced at lower SNR levels when just two subregions are combined as shown in Figure 5.1(b). Additional improvements are realized when combining three or more subregions as shown in Fig-
CHAPTER 5. RESULTS

ures 5.1(c) and 5.1(d). All the combinations are shown in Figure 5.2 for convenience of comparison. Combining all four subregions together resulted in the curve with the lowest probability of error at a fixed SNR value.

When considering the spectral subsets, it is clear to see that certain regions of the spectral range have greater impact and utility in separability. The FR was best in nearly all cases. However, the visible was best for shirt separability among pedestrians due to the textile color differences. Most of the pedestrians had a 100% cotton, or cotton blend, shirt fabric so the materials offered little separability in the SWIR. Additionally, it is clear that the 3-band RGB data in Figures 5.3 and 5.4 had much poorer classification performance when single subregions are assessed. Combining the subregions though offered improved classification performance for all spectral subregions.

While these results are favorable, especially with respect to separability at low SNR values, they are somewhat ideal given this limited dataset. Typical imaging systems have much higher SNR ratings, in the hundreds or thousands according to [13]. Given that the limited number of available reflectance samples, it was not known if adding uncorrelated Gaussian noise was appropriate for the particular reflectance data. It is expected that future work will gather additional subregion reflectance samples and further characterize spectral reflectance of pedestrians. Despite these known limitations of the dataset, the trends shown here illustrate which subregions had the most difficulty in detection and classification for the reflectance data. For the reflectance, the hair was highly separable among the pedestrians while the skin was the most difficult for the processing scheme used. The results also support the premise of this phenomenology study that combining subregion information enhances separability among pedestrians. These results will be contrasted with the pedestrian separability in remotely sensed imagery.
Figure 5.1: Plot of the probability of error versus SNR for the noise-added reflectance data. The curves for the individual subregions are seen in (a). The combinations for (b) two, (c) three, or (d) four subregions are also shown.
Figure 5.2: Showing the $P(\text{error}|\omega_{\text{POI}})$ family of curves for subregion combinations when the full range is used.
Figure 5.3: Plot of the probability of error versus SNR for the noise-added reflectance data when only the RGB data is used. The curves for the individual subregions are seen in (a). The combinations for (b) two, (c) three, or (d) four subregions are also shown.
Figure 5.4: Showing the $P|\text{error}|\omega_{POI}$ family of curves for subregion combinations when limited to RGB bands.
Figure 5.5: Plot of the probability of error versus SNR for the noise-added reflectance data when only the Vis data is used. The curves for the individual subregions are seen in (a). The combinations for (b) two, (c) three, or (d) four subregions are also shown.
Figure 5.6: Showing the $P(\text{error}|\omega_{POI})$ family of curves for subregion combinations when limited to the Vis spectral range.
Figure 5.7: Plot of the probability of error versus SNR for the noise-added reflectance data when only the VNIR data is used. The curves for the individual subregions are seen in (a). The combinations for (b) two, (c) three, or (d) four subregions are also shown.
Figure 5.8: Showing the $P(\text{error} | \omega_{POI})$ family of curves for subregion combinations when limited to the VNIR spectral range.
Figure 5.9: Plot of the probability of error versus SNR for the noise-added reflectance data when only the SWIR1 data is used. The curves for the individual subregions are seen in (a). The combinations for (b) two, (c) three, or (d) four subregions are also shown.
Figure 5.10: Showing the $P(\text{error}|\omega_{POI})$ family of curves for subregion combinations when limited to the SWIR1 spectral range.
Figure 5.11: Plot of the probability of error versus SNR for the noise-added reflectance data when only the SWIR2 data is used. The curves for the individual subregions are seen in (a). The combinations for (b) two, (c) three, or (d) four subregions are also shown.
Figure 5.12: Showing the $P(\text{error}|\omega_{\text{POI}})$ family of curves for subregion combinations when limited to the SWIR2 spectral range.
Table 5.1: Summary table of $P(\text{error}|\omega_{POI})$ for pedestrian subregion spectral reflectance combinations at SNR = 5.

<table>
<thead>
<tr>
<th>Combo</th>
<th>FR</th>
<th>RGB</th>
<th>Vis</th>
<th>VNIR</th>
<th>SWIR 1</th>
<th>SWIR 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hair</td>
<td>0.250</td>
<td>0.860</td>
<td>0.640</td>
<td>0.516</td>
<td>0.465</td>
<td>0.610</td>
</tr>
<tr>
<td>Face</td>
<td>0.906</td>
<td>1.000</td>
<td>0.985</td>
<td>0.973</td>
<td>0.977</td>
<td>0.833</td>
</tr>
<tr>
<td>Shirt</td>
<td>0.525</td>
<td>0.707</td>
<td>0.314</td>
<td>0.534</td>
<td>0.941</td>
<td>0.934</td>
</tr>
<tr>
<td>Trousers</td>
<td>0.406</td>
<td>0.903</td>
<td>0.652</td>
<td>0.481</td>
<td>0.820</td>
<td>0.928</td>
</tr>
<tr>
<td>Hair-Face</td>
<td>0.178</td>
<td>0.896</td>
<td>0.801</td>
<td>0.642</td>
<td>0.388</td>
<td>0.320</td>
</tr>
<tr>
<td>Hair-Shirt</td>
<td>0.082</td>
<td>0.256</td>
<td>0.111</td>
<td>0.279</td>
<td>0.424</td>
<td>0.762</td>
</tr>
<tr>
<td>Hair-Trousers</td>
<td>0.043</td>
<td>0.470</td>
<td>0.273</td>
<td>0.168</td>
<td>0.452</td>
<td>0.827</td>
</tr>
<tr>
<td>Face-Shirt</td>
<td>0.269</td>
<td>0.600</td>
<td>0.363</td>
<td>0.334</td>
<td>0.879</td>
<td>0.914</td>
</tr>
<tr>
<td>Face-Trousers</td>
<td>0.248</td>
<td>0.871</td>
<td>0.421</td>
<td>0.299</td>
<td>0.781</td>
<td>0.881</td>
</tr>
<tr>
<td>Shirt-Trousers</td>
<td>0.136</td>
<td>0.305</td>
<td>0.158</td>
<td>0.137</td>
<td>0.656</td>
<td>0.827</td>
</tr>
<tr>
<td>Hair-Face-Shirt</td>
<td>0.031</td>
<td>0.429</td>
<td>0.219</td>
<td>0.126</td>
<td>0.277</td>
<td>0.573</td>
</tr>
<tr>
<td>Hair-Face-Trousers</td>
<td>0.019</td>
<td>0.531</td>
<td>0.248</td>
<td>0.109</td>
<td>0.305</td>
<td>0.606</td>
</tr>
<tr>
<td>Hair-Shirt-Trousers</td>
<td>0.018</td>
<td>0.222</td>
<td>0.081</td>
<td>0.076</td>
<td>0.292</td>
<td>0.652</td>
</tr>
<tr>
<td>Face-Shirt-Trousers</td>
<td>0.051</td>
<td>0.302</td>
<td>0.124</td>
<td>0.077</td>
<td>0.582</td>
<td>0.807</td>
</tr>
<tr>
<td>Hair-Face-Shirt-Trousers</td>
<td>0.005</td>
<td>0.206</td>
<td>0.089</td>
<td>0.034</td>
<td>0.188</td>
<td>0.475</td>
</tr>
</tbody>
</table>
5.2 Probability of Error for POI Subregions in Remotely Sensed Data

The probability of error for POI subregion classification, versus all other pedestrians, was assessed using two images from the HYMNS-P dataset, shown in Figures 5.13 and 5.14, and also three images from the GLHR HSI dataset shown in Figures 5.15 through 5.17. Figure 5.13 from the HYMNS-P dataset was labeled scene 1, pose 1, scan 1. Figure 5.14 from the HYMNS-P dataset was labeled scene 3, pose 1, scan 1. More information about these scenes is contained in Appendix A. The process outlined in Section 4.3.5 was followed for this assessment. The pedestrians are each labeled with their respective letter identifiers. Note that there was a pedestrian laying down taking sky images in the HYMNS-P scenes, as can be marginally seen in the lower right of both images. Additionally, there was a roaming pedestrian in the HYMNS-P scenes which is seen in Figure 5.14 to the right of pedestrian “L”. This roaming pedestrian was collecting additional ground truth data during the imagery collection and was not included as a POI during this portion of the study. For the GLHR HSI scenes, there were additional pedestrians which were not considered for this portion of the study because they did not consistently appear in all three images.

As can be seen in Figures 5.13 and 5.14, the pedestrians had the sun to their rear, so their surfaces facing the imager were indirectly illuminated. Additionally, some were partially occluded, while others were not.

The results of the subregion classification error per pedestrian are given in Appendix E. For convenience, the results of the test-on-train case for the image in Figure 5.13 in included in this chapter as Figure 5.18. In the graphs the data are shown for the probability of error per subregion when each pedestrian was treated as the POI. The different symbols correspond to the respective subregions. The graphs offer insight on a case-by-case basis for each of the pedestrians shown in the two source images of Figures 5.13 and 5.14. For this analysis, spectral subsets were assessed as indicated to show which spectral regions potentially offered sufficient or degraded separability performance among the subregions. The graphs show a wide distribution of the probability of error for the several pedestrians which is indicative of their several locations, number of pixels per subregion, and geometric orientations.
The results of the graphs in Figures E.1 through E.12 are summarized in Tables 5.2 and 5.3. The means and standard deviations of the probability of error for the pedestrians of the respective images are grouped according to subregion and spectral subset. It can be seen that the 3-band RGB offered the poorest results for all subregions with the highest probability of error and comparatively low standard deviation. The SWIR 2 bands offered similar results. By inspection skin was the most difficult to separate among the pedestrians which corresponds to the results in Figure 5.1(a). By contrast the torso and trousers had better results in full range, visible and VNIR spectral regions, though the standard deviations were large. Again, this is for a limited dataset and the results are the average for all pedestrians in their respective locations, so the standard deviations are expected to be larger. It is interesting that the hair was most separable in the full range and VNIR of the reflectance analysis in Section 5.1. However, it was not the most distinguishable feature in the imagery despite the results shown in Figure 5.1(a). It is not known directly why that is at this time. It could be hypothesized that the spatial resolution (ground sample distance approximately 2.5
cm, nominally) only afforded spectrally mixed pixels for the hair and skin subregions. However, this notion could not be verified. Further analysis would need to be performed which looks at more pixels on subregion and other noise sources. As it was, the average number of hair pixels per pedestrian was approximately 17. This was the lowest of all the subregions and that is affected by pedestrian distance and orientation with respect to the sensor.

Table 5.2: Summary table of the subregion probability of error from HYMNS-P image 1 data results shown in Figures E.1 through E.6.

<table>
<thead>
<tr>
<th></th>
<th>Torso</th>
<th>Skin</th>
<th>Trousers</th>
<th>Hair</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>s.d.</td>
<td>mean</td>
<td>s.d.</td>
</tr>
<tr>
<td>FR</td>
<td>0.477</td>
<td>0.363</td>
<td>0.958</td>
<td>0.083</td>
</tr>
<tr>
<td>RGB</td>
<td>0.865</td>
<td>0.176</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>VIS</td>
<td>0.651</td>
<td>0.341</td>
<td>1.000</td>
<td>0.002</td>
</tr>
<tr>
<td>VNIR</td>
<td>0.456</td>
<td>0.363</td>
<td>0.950</td>
<td>0.098</td>
</tr>
<tr>
<td>SWIR1</td>
<td>0.785</td>
<td>0.313</td>
<td>0.980</td>
<td>0.037</td>
</tr>
<tr>
<td>SWIR2</td>
<td>0.911</td>
<td>0.222</td>
<td>1.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>
Figure 5.15: The first GLHR HSI scene with the pedestrians labeled according to their respective letter identifier. Note the sky was overcast during the collect.

Table 5.3: Summary table of the subregion probability of error from HYMNS-P image 2 data results shown in Figures E.7 through E.12. For these results, the mean spectral radiance data of each subregion from HYMNS-P image 1 was used to compute spectral distances.

<table>
<thead>
<tr>
<th></th>
<th>Torso</th>
<th>Skin</th>
<th>Trousers</th>
<th>Hair</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>s.d.</td>
<td>mean</td>
<td>s.d.</td>
</tr>
<tr>
<td>FR</td>
<td>0.377</td>
<td>0.335</td>
<td>0.906</td>
<td>0.205</td>
</tr>
<tr>
<td>RGB</td>
<td>0.788</td>
<td>0.310</td>
<td>0.969</td>
<td>0.097</td>
</tr>
<tr>
<td>VIS</td>
<td>0.553</td>
<td>0.375</td>
<td>0.975</td>
<td>0.060</td>
</tr>
<tr>
<td>VNIR</td>
<td>0.360</td>
<td>0.337</td>
<td>0.901</td>
<td>0.183</td>
</tr>
<tr>
<td>SWIR1</td>
<td>0.832</td>
<td>0.314</td>
<td>0.949</td>
<td>0.142</td>
</tr>
<tr>
<td>SWIR2</td>
<td>0.998</td>
<td>0.006</td>
<td>0.990</td>
<td>0.040</td>
</tr>
</tbody>
</table>

Inspection of the summary results in this section indicate that clothing tended to be the dominant feature of the pedestrian in remotely sensed imagery. It is interesting to note that the average probability of error among the pedestrians is relatively high. However, additional insight can be gleaned by considering the three curves shown in Figure 2.5. In that plot, shirt spectra for pedestrians B, E, and I were compared. The shirt materials were a blue 100% polyester for pedestrian B, a reddish brown 100% cotton for pedestrian E, and a yellow 50/50 cotton/polyester blend for pedestrian I. Additional information about these three pedestrians is contained in Table A.2. The results of computing the spectral adjusted Euclidean distance for these three spectral curves are shown in Table 5.7. By inspection, it is clear that RGB bands offer the most separation among the
Figure 5.16: The second GLHR HSI scene with the pedestrians moved to a new location. They are labeled according to their respective letter identifier. Note the sky was overcast during the collect.

Table 5.4: Summary table of the subregion probability of error from GLHR HSI image 1 data results shown in Figures E.13 through E.18.

<table>
<thead>
<tr>
<th></th>
<th>Torso</th>
<th>Skin</th>
<th>Trousers</th>
<th>Hair</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>s.d.</td>
<td>mean</td>
<td>s.d.</td>
<td>mean</td>
</tr>
<tr>
<td>FR</td>
<td>0.345</td>
<td>0.233</td>
<td>0.990</td>
<td>0.025</td>
</tr>
<tr>
<td>RGB</td>
<td>0.624</td>
<td>0.321</td>
<td>0.999</td>
<td>0.001</td>
</tr>
<tr>
<td>VIS</td>
<td>0.275</td>
<td>0.336</td>
<td>0.999</td>
<td>0.002</td>
</tr>
<tr>
<td>VNIR</td>
<td>0.315</td>
<td>0.222</td>
<td>0.995</td>
<td>0.008</td>
</tr>
<tr>
<td>SWIR1</td>
<td>0.792</td>
<td>0.359</td>
<td>0.998</td>
<td>0.003</td>
</tr>
<tr>
<td>SWIR2</td>
<td>0.796</td>
<td>0.357</td>
<td>1.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

spectral samples. This is intuitive since the colors are bright and optimized for a visual spectrum response. Among all the samples though, it is interesting to note that overall the 100% cotton and 100% polyester were spectrally closer for the Euclidean distance. The blend tended to be more separated. Some of this stems from the fact that the Euclidean distance is easily biased when there are large spectral magnitude differences which can easily be seen for the 60/40 cotton/poly blend at 560 nm versus the other curves. Note that in the SWIR, the 60/40 cotton/poly blend fabric tended to be spectrally similar to both of the other materials.

Comparing this analysis to the results for the HYMNS-P data in Sections 5.1 and 5.2 and inspecting the ground truth data in Appendix A show why it was difficult to separate the samples
in the SWIR. Though there are spectral features that distinguishable in the SWIR bands, most of the pedestrians had primarily cotton shirts which makes it difficult to distinguish among the pedestrians for this particular subregion in the SWIR given the data available.

Inspection of Tables 5.2 and 5.3 shows the interesting result that subregions were more distinguishable in the second HYNMS-P image despite using radiance data from the first image. To better understand this the mean spectral radiance of the two HYNMS-P images is shown in Figure 5.19. The solid line is from the data shown in Figure 5.13 while the dashed line is from the data shown in Figure 5.14. By inspection, it can be seen that the second image was slightly brighter than the first image. Comparing this to result to the skyview images does not significantly explain
why the results would be better on the second image in Table 5.3. In those skyview images, there appeared to be more clouds in the second image, but there could have been one slightly obscuring the sun in the first image.

A second test of subregion separability was conducted where the probability of error was calculated using the second HYMNS-P image (shown in Figure 5.14) as the source image. The subregion data from that image was used as the training data for performing the binary classification. The same process was followed as before where the probability of error among the subregions for the source image served as the test-on-train case. Then the spectral mean of each subregion for each POI, in turn, was used to perform the binary classification on the subsequent image.

The results by pedestrian are included in Appendix E.7 (Figures E.31 through E.42) and summarized in Tables 5.8 and 5.9. Comparing the results in Table 5.8 with those in Table 5.3 indicate that the probability of error was virtually the same for this particular image whether using it for the target’s spectral information or using the data from the image shown in Figure 5.13 as the target spectral information. The results in Table 5.9 indicate a classification performance drop.
Table 5.6: Summary table of the subregion probability of error from GLHR HSI image 3 data results shown in Figures E.25 through E.30. For these results, the mean spectral radiance data of each subregion from GLHR HSI image 1 was used to compute spectral distances.

<table>
<thead>
<tr>
<th></th>
<th>Torso</th>
<th>Skin</th>
<th>Trousers</th>
<th>Hair</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>s.d.</td>
<td>mean</td>
<td>s.d.</td>
</tr>
<tr>
<td>FR</td>
<td>0.364</td>
<td>0.290</td>
<td>0.745</td>
<td>0.372</td>
</tr>
<tr>
<td>RGB</td>
<td>0.658</td>
<td>0.340</td>
<td>0.969</td>
<td>0.061</td>
</tr>
<tr>
<td>VIS</td>
<td>0.317</td>
<td>0.331</td>
<td>0.787</td>
<td>0.357</td>
</tr>
<tr>
<td>VNIR</td>
<td>0.359</td>
<td>0.306</td>
<td>0.827</td>
<td>0.366</td>
</tr>
<tr>
<td>SWIR1</td>
<td>0.773</td>
<td>0.331</td>
<td>0.964</td>
<td>0.055</td>
</tr>
<tr>
<td>SWIR2</td>
<td>0.718</td>
<td>0.350</td>
<td>0.907</td>
<td>0.245</td>
</tr>
</tbody>
</table>

Table 5.7: Spectral distance of the spectral reflectance data from three clothing material types using the adjusted Euclidean distance for each spectral range indicated.

<table>
<thead>
<tr>
<th>Spectral Range</th>
<th>Brown 100% Cotton vs. Yellow 67/33 Blend</th>
<th>Brown 100% Cotton Vs. Blue 100% Polyester</th>
<th>Yellow 67/33 Blend vs. Blue 100% Polyester</th>
</tr>
</thead>
<tbody>
<tr>
<td>FR</td>
<td>0.065</td>
<td>0.051</td>
<td>0.067</td>
</tr>
<tr>
<td>RGB</td>
<td>0.367</td>
<td>0.148</td>
<td>0.348</td>
</tr>
<tr>
<td>VIS</td>
<td>0.159</td>
<td>0.079</td>
<td>0.154</td>
</tr>
<tr>
<td>VNIR</td>
<td>0.113</td>
<td>0.064</td>
<td>0.110</td>
</tr>
<tr>
<td>SWIR1</td>
<td>0.044</td>
<td>0.060</td>
<td>0.054</td>
</tr>
<tr>
<td>SWIR2</td>
<td>0.037</td>
<td>0.082</td>
<td>0.083</td>
</tr>
</tbody>
</table>

The only explanation at this time for these results is that the image in Figure 5.14 simply had a higher SNR, although there was only a slight difference between the spectral means shown in Figure 5.19.

One thing that should be pointed out is that despite the poor classification results when looking at the average error rate, there were instances where certain subregions for certain pedestrians that had a relatively good performance. One example is shown in Figure 5.18 where the torsos of pedestrians A, B, G, H, L and W were fairly well distinguishable. If we look at their positions in Figure 5.13 we can see that all six were well visible to the imager and had solid colors. If we look at the metadata for each pedestrian shown in Table A.2 we see that pedestrian B had a 100% polyester shirt while the others had 100% cotton shirts. This is not particularly telling, however the brighter solid colors tend to be more spectrally dissimilar in the visible spectrum. As a result, the Euclidean distance tends to key on these large variations versus the minor variations in the infrared as was indicated in the results Table 5.7. Additionally, these results are for this one
CHAPTER 5. RESULTS

Figure 5.19: Comparing the mean spectral radiance for the HYMNS-P images shown in Figures 5.13 and 5.14.

dataset. Many more samples could be gathered to further characterize the separability among the pedestrians.

Table 5.8: Summary table of the subregion probability of error from HYMNS-P binary classification results shown in Figures E.31 through E.36. The mean spectral radiance of each subregion from the second HYMNS-P image was used as the target data and served as the test-on-train case.

<table>
<thead>
<tr>
<th></th>
<th>Torso mean</th>
<th>Torso s.d.</th>
<th>Skin mean</th>
<th>Skin s.d.</th>
<th>Trousers mean</th>
<th>Trousers s.d.</th>
<th>Hair mean</th>
<th>Hair s.d.</th>
</tr>
</thead>
<tbody>
<tr>
<td>FR</td>
<td>0.377</td>
<td>0.335</td>
<td>0.906</td>
<td>0.205</td>
<td>0.372</td>
<td>0.309</td>
<td>0.595</td>
<td>0.361</td>
</tr>
<tr>
<td>RGB</td>
<td>0.788</td>
<td>0.310</td>
<td>0.969</td>
<td>0.097</td>
<td>0.792</td>
<td>0.346</td>
<td>0.875</td>
<td>0.244</td>
</tr>
<tr>
<td>VIS</td>
<td>0.553</td>
<td>0.375</td>
<td>0.975</td>
<td>0.060</td>
<td>0.596</td>
<td>0.358</td>
<td>0.762</td>
<td>0.337</td>
</tr>
<tr>
<td>VNIR</td>
<td>0.360</td>
<td>0.337</td>
<td>0.901</td>
<td>0.183</td>
<td>0.348</td>
<td>0.305</td>
<td>0.612</td>
<td>0.324</td>
</tr>
<tr>
<td>SWIR1</td>
<td>0.832</td>
<td>0.314</td>
<td>0.949</td>
<td>0.142</td>
<td>0.787</td>
<td>0.344</td>
<td>0.792</td>
<td>0.339</td>
</tr>
<tr>
<td>SWIR2</td>
<td>0.998</td>
<td>0.006</td>
<td>0.990</td>
<td>0.040</td>
<td>0.962</td>
<td>0.242</td>
<td>0.820</td>
<td>0.242</td>
</tr>
</tbody>
</table>
Table 5.9: Summary table of the subregion probability of error from HYMNS-P binary classification results shown in Figures E.37 through E.42 where the mean spectral radiance of the second image was used as the target data.

<table>
<thead>
<tr>
<th></th>
<th>Torso mean</th>
<th>s.d.</th>
<th>Skin mean</th>
<th>s.d.</th>
<th>Trousers mean</th>
<th>s.d.</th>
<th>Hair mean</th>
<th>s.d.</th>
</tr>
</thead>
<tbody>
<tr>
<td>FR</td>
<td>0.477</td>
<td>0.363</td>
<td>0.958</td>
<td>0.083</td>
<td>0.415</td>
<td>0.339</td>
<td>0.629</td>
<td>0.354</td>
</tr>
<tr>
<td>RGB</td>
<td>0.865</td>
<td>0.176</td>
<td>1.000</td>
<td>0.000</td>
<td>0.956</td>
<td>0.053</td>
<td>0.942</td>
<td>0.141</td>
</tr>
<tr>
<td>VIS</td>
<td>0.651</td>
<td>0.341</td>
<td>1.000</td>
<td>0.002</td>
<td>0.730</td>
<td>0.255</td>
<td>0.875</td>
<td>0.209</td>
</tr>
<tr>
<td>VNIR</td>
<td>0.456</td>
<td>0.363</td>
<td>0.950</td>
<td>0.098</td>
<td>0.452</td>
<td>0.318</td>
<td>0.751</td>
<td>0.326</td>
</tr>
<tr>
<td>SWIR1</td>
<td>0.786</td>
<td>0.313</td>
<td>0.980</td>
<td>0.037</td>
<td>0.702</td>
<td>0.280</td>
<td>0.806</td>
<td>0.310</td>
</tr>
<tr>
<td>SWIR2</td>
<td>0.911</td>
<td>0.222</td>
<td>1.000</td>
<td>0.000</td>
<td>0.915</td>
<td>0.230</td>
<td>0.892</td>
<td>0.210</td>
</tr>
</tbody>
</table>

5.3 Binary Classification Error When Combining Subregions in HYMNS-P Imagery

In addition to looking at distinguishing between pedestrians in real-world imagery using single subregions, spectral information was combined using different subregion combinations. This was similar to the process outlined using the reflectance data with noise added. For this part of the research, several combinations of the pixel radiance vectors were concatenated to generate a distribution of samples. For each subregion, the mean was computed and the mean pixel vectors were concatenated according to the combination under test. The spectral distance between the mean pixel vector and the sample combinations was computed for the POI and the non-POI samples. Binary classification was then performed. The classification performance was assessed for the image in Figure 5.13 as the test-on-train case and also for the image shown in Figure 5.14 using the subregion mean spectral radiance information from the first image.

The results are graphically shown in Appendix E.7 (Figures E.43 through E.64) and summarized in Tables 5.10 and 5.11. The results shown in Table 5.10 had a much higher than expected probability of error when using the real-world imagery versus the spectral reflectance results shown in Section 5.1. However, two interesting items are apparent from the data shown. The Torso-Trousers two-subregion combination performed the best in the Full Range and the VNIR among all combinations. Note that the standard deviations for the binary classification performance among the pedestrians was similar to the results shown in the single subregions. Inspection of Table 5.11
shows a similar result, though the classification performance was poorer. Looking at the graphical source data shown in Appendix E.7 does not maintain the same trend where pedestrians A, B, G, H, L and W were fairly well distinguishable when compared with using single subregions for the binary classification. At this time, it is not known exactly why this is. Three possible explanations are proposed, which could be explored further in future work. First, the subregions pixels being selected may have had errors or may have had spectral mixing. Secondly, the pedestrian BRDF effects of the subregions may be causing significant changes in spectral reflectance. Finally, when combining the subregion information, the differences in radiance between image one and image two could be accentuated.

5.4 Binary Classification Error for POI Subregions After Illumination Changes

The probability of error for POI subregion classification, versus all other pedestrians, after illumination changes was assessed using the three synthetically generated DIRSIG images shown in Figure 4.15. Each of the pedestrians were labeled according to the scheme shown in Figure 5.20. Note that the pedestrians were in the same location for each of the three images used so the only variation was the solar illumination angle.

The results for this assessment is summarized in Tables 5.12 through 5.14. Graphs similar to the one shown in Figure 5.18 were generated to illustrate the probability of error per subregion per pedestrian and are included in Appendix E, Figures E.65 through E.76. Inspection of the results in Table 5.12 indicate that the full-range and VNIR spectral regions tended to perform better among the subregions versus other spectral ranges. Also, hair tended to be slightly better overall than other subregions in these two spectral ranges while skin continued to be difficult to distinguish. Note that the synthetic imagery was rendered using delta sampling per pixel so linear spectral mixing was not present in the imagery. As such, the results with the classification performance on the hair subregion support the findings shown in Figure 5.1 where the hair reflectance samples were more distinguishable among pedestrians. Comparing the results from the test-on-train results in
Table 5.10: Summary table of the subregion probability of error shown in Figures E.43 through E.53.

<table>
<thead>
<tr>
<th>Combo</th>
<th>FR mean s.d.</th>
<th>RGB mean s.d.</th>
<th>Vis mean s.d.</th>
<th>VNIR mean s.d.</th>
<th>SWIR1 mean s.d.</th>
<th>SWIR2 mean s.d.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hair-Skin</td>
<td>0.658 0.366</td>
<td>0.938 0.140</td>
<td>0.875 0.209</td>
<td>0.714 0.314</td>
<td>0.800 0.307</td>
<td>0.850 0.236</td>
</tr>
<tr>
<td>Hair-Torso</td>
<td>0.629 0.354</td>
<td>0.942 0.141</td>
<td>0.875 0.209</td>
<td>0.750 0.326</td>
<td>0.806 0.310</td>
<td>0.892 0.210</td>
</tr>
<tr>
<td>Hair-Trousers</td>
<td>0.658 0.347</td>
<td>0.926 0.142</td>
<td>0.870 0.211</td>
<td>0.712 0.327</td>
<td>0.800 0.307</td>
<td>0.843 0.235</td>
</tr>
<tr>
<td>Skin-Torso</td>
<td>0.905 0.156</td>
<td>0.999 0.005</td>
<td>1.000 0.000</td>
<td>0.901 0.131</td>
<td>0.928 0.179</td>
<td>0.995 0.021</td>
</tr>
<tr>
<td>Skin-Trousers</td>
<td>0.908 0.182</td>
<td>0.999 0.005</td>
<td>0.996 0.012</td>
<td>0.898 0.134</td>
<td>0.926 0.179</td>
<td>0.995 0.021</td>
</tr>
<tr>
<td>Torso-Trousers</td>
<td>0.512 0.363</td>
<td>0.912 0.081</td>
<td>0.640 0.289</td>
<td>0.445 0.343</td>
<td>0.837 0.296</td>
<td>0.940 0.109</td>
</tr>
<tr>
<td>Hair-Skin-Torso</td>
<td>0.658 0.366</td>
<td>0.938 0.140</td>
<td>0.875 0.209</td>
<td>0.714 0.314</td>
<td>0.800 0.307</td>
<td>0.850 0.236</td>
</tr>
<tr>
<td>Hair-Skin-Trousers</td>
<td>0.693 0.349</td>
<td>0.926 0.142</td>
<td>0.870 0.211</td>
<td>0.700 0.317</td>
<td>0.800 0.307</td>
<td>0.838 0.232</td>
</tr>
<tr>
<td>Hair-Torso-Trousers</td>
<td>0.658 0.347</td>
<td>0.926 0.142</td>
<td>0.870 0.211</td>
<td>0.712 0.327</td>
<td>0.800 0.307</td>
<td>0.843 0.235</td>
</tr>
<tr>
<td>Skin-Torso-Trousers</td>
<td>0.908 0.182</td>
<td>0.999 0.005</td>
<td>0.996 0.012</td>
<td>0.898 0.134</td>
<td>0.926 0.179</td>
<td>0.995 0.021</td>
</tr>
<tr>
<td>Hair-Skin-Torso-Trousers</td>
<td>0.633 0.339</td>
<td>0.931 0.144</td>
<td>0.857 0.216</td>
<td>0.754 0.299</td>
<td>0.783 0.282</td>
<td>0.837 0.234</td>
</tr>
</tbody>
</table>

Table 5.12 with those in Tables 5.13 and 5.14 indicate that there is little classification performance loss when using the directly illuminated radiance data on subsequent images. Again, these are averaged results for all pedestrians in their respective positions. Individual positions have varied results and the interested reader is referred to Appendix E to study the individual pedestrian cases.
### Table 5.11: Summary table of the subregion probability of error shown in Figures E.54 through E.64.

<table>
<thead>
<tr>
<th>Combo</th>
<th>FR mean</th>
<th>s.d.</th>
<th>RGB mean</th>
<th>s.d.</th>
<th>Vis mean</th>
<th>s.d.</th>
<th>VNIR mean</th>
<th>s.d.</th>
<th>SWIR1 mean</th>
<th>s.d.</th>
<th>SWIR2 mean</th>
<th>s.d.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hair-Skin</td>
<td>0.803</td>
<td>0.242</td>
<td>0.928</td>
<td>0.198</td>
<td>0.898</td>
<td>0.210</td>
<td>0.839</td>
<td>0.236</td>
<td>0.943</td>
<td>0.161</td>
<td>0.970</td>
<td>0.115</td>
</tr>
<tr>
<td>Hair-Torso</td>
<td>0.747</td>
<td>0.318</td>
<td>0.928</td>
<td>0.198</td>
<td>0.923</td>
<td>0.209</td>
<td>0.850</td>
<td>0.232</td>
<td>0.905</td>
<td>0.266</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Hair-Trousers</td>
<td>0.749</td>
<td>0.313</td>
<td>0.928</td>
<td>0.198</td>
<td>0.907</td>
<td>0.211</td>
<td>0.850</td>
<td>0.232</td>
<td>0.901</td>
<td>0.267</td>
<td>0.963</td>
<td>0.143</td>
</tr>
<tr>
<td>Skin-Torso</td>
<td>0.998</td>
<td>0.006</td>
<td>0.991</td>
<td>0.025</td>
<td>0.992</td>
<td>0.026</td>
<td>0.998</td>
<td>0.006</td>
<td>0.997</td>
<td>0.007</td>
<td>0.996</td>
<td>0.008</td>
</tr>
<tr>
<td>Skin-Trousers</td>
<td>0.998</td>
<td>0.006</td>
<td>0.988</td>
<td>0.026</td>
<td>0.991</td>
<td>0.026</td>
<td>0.998</td>
<td>0.006</td>
<td>0.988</td>
<td>0.036</td>
<td>0.996</td>
<td>0.008</td>
</tr>
<tr>
<td>Torso-Trousers</td>
<td>0.752</td>
<td>0.271</td>
<td>0.948</td>
<td>0.081</td>
<td>0.844</td>
<td>0.250</td>
<td>0.719</td>
<td>0.283</td>
<td>0.940</td>
<td>0.129</td>
<td>0.996</td>
<td>0.011</td>
</tr>
<tr>
<td>Hair-Skin-Torso</td>
<td>0.803</td>
<td>0.242</td>
<td>0.928</td>
<td>0.198</td>
<td>0.898</td>
<td>0.210</td>
<td>0.839</td>
<td>0.236</td>
<td>0.943</td>
<td>0.101</td>
<td>0.970</td>
<td>0.115</td>
</tr>
<tr>
<td>Hair-Skin-Trousers</td>
<td>0.795</td>
<td>0.254</td>
<td>0.928</td>
<td>0.198</td>
<td>0.898</td>
<td>0.210</td>
<td>0.850</td>
<td>0.232</td>
<td>0.951</td>
<td>0.099</td>
<td>0.963</td>
<td>0.143</td>
</tr>
<tr>
<td>Hair-Torso-Trousers</td>
<td>0.749</td>
<td>0.313</td>
<td>0.928</td>
<td>0.198</td>
<td>0.907</td>
<td>0.211</td>
<td>0.850</td>
<td>0.232</td>
<td>0.901</td>
<td>0.267</td>
<td>0.963</td>
<td>0.143</td>
</tr>
<tr>
<td>Skin-Torso-Trousers</td>
<td>0.998</td>
<td>0.006</td>
<td>0.988</td>
<td>0.026</td>
<td>0.991</td>
<td>0.026</td>
<td>0.998</td>
<td>0.006</td>
<td>0.988</td>
<td>0.036</td>
<td>0.996</td>
<td>0.008</td>
</tr>
<tr>
<td>Hair-Skin-Torso</td>
<td>0.754</td>
<td>0.304</td>
<td>0.956</td>
<td>0.155</td>
<td>0.928</td>
<td>0.165</td>
<td>0.861</td>
<td>0.216</td>
<td>0.890</td>
<td>0.268</td>
<td>0.963</td>
<td>0.143</td>
</tr>
</tbody>
</table>

### Table 5.12: Summary table of the subregion probability of error from DIRSIG image 1 data results shown in Figures E.65 through E.70.

<table>
<thead>
<tr>
<th>Combo</th>
<th>Torso mean</th>
<th>s.d.</th>
<th>Skin mean</th>
<th>s.d.</th>
<th>Trousers mean</th>
<th>s.d.</th>
<th>Hair mean</th>
<th>s.d.</th>
</tr>
</thead>
<tbody>
<tr>
<td>FR</td>
<td>0.699</td>
<td>0.209</td>
<td>0.936</td>
<td>0.132</td>
<td>0.570</td>
<td>0.265</td>
<td>0.471</td>
<td>0.383</td>
</tr>
<tr>
<td>RGB</td>
<td>0.934</td>
<td>0.193</td>
<td>0.988</td>
<td>0.009</td>
<td>0.764</td>
<td>0.376</td>
<td>0.895</td>
<td>0.245</td>
</tr>
<tr>
<td>VIS</td>
<td>0.597</td>
<td>0.342</td>
<td>0.988</td>
<td>0.028</td>
<td>0.567</td>
<td>0.300</td>
<td>0.659</td>
<td>0.375</td>
</tr>
<tr>
<td>VNIR</td>
<td>0.673</td>
<td>0.230</td>
<td>0.945</td>
<td>0.138</td>
<td>0.604</td>
<td>0.258</td>
<td>0.544</td>
<td>0.417</td>
</tr>
<tr>
<td>SWIR1</td>
<td>0.934</td>
<td>0.078</td>
<td>0.964</td>
<td>0.070</td>
<td>0.869</td>
<td>0.257</td>
<td>0.628</td>
<td>0.378</td>
</tr>
<tr>
<td>SWIR2</td>
<td>0.917</td>
<td>0.076</td>
<td>0.913</td>
<td>0.122</td>
<td>0.895</td>
<td>0.191</td>
<td>0.741</td>
<td>0.314</td>
</tr>
</tbody>
</table>
Figure 5.20: The synthetically generated pedestrian scene with the pedestrians labeled according to their respective letter identifier. Note the pedestrians were in the same location for each of the sun angles used.

Table 5.13: Summary table of the subregion probability of error from DIRSIG image 2 data results shown in Figures E.71 through E.76.

<table>
<thead>
<tr>
<th></th>
<th>Torso</th>
<th>Skin</th>
<th>Trousers</th>
<th>Hair</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>s.d.</td>
<td>mean</td>
<td>s.d.</td>
</tr>
<tr>
<td>FR</td>
<td>0.699</td>
<td>0.208</td>
<td>0.937</td>
<td>0.133</td>
</tr>
<tr>
<td>RGB</td>
<td>0.922</td>
<td>0.187</td>
<td>0.999</td>
<td>0.005</td>
</tr>
<tr>
<td>VIS</td>
<td>0.584</td>
<td>0.328</td>
<td>0.987</td>
<td>0.028</td>
</tr>
<tr>
<td>VNIR</td>
<td>0.672</td>
<td>0.228</td>
<td>0.946</td>
<td>0.138</td>
</tr>
<tr>
<td>SWIR1</td>
<td>0.936</td>
<td>0.078</td>
<td>0.964</td>
<td>0.070</td>
</tr>
<tr>
<td>SWIR2</td>
<td>0.915</td>
<td>0.077</td>
<td>0.914</td>
<td>0.122</td>
</tr>
</tbody>
</table>

Table 5.14: Summary table of the subregion probability of error from DIRSIG image 3 data results shown in Figures E.77 through E.82.

<table>
<thead>
<tr>
<th></th>
<th>Torso</th>
<th>Skin</th>
<th>Trousers</th>
<th>Hair</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>s.d.</td>
<td>mean</td>
<td>s.d.</td>
</tr>
<tr>
<td>FR</td>
<td>0.700</td>
<td>0.211</td>
<td>0.937</td>
<td>0.133</td>
</tr>
<tr>
<td>RGB</td>
<td>0.918</td>
<td>0.195</td>
<td>0.998</td>
<td>0.010</td>
</tr>
<tr>
<td>VIS</td>
<td>0.596</td>
<td>0.341</td>
<td>0.988</td>
<td>0.026</td>
</tr>
<tr>
<td>VNIR</td>
<td>0.669</td>
<td>0.231</td>
<td>0.945</td>
<td>0.138</td>
</tr>
<tr>
<td>SWIR1</td>
<td>0.929</td>
<td>0.091</td>
<td>0.964</td>
<td>0.069</td>
</tr>
<tr>
<td>SWIR2</td>
<td>0.916</td>
<td>0.078</td>
<td>0.910</td>
<td>0.120</td>
</tr>
</tbody>
</table>
CHAPTER 5. RESULTS

5.5 Unsupervised Subregion Segmentation

The results of looking at the natural clusterings using the *k*-means algorithm (see Section 4.4) with the Euclidean distance, spectral angle, and spectral correlation are shown in Figures 5.21, 5.22, and 5.23, respectively. The results shown are from using Pedestrian E from the HYMNS-P dataset as he was positioned in Scene 2, Pose 1, where the pedestrians were approximately 1 step apart and directly facing the direction of the imager. The full scene can be seen in Figure A.6. For the Euclidean distance in Figure 5.21, when only four clusters are used, the shirt and trousers were generally differentiated, but other subregions were clustered with either the shirt or trousers subregion. It would appear that 6 or more clusters offer consistent separation among the subregions, however it is clear that pixels illuminated differently such as the top of the shoulders and top of the head were consistently clustered differently than their respective subregion. It is interesting to note that the shadow was clustered with one of the clothing subregions in almost every case. It is not known why this was the case.

The results of the clusterings for the radiance data using the cosine distance are shown in Figure 5.22. By inspection it would appear that this metric offers improved performance over the other metrics previously used for each number of groupings. There is consistent homogeneity among the subregions and skin as well as the shadow region are not grouped with other materials. The illumination differences between the tops of shoulders and the front of shirt are still confused; however, this may be due to pixel mixing as well.

The results of the clusterings for the radiance data using the correlation distance metric are shown in Figure 5.23. These results look similar to those from the cosine distance shown in Figure 5.22. However, there were differences when looking at the hair subregion for the case when five clusters were desired. The hair subregion was segmented into two clusters corresponding to what appeared as a location where the highlight was strongest.

Since automated segmentation was not a primary objective of this work, these results were not further investigated. This was just used to illustrate how similar the subregion pixels were among the subregions for a particular pedestrian. Future work may pursue building on these results to establish a framework to have a more robust segmentation capability.
Figure 5.21: Comparing natural clustering of the pixel vectors using the Squared Euclidean distance metric with the $k$-Means classification algorithm.
Figure 5.22: Comparing natural clustering of the pedestrian pixel vectors using the spectral angle distance metric with the \textit{k-Means} classification algorithm.
Figure 5.23: Comparing natural clustering of the pedestrian pixel vectors using the spectral correlation distance metric with the $k$-Means classification algorithm.
5.6 Assessing Spectral Distance Measures for Pedestrian Subregion Detectability

The scene-wide detection of subregion pixels between images was performed following the process outlined in Sections 4.5. The results of this detection analysis is below. The raw ROC curves, which served as the source data, are contained in Appendix F. The AUC values are tabulated in Tables 5.15 through 5.19 for each spectral subset according to image and subregion for each distance metric used. Note that for the AUC metric, higher numbers are better. For convenience, the results are also shown graphically in Figures 5.24 through 5.28 where the results of all five selected images between the two datasets can be compared. The images are referenced according to the HYMNS-P first image or second image and the Ground Level (GL) images shown in Section 4.5. It is interesting to note that there is consistency among the images for the test-on-train case and the subsequent detection.

A summary of the mean and standard deviations of the AUC scores for each subregion and distance metric across all five images are given in Table 5.20. Inspection of this table reveals that the 3-band RGB imagery had the worst detection results while the full range and VNIR imagery seemed to be better suited for distinguishing target pixels from the background. It is also apparent that the Torso remains the most salient subregion of the pedestrian for detection. These subregion pixel detection results are only for the pixels of interest from the POI’s subregions. If a person were interested in detecting all pixels for a single subregion among the several pedestrians, then these results would be improved since many false alarms in the case here came from other pedestrians.
Table 5.15: Summary of the AUC metrics for the ROC curves generated using the full spectral range.

<table>
<thead>
<tr>
<th>Image</th>
<th>Subregion</th>
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<th>SAM</th>
<th>Correlation</th>
<th>Matched Filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>HYMNS-P 1</td>
<td>Torso</td>
<td>0.816</td>
<td>0.893</td>
<td>0.766</td>
<td>0.762</td>
</tr>
<tr>
<td></td>
<td>Skin</td>
<td>0.458</td>
<td>0.508</td>
<td>0.562</td>
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</tr>
<tr>
<td></td>
<td>Trousers</td>
<td>0.682</td>
<td>0.791</td>
<td>0.713</td>
<td>0.673</td>
</tr>
<tr>
<td></td>
<td>Hair</td>
<td>0.277</td>
<td>0.195</td>
<td>0.226</td>
<td>0.722</td>
</tr>
<tr>
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<td>Torso</td>
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<td>0.686</td>
<td>0.559</td>
<td>0.709</td>
</tr>
<tr>
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<td>0.280</td>
<td>0.274</td>
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</tr>
<tr>
<td></td>
<td>Trousers</td>
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<tr>
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<td>Hair</td>
<td>0.182</td>
<td>0.258</td>
<td>0.262</td>
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<tr>
<td>GLHR HSI 1</td>
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<td>0.881</td>
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<td>0.453</td>
<td>0.619</td>
<td>0.699</td>
</tr>
<tr>
<td>GLHR HSI 2</td>
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<td>0.404</td>
<td>0.713</td>
<td>0.828</td>
<td>0.794</td>
</tr>
<tr>
<td>Target from GLHR HSI 1</td>
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</tr>
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<td>0.809</td>
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Table 5.16: Summary of the AUC metrics for the ROC curves generated using the 3-band red, blue, green imagery.

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<th>Correlation</th>
<th>Matched Filter</th>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Torso</td>
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<td>0.115</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Skin</td>
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<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Trousers</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Hair</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>HYMNS-P 2 Target from HYMNS-P 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Torso</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Skin</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Trousers</td>
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<td>0.000</td>
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<tr>
<td>Hair</td>
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<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
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<td></td>
</tr>
<tr>
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</tr>
<tr>
<td>Hair</td>
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<td>0.000</td>
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</tr>
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</tr>
<tr>
<td>Torso</td>
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</tr>
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<td>0.000</td>
<td>0.001</td>
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<td>0.000</td>
<td>0.000</td>
</tr>
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<td>Hair</td>
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<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
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</tr>
<tr>
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</tr>
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<td>Skin</td>
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<td>0.000</td>
<td>0.000</td>
<td>0.066</td>
</tr>
<tr>
<td>Trousers</td>
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<td>0.000</td>
<td>0.001</td>
</tr>
<tr>
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<td>0.000</td>
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### Table 5.17: Summary of the AUC metrics for the ROC curves generated using the 22-band visible imagery.

<table>
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<tbody>
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<td><strong>HYMNS-P 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Torso</td>
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<td>0.885</td>
<td>0.962</td>
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<td>Skin</td>
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<tr>
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<tr>
<td>Hair</td>
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<td>0.727</td>
<td>0.107</td>
</tr>
<tr>
<td><strong>HYMNS-P 2</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Target from HYMNS-P 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Torso</td>
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<td>0.934</td>
<td>0.939</td>
<td>0.731</td>
</tr>
<tr>
<td>Skin</td>
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<td>0.366</td>
<td>0.658</td>
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</tr>
<tr>
<td>Trousers</td>
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<td>0.444</td>
<td>0.801</td>
<td>0.505</td>
</tr>
<tr>
<td>Hair</td>
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<td>0.040</td>
<td>0.284</td>
<td>0.000</td>
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<tr>
<td><strong>GLHR HSI 1</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Torso</td>
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<td>0.001</td>
</tr>
<tr>
<td><strong>GLHR HSI 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Target from GLHR HSI 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Torso</td>
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<td><strong>GLHR HSI 3</strong></td>
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<td></td>
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<tr>
<td>Target from GLHR HSI 1</td>
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<td></td>
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Table 5.18: Summary of the AUC metrics for the ROC curves generated using the 39-band VNIR imagery.

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<td>0.846</td>
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<tr>
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<tr>
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Table 5.19: Summary of the AUC metrics for the ROC curves generated using the 114-band SWIR imagery.

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<td>0.097</td>
<td>0.071</td>
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<tr>
<td>Torso</td>
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<td>0.001</td>
<td>0.002</td>
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</tr>
<tr>
<td>Skin</td>
<td>0.335</td>
<td>0.014</td>
<td>0.032</td>
<td>0.032</td>
</tr>
<tr>
<td>Trousers</td>
<td>0.013</td>
<td>0.000</td>
<td>0.000</td>
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</tr>
<tr>
<td>Hair</td>
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<td>0.233</td>
<td>0.117</td>
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<tr>
<td>GLHR HSI 1</td>
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<tr>
<td>Torso</td>
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<td>0.000</td>
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<tr>
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<td>Hair</td>
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<td>GLHR HSI 3</td>
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<td>Target from GLHR HSI 1</td>
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</tr>
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<td>0.649</td>
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<td>Hair</td>
<td>0.059</td>
<td>0.023</td>
<td>0.007</td>
<td>0.522</td>
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</table>
Figure 5.24: Showing the distribution of the area under the curve for the respective subregion detections for the two HYMNS-P and three GLHR HSI images when using the full spectral range 450 - 2500 nm with 152 bands.
Figure 5.25: Showing the distribution of the area under the curve for the respective subregion detections for the two HYMNS-P and three GLHR HSI images when using 3-band red, green, blue color imagery from 450 - 700 nm.
Figure 5.26: Showing the distribution of the area under the curve for the respective subregion detections for the two HYMNS-P and three GLHR HSI images when using 22-bands in the visible spectrum from 450 - 700 nm.
Figure 5.27: Showing the distribution of the area under the curve for the respective subregion detections for the two HYMNS-P and three GLHR HSI images when using 39-bands in the VNIR spectrum from 450 - 1000 nm.
Figure 5.28: Showing the distribution of the area under the curve for the respective subregion detections for the two HYMNS-P and three GLHR HSI images when using 114-bands in the VNIR spectrum from 1000 - 2500 nm.
Table 5.20: Summary results of the AUC for the detection analysis per image for the subregions and distance metrics used.

<table>
<thead>
<tr>
<th></th>
<th>Torso mean</th>
<th>Torso σ</th>
<th>Skin mean</th>
<th>Skin σ</th>
<th>Trousers mean</th>
<th>Trousers σ</th>
<th>Hair mean</th>
<th>Hair σ</th>
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<tbody>
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<tr>
<td>EU</td>
<td>0.590</td>
<td>0.174</td>
<td>0.391</td>
<td>0.059</td>
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<td>0.183</td>
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<td>0.500</td>
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<tr>
<td>CO</td>
<td>0.762</td>
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<td>0.309</td>
<td>0.240</td>
<td>0.505</td>
<td>0.170</td>
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<td>0.377</td>
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<td>0.407</td>
<td>0.263</td>
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<td>0.218</td>
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<tr>
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<td>0.000</td>
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</tr>
<tr>
<td>MF</td>
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<td>0.203</td>
<td>0.013</td>
<td>0.029</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Vis</td>
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</tr>
<tr>
<td>EU</td>
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<td>0.076</td>
<td>0.119</td>
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<td>0.513</td>
<td>0.128</td>
<td>0.038</td>
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<td>0.570</td>
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<td>0.415</td>
<td>0.231</td>
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<td>MF</td>
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<td>0.054</td>
<td>0.172</td>
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<td>0.266</td>
<td>0.024</td>
<td>0.047</td>
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<tr>
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<td>0.216</td>
<td>0.317</td>
<td>0.075</td>
<td>0.202</td>
<td>0.262</td>
<td>0.185</td>
<td>0.112</td>
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<td>0.135</td>
<td>0.329</td>
<td>0.199</td>
<td>0.463</td>
<td>0.215</td>
<td>0.322</td>
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<td>0.424</td>
<td>0.201</td>
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<td>0.262</td>
<td>0.495</td>
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<tr>
<td>MF</td>
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<td>0.039</td>
<td>0.273</td>
<td>0.094</td>
<td>0.363</td>
<td>0.256</td>
<td>0.235</td>
<td>0.137</td>
</tr>
<tr>
<td>SWIR</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EU</td>
<td>0.104</td>
<td>0.111</td>
<td>0.326</td>
<td>0.066</td>
<td>0.039</td>
<td>0.059</td>
<td>0.103</td>
<td>0.044</td>
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<td>0.125</td>
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<td>0.000</td>
<td>0.066</td>
<td>0.095</td>
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<td>0.287</td>
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<td>0.190</td>
<td>0.071</td>
<td>0.100</td>
<td>0.523</td>
<td>0.197</td>
</tr>
</tbody>
</table>
5.7 Subregion Detection after changes in Illumination

The results of the AUC for detection under varying illumination (see Section 4.6) and times of day are shown in Tables 5.21 and 5.22. The raw ROC curves are contained in Appendix F.7. Again, the full spectral range, minus the bad bands, was used for the detection.

The results contained in Table 5.21 compare the detection performance of the DIRSIG data in the indirect illumination case with the real-world data shown in Figure 4.8. By inspection, it can be seen that detection performance tends to be lower for all subregions when using the Euclidean distance metric. Other distance metrics are either above or below the comparison real-world results up to about 30% depending on the subregion. The one extreme case is for the skin detection using the matched filter where in the real-world data the performance was low but for the DRISIG data it was very high. Detection performance for other subregions using the matched filter were similar in magnitude difference as the other distance metrics. These differences should be kept in mind when comparing the results of the synthetic imagery with the real-world imagery.

Inspection of Table 5.22 indicates that for the chosen POI, as the illumination intensity increases from partial direct (PD) to full direct (FD) illumination, the subregions are more distinguishable. This is readily apparent with the skin, which demonstrated the poorest separability among the subregions in the previous analysis. Conversely, when the spectra are collected from a FD illumination case and then used to detect subregions in the PD illuminated image or indirectly illuminated image, the detection performance decreases. This illustrates the difficulty in detecting under changing illumination conditions. Further analysis would need to be done to maintain a constant sun angle and compare detection statistics of a POI in both shadow and direct illumination.
### Table 5.21: Comparing AUC metrics for the detection performance between the real-world and the synthetic DIRSIG images with similar characteristics.

<table>
<thead>
<tr>
<th>Subregion</th>
<th>Euclidean</th>
<th>SAM</th>
<th>Correlation</th>
<th>Matched Filter</th>
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<tr>
<td>HYMNS-P 1</td>
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<td></td>
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</tr>
<tr>
<td>Torso</td>
<td>0.816</td>
<td>0.893</td>
<td>0.766</td>
<td>0.762</td>
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<tr>
<td>Skin</td>
<td>0.458</td>
<td>0.508</td>
<td>0.562</td>
<td>0.260</td>
</tr>
<tr>
<td>Trousers</td>
<td>0.682</td>
<td>0.791</td>
<td>0.713</td>
<td>0.673</td>
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<tr>
<td>Hair</td>
<td>0.277</td>
<td>0.195</td>
<td>0.226</td>
<td>0.722</td>
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<td>Synthetics</td>
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<td></td>
</tr>
<tr>
<td>Torso</td>
<td>0.488</td>
<td>0.773</td>
<td>0.663</td>
<td>0.922</td>
</tr>
<tr>
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<td>0.301</td>
<td>0.731</td>
<td>0.743</td>
<td>0.904</td>
</tr>
<tr>
<td>Trousers</td>
<td>0.640</td>
<td>0.906</td>
<td>0.823</td>
<td>0.954</td>
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<tr>
<td>Hair</td>
<td>0.109</td>
<td>0.428</td>
<td>0.338</td>
<td>0.613</td>
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</table>

### Table 5.22: Summary of the AUC metrics for the ROC curves generated from DIRSIG data under varying illumination.

<table>
<thead>
<tr>
<th>Subregion</th>
<th>Euclidean</th>
<th>SAM</th>
<th>Correlation</th>
<th>Matched Filter</th>
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</thead>
<tbody>
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<td>PD</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Torso</td>
<td>0.227</td>
<td>0.251</td>
<td>0.221</td>
<td>0.841</td>
</tr>
<tr>
<td>Skin</td>
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<td>0.413</td>
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<td>0.786</td>
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<tr>
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<td>0.034</td>
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</tr>
<tr>
<td>Hair</td>
<td>0.431</td>
<td>0.079</td>
<td>0.500</td>
<td>0.954</td>
</tr>
<tr>
<td>FD</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Torso</td>
<td>0.333</td>
<td>0.271</td>
<td>0.227</td>
<td>0.812</td>
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<tr>
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<tr>
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<td>0.071</td>
<td>0.024</td>
<td>0.506</td>
</tr>
<tr>
<td>Hair</td>
<td>0.613</td>
<td>0.229</td>
<td>0.306</td>
<td>0.939</td>
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<tr>
<td>PD with FD Spectra</td>
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<tr>
<td>Torso</td>
<td>0.206</td>
<td>0.471</td>
<td>0.139</td>
<td>0.762</td>
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<tr>
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<td>0.039</td>
<td>0.031</td>
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<td>0.656</td>
</tr>
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</table>
Chapter 6

Conclusions and Future Work

This chapter contains the conclusions realized from the outcomes of this work. In addition to the conclusions, several areas of continued study are enabled as a result of the lessons learned from this research on the phenomenology of pedestrian detection in a cluttered urban environment. Some of those areas of further investigation are outlined below, following the conclusions.

6.1 Conclusions

The several phenomenological aspects addressed within this work contributed to the basic understanding of pedestrian detection in an urban environment. As was established in Section 2.3, there are two potential ways to approach this problem. These included considering pedestrians as entities in known locations with already segmented subregions. This affords the approach of only considering separability between pedestrians without a stipulation on how the background environment materials confuse the separability. Conversely, for the case where an image-wide search is conducted for a particular pedestrian, the approach considers how spectrally similar or dissimilar a pedestrian is from the background. While there may be other workflows for detecting pedestrians in an urban environment, these two approaches were considered while conducting this work.

The fundamental research question outlined in the beginning was, “Can a pedestrian of interest be uniquely associated in hyperspectral imagery using a spectral feature vector derived from four
constituent subregions?" Through the various elements of this research, the evidence suggests that the combining of information increases the likelihood of uniquely distinguishing among pedestrians, even in spectrally limited data. Again, the absolute numbers reported tended to indicate a high classification error rate, but these were aggregated results for all pedestrians and for the particular datasets utilized. Several pedestrians where still highly distinguishable in their torso and trouser subregions from other pedestrians despite having similar clothing materials. Given most of the separability analysis for distinguishing among pedestrians was done using binary classification with only the adjusted Euclidean distance, results may be improved if a different similarity metric were used among the samples. Additionally, sensor characteristics were only marginally characterized with respect to noisy bands and pixels. Results would likely vary should a different sensor be used.

As a result of the work performed, many scientific impacts were realized. These included the development of a pedestrian focused spectral database, a collection of real-world and synthetic hyperspectral imagery, as well as several characteristics of processing associated with performing pedestrian subregion detection and association. Each of these are discussed below.

Development of empirical spectral database. Early in the research it was realized that the necessary spectral data for studying a pedestrian detection scenario as outlined in the context of this research did not exist. Through collaboration with the Air Force Research Laboratory, Air Force Institute of Technology, University of Dayton, and the Rochester Institute of Technology, an initial empirical spectral database was established. With the extensive ground truth that was gathered during the HYMNS-P data collect, several aspects of this research were enabled. This included both the pedestrian-to-pedestrian subregion separability studies, as well as, image wide pedestrian subregion detection. It was clear that the ground truth data was a great asset in understanding the phenomenology of the pedestrian separability in HSI data over what the previously collected ground level high resolution HSI data could provide.

Development of synthetic imagery dataset from real-world pedestrian data. The extensive spectral reflectance data that was captured during the HYMNS-P data collect, along with other contextual information that was gathered, enabled the generation of a synthetic pedestrian scene for use in DIRSIG. This artificial dataset, based on real-world measurements, enabled aspects of detection under illumination variability to be studied. It will also enable further studies on the phenomenol-
ogy of pedestrian detection and possibly tracking of pedestrians in an urban environment.

**Novel approach to assess spectral separability.** In addition to gathering the subregion spectral reflectance data, a novel approach was developed to understand spectrally separable pedestrian subregions in the one-vs-many case. Since the pedestrian separability was approached as a two-class binary classification problem, traditional methods report classification error using the total probability of error. However, there was a disproportionate number of pixels in the POI class versus the background class and the error probabilities of each class are weighted by their respective prior probabilities. As such, the probability of error for just the POI class provided better insight into impacts of noise on the subregion classification. For the work here, only the probability of error as a function of noise was considered. However, the same approach could be used to assess other aspects of pedestrian imaging and detection on the probability of error, per subregion.

**Utility of combining subregion spectral information for improved classification.** The approach developed to assess the spectral separability of reflectance samples enabled the ability to quantitatively assess the utility of combining the spectral information from each subregion of a POI. It also provided insight into determining which subregions provided the best classification performance when combined. Most surprisingly was seeing how significant a classification performance improvement was realized when just two subregions were combined. Further improvements were realized when three and four subregions were combined, but the improvement was not as significant as when comparing the two subregion cases to the single subregion classification error. Surprisingly, the combination of subregions also provided improved classification performance when spectral ranges were limited. It was noted that three-band reflectance data in the visible region had very poor performance in separating single subregions between pedestrians. However, combined subregions improved separability, even for the three-band data. Note that the results from combining subregion information in real-world imagery had a high probability of error for the data and approach used. Further work would need to be done to better assess the processing required to combine and assess the classification performance when combining subregion spectral data in real-world imagery.

**Spectral separability of pedestrian subregions in remote sensed imagery.** The spectral separability process used for the spectral reflectance data in the presence of noise was further applied
CHAPTER 6. CONCLUSIONS AND FUTURE WORK

138
to pedestrian subregions extracted from remotely sensed imagery. The results from the remotely sensed imagery, using both the HYMNS-P dataset and the GLHR HSI dataset, supported the findings where separability of noise added spectral reflectance samples was assessed. These findings included supporting the realization that skin was a very difficult subregion to separate among pedestrians. Conversely, the torso was the most salient feature among the pedestrians in the imagery, though hair was more separable in the spectral reflectance data. It was assumed that this was likely due to the spatial resolution in the imagery which led to skin and hair pixels having a high probability of being spatially mixed. Skin and hair are also spectrally similar leading to limited separability in the imagery. Also, the clothing was predominantly cotton for all pedestrians so separability was limited to the visible color differences leading to poor classification results. Though the classification errors were high, the reported numbers were averages for all pedestrians in all positions. As such, depending on the subregions considered, distinguishing between pedestrians could be achieved with greater than 60% accuracy when using just the clothing subregions.

Separability and detection performance in limited spectral ranges. A significant contribution of this work involved assessing which spectral ranges provided sufficient spectral information to ensure sufficient separability between subregions. Based on the evidence, the full solar reflectance spectral range from 400 - 2500 nm was not needed for robust pedestrian POI classification. VNIR (450 - 1000 nm) tended to produce similar results to the full range results of detecting the clothing features of each of the pedestrians. The SWIR bands tended to offer marginal distinguishability between pedestrian subregions. This was due in part to the commonality among the fabrics worn by the pedestrians. As such, most of the spectral differences occurred in the visible spectrum due to the different colors used. Other techniques not specifically pursued in this work could still be utilized to further improve subregion detection, such as the NDSI and melanin estimation discussed in [7].

Assessing distance metrics for subregion spectral clustering and detection. In a limited sense, this work provided insight into the impacts of different distance metrics on the natural spectral clusterings of the pedestrian subregions. This was evident when using the \textit{k-means} clustering algorithm and looking at a range of clusters that lead to homogeneous regions on the pedestrian. It was evident that the distance metrics used lead to different associations based on subregion. This
was further demonstrated when looking at the scene wide subregion detection performance. Each subregion tended to be best detected with a different distance metric. However, the SAM metric tended to provide the most favorable results for the case where only 5 clusters were desired. In that case the four subregions were distinguished as respective clusters and the background (asphalt) maintained its own cluster. Further work might include looking at other processing techniques to assess hybrid approaches to pedestrian detection and classification.

Detection across illumination changes. Another investigation of this work lead to the characterization of pedestrian subregion detection under changing illumination conditions, albeit in a limited case at this point. Remote sensing research has often looked at the impacts of shadowing on target detectability, but this work specifically looked at the impacts to detection from changes to illumination onto a pedestrian. The results suggest that detecting a shadowed or indirectly illuminated subregion using a spectral sample from a brightly illuminated pixel is achievable. This stems from the fact that the detection performance remained fairly high for the spectral matched filter. Further work is needed in this area to better assess the illumination combinations under which a pedestrian may be exposed within the time frame of a tracking period.

In reviewing the results, it is apparent that the classification of the pedestrians can be enhanced when combining the subregions according to spectral reflectance characteristics. It was demonstrated that just using the spectral reflectance information from two subregions could drastically improve the separability among pedestrians. For real-world imagery, using the spectral information from single subregions yielded a greater than 60% classification accuracy. However, using the combined subregion spectral information in real-world imagery did not yield the same improvement as was shown when using the spectral reflectance data. Some of the discrepancy may be due to the datasets used or the processing scheme utilized for the analysis. On the other hand, the spectral reflectance data, real-world, and synthetic imagery did show that the VNIR spectral range (400 - 1000 nm) offered good classification performance when compared to the full range (400 - 2500 nm) as well as other spectral subsets. Finally, the datasets garnered during this research, as well as the analysis framework established in this dissertation can be utilized to further characterize the pedestrian phenomenology in remotely sensed hyperspectral imagery. This would ultimately lead to further improvements in distinguishability between pedestrians.
6.2 Future Work

Several areas of future work are proposed to further study the phenomenology of pedestrian detection. Many of these areas of proposed future work are enabled by the work performed so far. In this section, several potential continuations of this work are presented.

6.2.1 Additional Pedestrian HSI Data Gathering

The results presented in this work so far were based on the limited dataset gathered during this research. As such, the logical question is how universal are these results? In order to address this, additional data would need to be gathered and added to the empirical spectral database for further analysis. Additional data would include taking spectral reflectance measurements of individual subregions on a large number of pedestrians. During the HYMNS-P data collection, only a single reflectance measurement was captured per subregion (aside from the skin which had measurements of the face, arm, and in some instances leg). By taking several measurements over a subregion of a pedestrian, the POI within class subregion variability can be addressed. Other data would include additional outdoor images with pedestrians in a varied environment with the sun directly illuminating the subregions facing the HSI sensor. Pedestrians would again move around from full illumination to shade. Interesting shading sources would be trees, canopies, and buildings. Clothing of different colors and material types should also be investigated. This additional data would support developing a robust understanding of the statistical distributions of the spectral data among pedestrians.

6.2.2 Pedestrian BRDF Effects

One of the desired outcomes of this work in, the beginning, was to address the BRDF of the pedestrian. Though an extensive background study was performed (see Appendix D), it was realized that there is not sufficient data to properly assess the BRDF models previously developed for non-HSI data. Additional work would need to be performed to properly characterize and extend the utility of these models out into the SWIR reflective region (up to 2500 nm) so there is scientific tractability in using the models. As such, some of the background research has been done, but the
bulk of the research is left for future work.

6.2.3 HSI Spectral Resolution Requirements

One aspect of spectral resolution that was addressed in this work involved looking at separability and detectability using tri-band color imagery. The color imagery used in the assessment was based on converting the high dimensional HSI data in the visible region (450 - 700 nm) to tri-color imagery according to the standard observer’s visual response. That type of analysis could be further extended to reduce the spectral resolution from 8 - 12 nm in the HYMNS-P HSI data to assess impacts on subregion detectability and separability. This could be done with the existing imagery by spectrally smoothing it. Ultimately this would lead to an understanding of the system requirements needed to image pedestrians leading to robust detection of the POI.

6.2.4 HSI Spatial Resolution Requirements

Another area that was not addressed was the spatial resolution requirements needed for accurate subregion detection. The HYMNS-P data provided nominally 2.5 cm ground sample distance (GSD) on the pedestrians. Additional work would look at the trade space of reducing resolution and still enabling unique labeling of the pedestrians.

6.2.5 Classification Error Versus Solar Illumination Angle

One of the initial assumptions of this work involved detecting a pedestrian over a relatively short amount of time. This was referred to as the tracking period. Despite this assumption, one of the aspects of detectability and distinguishability not addressed in this work deals with imaging early or late in the day when the solar zenith angle is greatest. A process similar to the one outlined for the SNR analysis in Section 4.3.2 could be followed for comparing changes in solar zenith angle.

For this proposed work, the spectral reflectance samples would be modulated with a set SNR level similar to a typical HSI system, such as 300 in the case of the HST3. These noisy reflectance samples would then be used by MODTRAN to simulate the sensor reaching radiance for a range of solar zenith angles and a fixed atmosphere. Comparisons between pedestrian distinguishability
would be compared for solar angle variation at solar noon and in the morning or afternoon. It is proposed that the solar angle over a tracking period in the early morning or late afternoon would have greater impacts on the detectability versus changes in solar angle at mid day. Again, the spectral distance metrics would be used to test similarity between the sensor reaching radiance at a reference time versus other times.

### 6.2.6 Spectral Variations of Moist Skin

Another area of investigation involves looking at moisture on the skin. As a quick look, the spectral reflectance of forearm skin was measured before and after applying a layer of distilled water. The context pictures of the skin before and after applying water are shown in Figure 6.1. The spectral reflectance profiles for each of the volunteers are plotted below the respective context images. By inspection it can be seen that four of the five volunteers had small variations while one had a significant variation. Future work would take additional measurements in order to better characterize moisture on the skin. For the study, other substances such as lotions, saline, or cosmetic products could be used during the assessment.

![Ped 2A](image1.png) ![Ped 2B](image2.png) ![Ped 2C](image3.png) ![Ped 2D](image4.png) ![Ped PI](image5.png)

Dry = 0.626580
Wet = 0.655362

Dry = 0.588532
Wet = 0.687581

Dry = 0.611509
Wet = 0.613227

Dry = 0.638788
Wet = 0.691598

Dry = 0.609750
Wet = 0.692336

Figure 6.1: Showing the impact of water on the surface of the skin to the NDSI values for five test subjects with varied skin types.
6.2.7 Data processing for POI Classification from Remotely Sensed Imagery

Many different approaches exist for processing the HSI data with the intent to distinguish among spectral samples [12]. These processing schemes could be used to aid in preprocessing the data and performing the binary classification of pedestrians as POI or non-POI. Given there are many types of classifiers, each could be assessed for suitability in maintaining separability among the pedestrians as their spectral radiance profiles undergo changes over a tracking period. Provided there are a sufficient number of pixels on each subregion, classifiers such as majority vote or decision trees may be suitable.

Besides the binary classification of pedestrians as POI and non-POI, processing also needs to be further developed for automated segmentation of the pedestrians into subregions. During the course of this work, an automated subregion detection scheme was considered. The process involved applying a subregion mask based on the human blob model described in Section 3.1. Masks were created for head, torso, and trouser subregions. The dominant cluster within each subregion mask was assumed to be the pixels containing the respective subregion material. Additionally, the NDSI as described in Section 3.3 was incorporated to try and produce a skin pixel mask. It offered marginal results for the thresholds selected. Ultimately this automated segmentation development was discontinued because it was beyond the scope of this work. However, further work can be performed in this area seeking to validate a pedestrian segmentation algorithm which will identify the particular subregions. Techniques such as the NDSI could be used to better detect the particular materials of interest in the segmentation algorithm.
Appendix A

HYperspectral Measurements of Natural Signatures from Pedestrians

A.1 Overview

During the course of this research, it was determined that a unique dataset would be required. Despite other HSI datasets of pedestrians known to exist [6, 7], they were limited in their experimental scope. As a result, they either did not cover the full spectral range of interest or lacked the necessary ground truth to fully understand the environmental aspects of the pedestrians and their background. Therefore a new, operationally relevant, HSI dataset of pedestrians in a complex urban environment was collected [50].

The HYperspectral Measurements of Natural Signatures from Pedestrians (HYMNS-P) data collect was initiated to collect operationally relevant hyperspectral data of pedestrians in an urban environment. The goal was to image pedestrians individually and collectively in different groupings within a cluttered environment in order to support phenomenological studies. At the outset,
consideration was given to how the data could be collected and documented such that it would be relevant to future work in addition to the research reported in this dissertation. The objectives of the data set included capturing calibrated HSI data of individual and grouped pedestrians in known locations. The pedestrians were to be in different poses in each frame with varied illumination while viewed from an elevated vantage point. The desired scene was an urban environment with a mixture of walkways, grass, trees, shade sources, and asphalt.

A.2 Methodology

A.2.1 Institute Review Board Approvals

The collection requirements of this dataset included use of human subjects. With that in mind, an application was submitted to the Rochester Institute of Technology Institute Review Board (IRB) for approval for conducting research using live human subjects. This application included provisions for collecting hyperspectral image data on pedestrians in natural poses in natural environments as well as collecting surface reflectance measurements using field spectrometers. The locations for conducting research included the IDCAST facility in Dayton, Ohio, as well as the Chester F. Carlson Center for Imaging Science at the Rochester Institute of Technology in Rochester, New York. The IRB approval was granted on 17 May 2011 and is included in Figure A.1. In addition to the RIT IRB, coordination was conducted with the IRBs of the Air Force Institute of Technology and the Air Force Research Laboratory in Dayton, Ohio, since they were providing equipment and manpower. It was determined that their oversight was not needed since these organizations would not be maintaining the data we collected under the HYMNS-P data collect. Therefore, RIT maintained cognizant authority over the data collected. Subsequent data use agreements were worked out on a case-by-case basis in order to share the data among collaborators.

A.2.2 Scenes

The HYMNS-P data collect was conducted on 21 June 2011 to coincide with the summer solstice, ensuring a high sun angle with strong illumination to improve the signal-to-noise ratio. In order to
Figure A.1: IRB Form C signed by the IRB Chair for the HYMNS-P data collection campaign.
support a building mounted sensor geometry, the data collect was conducted at the Institute for Development and Commercialization of Advanced Sensor Technology (IDCAST) facility in Dayton, OH. The IDCAST building had controlled lab space and safe roof access to support placing the sensor and the sensor team during the data collect. With the sensor on the roof, it allowed for an elevation of about 48.5 feet and a depression angle of 25-degrees. This offered a slant range of approximately 126 feet and a spatial resolution of 1.5 inches at mid scene.

In order to maintain awareness of the pedestrians and their poses, there were six specific scenes that were devised as outlined in Figure A.2. The scenes consisted of placing 17 pedestrians within the field of view of the hyperspectral sensor. Five of the pedestrians remained in the same spatial location between scenes. Six pedestrians were moved between scenes to get differences between illumination, background, occlusion, and pedestrian spacing. In addition to the spatial locations, the pedestrians were imaged while everyone was facing the sensor, while turned at 45° away from the sensor, and while turned 90° away from the sensor. Note, positions shown in Figure A.2 are representative of the relative locations and not absolute with respect to the actual scenes imaged. This provided 18 unique scene scenarios with pedestrians present. Figures A.3 through A.20 are true color images of each of these scenes which were captured between about 1040 EDT and 1140 EDT on the day of the collect. The time available for imagery collection was limited due to weather and volunteer pedestrian availability.
Figure A.2: Pedestrian scenario scenes for the HYMNS-P data collect. The three scenes along the top row had the pedestrians standing shoulder-to-shoulder while the scenes along the bottom had the pedestrians standing one step apart. Pedestrians were posed standing facing the camera, turned $45^\circ$ from the imager and turned $90^\circ$ from the imager. Note, positions shown are representative of the relative locations and not absolute with respect to the actual scenes imaged.

Figure A.3: True color image of the HYMNS-P scene for pedestrians in Scene 1, Pose 1, where pedestrians were facing the imager.

Figure A.4: True color image of the HYMNS-P scene for pedestrians in Scene 1, Pose 2, where pedestrians were turned approximately $45^\circ$ away from facing the imager.
Figure A.5: True color image of the HYMNS-P scene for pedestrians in Scene 1, Pose 3, where pedestrians were turned approximately 90° away from facing the imager.

Figure A.6: True color image of the HYMNS-P scene for pedestrians in Scene 2, Pose 1, where pedestrians were facing the imager.

Figure A.7: True color image of the HYMNS-P scene for pedestrians in Scene 2, Pose 2, where pedestrians were turned approximately 45° away from facing the imager.
Figure A.8: True color image of the HYMNS-P scene for pedestrians in Scene 2, Pose 3, where pedestrians were turned approximately 90° away from facing the imager.

Figure A.9: True color image of the HYMNS-P scene for pedestrians in Scene 3, Pose 1, where pedestrians were facing the imager.

Figure A.10: True color image of the HYMNS-P scene for pedestrians in Scene 3, Pose 2, where pedestrians were turned approximately 45° away from facing the imager.

Figure A.11: True color image of the HYMNS-P scene for pedestrians in Scene 3, Pose 3, where pedestrians were turned approximately 90° away from facing the imager.
Figure A.12: True color image of the HYMNS-P scene for pedestrians in Scene 4, Pose 1, where pedestrians were facing the imager.

Figure A.13: True color image of the HYMNS-P scene for pedestrians in Scene 4, Pose 2, where pedestrians were turned approximately 45° away from facing the imager.

Figure A.14: True color image of the HYMNS-P scene for pedestrians in Scene 4, Pose 3, where pedestrians were turned approximately 90° away from facing the imager.

Figure A.15: True color image of the HYMNS-P scene for pedestrians in Scene 5, Pose 1, where pedestrians were facing the imager.
Figure A.16: True color image of the HYMNS-P scene for pedestrians in Scene 5, Pose 2, where pedestrians were turned approximately 45° away from facing the imager.

Figure A.17: True color image of the HYMNS-P scene for pedestrians in Scene 5, Pose 3, where pedestrians were turned approximately 90° away from facing the imager.

Figure A.18: True color image of the HYMNS-P scene for pedestrians in Scene 6, Pose 1, where pedestrians were facing the imager.

Figure A.19: True color image of the HYMNS-P scene for pedestrians in Scene 6, Pose 2, where pedestrians were turned approximately 45° away from facing the imager.
Figure A.20: True color image of the HYMNS-P scene for pedestrians in Scene 6, Pose 3, where pedestrians were turned approximately 90° away from facing the imager.
A.2.3 Instrumentation

HyperSPecTIR Instrument 3

For this data collect, hyperspectral imagery was collected using the HyperSpecTIR Instrument 3 (HST3) [51] provided by collaboration with the Air Force Institute of Technology in Dayton, OH. The HST3 is a full-range (450 - 2450 nm) whisk-broom style imaging spectrometer. The instrument uses a 2-dimensional sensor array with 256 spatial pixels which are sampled in 240 spectral bands of which 227 are unique. The sensor has a spatial resolution of 1-mrad instantaneous field of view per pixel and can be configured to capture 100 to 1,000 pixels in cross-track. The HST3 was originally designed as an airborne sensor for collecting high-spatial resolution hyperspectral imagery. The sensor, as currently configured, is shown in Figure A.21. The sensor is housed in a rolling travel hard case for performing ground level hyperspectral imaging. During the HYMNS-P data collect, the sensor was placed on the roof of the three-story IDCAST building, 48.5 feet up from ground level and with a 25 degree depression angle from horizontal. Context images of the imager as mounted on the building are shown in Figure A.22.

Figure A.21: Photo of the HST3 sensor as mounted in the rolling travel hard case. The controller is seen on the table behind the sensor.
Figure A.22: Photo of the HST3 sensor as mounted on the roof in (a). The view from the perspective of the pedestrians is shown in (b) and an overall context view of the building is shown in (c). Note, there was a second tent on the roof in support of another simultaneous imaging experiment which was not included as part of the HYMNS-P data collect.
Analytical Spectral Devices (ASD) FieldSpec Pro Spectroradiometer

Several spectral reflectance measurements of the pedestrians as well as the sky irradiance measurements were performed using an Analytical Spectral Devices (ASD) Full Range (FR) FieldSpec Pro spectroradiometer. The ASD FR FieldSpec Pro spectroradiometer is capable of taking measurements from 350 - 2500 nm with a spectral resolution of 3 - 12 nm, depending on the portion of the spectrum [61]. It is configurable for recording reflectance, transmittance, radiance, or irradiance measurements. During the HYMNS-P data collect, there were three ASD FR FieldSpec Pro spectroradiometers used. Each one was only configured for reflectance or irradiance, depending on the assigned function.

For the reflectance measurements, the RIT contact probe was used [62]. The probe contains an illumination source within an integrating sphere to provide uniform illumination across the sample. The input fiber optic to the ASD FR FieldSpec Pro was bare which gave a 25° field of view (FOV) and was placed 40° from the surface normal. The probe measured approximately a 0.92 cm² portion of the surface area of the sample. The whole assembly was mounted on a tripod for the convenience of the pedestrians during measurements. An example illustration of the probe’s design and use is shown in Figure A.23. Note that the contact probe was positioned on the sample such that no extraneous light entered into the measurement area. Appendix B reports on a study to compare the reflectance measurements collected by this contact probe and a spectrometer designed for diffuse hemispherical reflectance measurements.

The spectral irradiance measurements were performed using two in-scene ASD FR FieldSpec Pro spectroradiometers. They were configured with the Original Equipment Manufacture (OEM) full-sky irradiance attachments as provided by ASD [63]. For the spectroradiometer in the shade of the canopy, the FieldSpec Full Sky Irradiance Remote Cosine Receptor was used. This attachment has a diffuse optic with near 180° FOV. The spectroradiometer in the direct sunlight was fitted with the ASD Reflective Cosine Receptor. This attachment contains a sample of Spectralon which reflects the incident light into the bare fiber optic of the spectroradiometer. The difference in irradiance measurement attachments was simply a result of the availability of the equipment.
Figure A.23: Illustration of the RIT contact probe when used to measure the spectral reflectance of a sample. The simple schematic is shown in (a) and the actual probe as mounted during the spectral reflectance measurements. An integrating sphere directs uniform illumination onto a sample and reflected radiance is measured by the bare fiber optic of the ASD spectrometer at 40° off the sample normal.

**Spectra Vista Corporation HR1024 Spectroradiometer**

Reflectance measurements of the scene materials were performed using a Spectra Vista Corporation (SVC) High Resolution (HR) 1024 field spectrometer. The SVC HR-1024 is a non-imaging spectroradiometer which collects in the wavelengths 350 - 2500 nm which can collect up to 1024 unique bands across the operating spectrum [64]. It has a spectral resolution of 3.5 - 9.5 nm, depending on the portion of the operating spectrum. It can be configured with several different accessories. For the material measurements in the HYMNS-P data collection scene, the SVC HR-1024 had a 4° fore optic and the instrument was hand-held at approximately 3 feet above each material.

**A.2.4 Ground Truth**

In order to support the needs of a phenomenological study, several aspects of ground truth were collected during the HYMNS-P data collection. Ground truth items are listed in Table A.1. Elements included collecting high resolution photos of each pedestrian individually and of each scene so relative positions were known. A spectroradiometer was used to record high resolution reflectance measurements of each pedestrian’s hair, exposed skin, shirt, and trousers/shorts. For
the skin spectral measurements, each pedestrian’s cheek, fore arm and leg (if wearing shorts) were measured. Spectral curves per subregion for the measurements of the several pedestrians are shown in Figures A.24 to A.28. Also, each pedestrian completed a self-assessment which included height, weight, hair color, clothing fabric type, sunscreen brand/SPF level if applied, and their skin type from the Fitzpatrick Skin Type scale. An example of the self-assessment survey is shown in Figure A.29.

Several calibration targets were placed around the scene. There were four sets of white and dark calibration targets for performing in-scene radiance to reflectance conversion using the empirical line method [13]. The white and black panels were placed both flat on the ground and propped up facing the camera to mimic the illumination aspects of the pedestrians where some of the body was in direct sunlight and certain aspects were indirectly illuminated by ambient light only. A bar chart
Figure A.25: Ensemble of spectral reflectance measurement curves of facial skin from the several volunteer pedestrians in the HYMNS-P data collect.
Figure A.26: Ensemble of spectral reflectance measurement curves of arm skin from the several volunteer pedestrians in the HYMNS-P data collect.
Figure A.27: Ensemble of spectral reflectance measurement curves of shirts from the several volunteer pedestrians in the HYMNS-P data collect.
Figure A.28: Ensemble of spectral reflectance measurement curves of trousers or shorts from the several volunteer pedestrians in the HYMNS-P data collect.
Subject Questionnaire

Subject Identifier Letter: __________

Height: ________________

Weight: ________________

Hair Color: ________________

Clothing fabric type and blend (i.e., 30% Cotton, 70% Polyester):

Shirt: ________________

Trousers/Shorts: ________________

Hat (if any): ________________

Sunscreen Brand
and SPF applied
(if applicable): ________________

Skin Type (Using Scale Below): __________

T. B. Fitzpatrick Skin Type Scale

TYPE 1: Highly sensitive, always burns, never tans. Example: Red hair with freckles

TYPE 2: Very sun sensitive burns easily, tans minimally. Example: Fair skinned, fair haired Caucasians

TYPE 3: Sun sensitive skin, sometimes burns, slow tans to light brown. Example: Darker Caucasians.

TYPE 4: Minimally sun sensitive, burns minimally, always tans to moderate brown. Example: Mediterranean type Caucasians.

TYPE 5: Sun insensitive skin, rarely burns, tans well. Example: Some Hispanics, some Blacks.

TYPE 6: Sun insensitive, never burns, deeply pigmented. Example: Darker Blacks.

Figure A.29: An example of the self-assessment survey used by the volunteer pedestrians to record physical attributes pertinent to the HYMNS-P data collect. Each survey response maintained anonymity of the pedestrians participating.
and checker chart was also placed in the scene and positioned facing the camera approximately parallel to the focal plane to assist with confirming spatial resolution. There were also targets of a yellow shirt, and red and blue fabric which were used in another HSI data collect [31] to provide a basis of comparison between datasets.

Reflectance measurements of most all the materials in the scene (e.g., grass, asphalt, cement, soil, etc.) were taken. Simultaneous full sky and partial sky irradiance measurements were taken for each of the scenes using two spectroradiometers as annotated “ASD” in Figure A.2. The one that was shadowed was placed under the shade canopy over the asphalt.

Additional ground truth information included using a fish-eye camera placed in the center of the scene to capture visible spectrum sky images for each hyperspectral image. An example of the sky conditions is shown in Figure A.30. Finally, linear distance measurements to each pedestrian and target were taken so explicit relative positions could be known. The HYMNS-P dataset with the HSI data, ground truth, and metadata is available for future research. There were certain restrictions placed on the high-resolution photos of each of the pedestrians in order to protect their anonymity, but agreements can be made for sharing the full dataset.
Table A.1: List and description of items that were collected as ground truth during the HYMNS-P data collect.

<table>
<thead>
<tr>
<th>Item</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Downwelling spectral radiance</td>
<td>Collected during each image capture both in shade and direct sunlight using two field spectrometers.</td>
</tr>
<tr>
<td>Sky images</td>
<td>Collected during each image from the center of the scene showing cloud cover.</td>
</tr>
<tr>
<td>Pedestrian photos</td>
<td>High resolution true-color photographs of each pedestrian facing and standing sideways to the camera.</td>
</tr>
<tr>
<td>Pedestrian self-assessment metadata</td>
<td>Self-assessment questionnaires from each pedestrian capturing height, weight, gender, skin type, sunscreen, and fabric materials (e.g., cotton, rayon, etc.).</td>
</tr>
<tr>
<td>Hair reflectance spectra</td>
<td>Collected for each pedestrian in the scene. Measurement taken of hair on top of head.</td>
</tr>
<tr>
<td>Skin reflectance spectra</td>
<td>Collected for each pedestrian on their cheek, arm, and leg if exposed.</td>
</tr>
<tr>
<td>Shirt reflectance spectra</td>
<td>Collected for each pedestrian in the scene.</td>
</tr>
<tr>
<td>Trousers or Shorts spectra</td>
<td>Collected for each pedestrian in the scene.</td>
</tr>
<tr>
<td>Post collection skin spectra</td>
<td>Spectra of skin cheek, arm, and leg of a subset of pedestrians in the scene after the data collect.</td>
</tr>
<tr>
<td>Scene material Reflectance spectra</td>
<td>Measured for each material in the vicinities of the pedestrians. This included asphalt parking lot, concrete sidewalks, plants, calibration panels, and painted surfaces.</td>
</tr>
<tr>
<td>Position measurements</td>
<td>Measured geometries from sensor to each target within the scene as well as size measurements of sidewalks, medians, and other objects in the scene.</td>
</tr>
</tbody>
</table>
Table A.2: Listing of the metadata for each subregion as provided by pedestrians in HYMNS-P dataset.

<table>
<thead>
<tr>
<th>Ped ID</th>
<th>Hair Color</th>
<th>Shirt</th>
<th>Trousers</th>
<th>Hat</th>
<th>Sunscreen Brand</th>
<th>SPF</th>
<th>Skin Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Black</td>
<td>100% cotton, grey</td>
<td>100% cotton, tan</td>
<td>none</td>
<td></td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>lt brown</td>
<td>100% polyester, blue</td>
<td>100% cotton, khaki</td>
<td>none</td>
<td></td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>Black</td>
<td>100% cotton, white</td>
<td>100% cotton, brown</td>
<td>none</td>
<td>Generic</td>
<td>30</td>
<td>3</td>
</tr>
<tr>
<td>D</td>
<td>Black</td>
<td>100% cotton, white</td>
<td>100% cotton, beige</td>
<td>none</td>
<td>generic</td>
<td>30</td>
<td>3</td>
</tr>
<tr>
<td>E</td>
<td>Brown</td>
<td>100% cotton, brown</td>
<td>100% cotton, tan</td>
<td></td>
<td></td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>Brown</td>
<td>100% cotton, teal</td>
<td>100% cotton, tan</td>
<td>100% cotton</td>
<td></td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>G</td>
<td>Brown</td>
<td>unknown, yellow</td>
<td>100% cotton, blue</td>
<td>none</td>
<td></td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>dark brown</td>
<td>100% cotton, black</td>
<td>100% cotton, black</td>
<td>none</td>
<td></td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>light brown</td>
<td>60/40 cotton/poly (shirt, green), 96/4 cotton/spandex (cami, white)</td>
<td>99/1 cotton/spandex, blue</td>
<td>none</td>
<td></td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>J</td>
<td>brown</td>
<td>100% cotton, blue</td>
<td>100% cotton, white</td>
<td>none</td>
<td></td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>K</td>
<td>Black</td>
<td>100% cotton, yellow, tan, green pattern</td>
<td>cotton?, blue</td>
<td>none</td>
<td>generic</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>L</td>
<td>Blond</td>
<td>100% cotton, brown</td>
<td>98% cotton, 2% spandex, blue</td>
<td>none</td>
<td></td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>Brown</td>
<td>100% cotton, blue and tan stripes</td>
<td>100% cotton</td>
<td>none</td>
<td></td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>Black</td>
<td>100% cotton, blue and green stripes</td>
<td>100% cotton, khaki</td>
<td>none</td>
<td></td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>O</td>
<td>Brown</td>
<td>100% cotton, red</td>
<td>100% cotton, gray</td>
<td>none</td>
<td></td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>P</td>
<td>Black</td>
<td>100% cotton, blue</td>
<td>100% cotton, white</td>
<td>none</td>
<td></td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Q</td>
<td>Brown</td>
<td>100% cotton, red</td>
<td>60/40 cotton/poly, light tan</td>
<td>Mary Kay</td>
<td></td>
<td>30</td>
<td>3</td>
</tr>
</tbody>
</table>
Table A.3: Continuation of the metadata for each subregion as provided by pedestrians in HYMNS-P dataset.

<table>
<thead>
<tr>
<th>Ped ID</th>
<th>Hair Color</th>
<th>Shirt</th>
<th>Trousers</th>
<th>Hat</th>
<th>Sunscreen Brand</th>
<th>SPF</th>
<th>Skin type</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
<td>Brown</td>
<td>100% cotton, blue</td>
<td>70/30 cotton/nylon, brown</td>
<td>Equate Sport</td>
<td>30</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>S</td>
<td>Brown</td>
<td>100% cotton, white</td>
<td>100% cotton, tan</td>
<td>none</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T</td>
<td>Black</td>
<td>100% cotton, orange</td>
<td>unknown, white</td>
<td>unknown</td>
<td>50</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>U</td>
<td>Black</td>
<td>94/6 cotton/bamboo, brown</td>
<td>100% cotton, white</td>
<td>none</td>
<td>none</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>V</td>
<td>Brown</td>
<td>100% cotton, white</td>
<td>blue jeans</td>
<td>none</td>
<td>none</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>W</td>
<td>Blond</td>
<td>100% cotton, blue</td>
<td>100% cotton, brown</td>
<td>100% cotton</td>
<td>none</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>X</td>
<td>Brown</td>
<td>60/40 cotton/poly, red</td>
<td>98/2 cotton/spandex, black</td>
<td>Coppertone</td>
<td>15</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Y</td>
<td>Blond</td>
<td>100% cotton, white</td>
<td>100% cotton, black and white checker</td>
<td>none</td>
<td>none</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Z</td>
<td>Black</td>
<td>100% cotton, black</td>
<td>100% polyester, brown</td>
<td>none</td>
<td>none</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>1A</td>
<td>Brown</td>
<td>50/50 cotton/poly, red</td>
<td>100% cotton, beige</td>
<td>100% polyester, red</td>
<td>Coppertone</td>
<td>30</td>
<td>3</td>
</tr>
<tr>
<td>1B</td>
<td>Brown</td>
<td>50/50 cotton/poly, black</td>
<td>Jeans (cotton ?), blue</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1Z</td>
<td>Brown</td>
<td>undershirt: 57% cotton, 38% poly, 5% spandex, shirt: 100% cotton</td>
<td>98% cotton, 2% spandex</td>
<td>sunx</td>
<td>30</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>PI</td>
<td>Brown</td>
<td>100% cotton, red</td>
<td>67/33 cotton/poly, green</td>
<td>none</td>
<td>generic</td>
<td>30</td>
<td>2</td>
</tr>
</tbody>
</table>
A.3 Characterization of HYMNS-P Bad Bands List

The HYMNS-P images were collected outdoors and all the images were captured during the morning, before noon. The sensor maintains a bad bands list which is typically associated with the water absorption bands around 1400 and 1900 nm. A band-by-band analysis of a single HYMNS-P image indicated that there was some additional bands with low signal as well as significant streaking due to sensor scan. The white panel on the left side of the frame seen in Figure A.3 was used as a flat-field to test the in-scene band-by-band SNR.

A.3.1 Selecting Pixels

To test the SNR, a selection of pixels were taken from the calibration panel as shown in Figure A.31 where the black box indicates selection area across all bands.

![Figure A.31: Illustrating the locations of sample pixels taken from the calibration panel.](image-url)
A.3.2 Calculating the SNR

There are several methods that can be used to visualize the band-by-band signal-to-noise ratio (SNR) [13]. The SNR was calculated such that

\[ SNR(\lambda) = \frac{\mu(\lambda)}{\sigma(\lambda)} \]

where \( \mu(\lambda) \) is the mean digital count and \( \sigma(\lambda) \) is the standard deviation of the digital counts for the sample pixels at each band. Figure A.32 shows the family of curves for the mean signal magnitude, standard deviation and SNR of each image in the HYMNS-P dataset. By inspection, there are clear regions of consistent low SNR which can be counted as bad bands.

A.3.3 Selecting Bad Bands

These regions are shown in Figure A.33 with the continuous regions of bad bands overlaid with gray bars. The bands and corresponding wavelengths indicated in Figure A.33 are tabulated in Table A.4. Note that it is apparent that there are several additional bands (sixteen to be exact) with a high standard deviation across the sample area in spectral region 1700 - 2200 nm and at 2347 nm. However, the magnitude of the standard deviation is not consistent across all the scanned images, so it was anticipated there may be bad pixels on the focal plane at those wavelengths.

A.3.4 Assessing Noisy/Bad Pixels

The HST-3 imager was designed such that it captures a dark field and a white field for a scan-to-scan calibration. This was accomplished by inserting a dark shutter in front of the focal plane and then pointing the focal plane toward an on-board integrating sphere. During post processing, this calibration information was used to come up with a scan-to-scan bad pixel map. An example of one of the bad pixel maps is shown in Figure A.34. The bad pixel map was then used in post processing to convert the captured imagery data from digital counts to calibrated radiance units. According to the processing training documentation, the data undergoes an interpolation step which accounts for the bad pixels within a scan as well as adjusts the data bands from the
HST-3 calibrated wavelengths to a standardized set of wavelengths for post-mission analysis. The interpolation performed was a nearest-neighbor interpolation [65].

The bad pixel maps for each captured image was reviewed for consistency across the HYMNS-P dataset. It was found that the bad pixels were different for each scan and there was not a single bad pixel that was consistently bad across all the images. Therefore, it is likely there were noisy pixels, but none that were bad or non-responsive. Additionally, since the data was interpolated from the captured digital counts at the calibrated wavelengths, it is difficult, if not impossible, to directly correlate the observed noisy bands in Figure A.33 with the scan-to-scan calibration data.

With this in mind, a careful assessment as to the several bands outside of known atmospheric
Figure A.33: Selected bad band regions overlaid with gray bars.

water absorption regions which showed anomalous variation in the standard deviation curve of Figure A.33 was conducted. The objective was to see if any of the noisy bands in the region 1700 - 2347 (outside of the grayed-out area) had significantly noisy pixels and should therefore be removed from consideration for feature extraction. The anomalous spikes only occurred in singular images and were not consistently bad across images.

To compare band pixel noise according to location, the standard deviation of the range of the pixel digital counts according to spectral band pixel location was graphed for the 16 bands in question. The sample area shown in Figure A.31 for all 64 images in the HYMNS-P dataset was extracted and the standard deviation in each pixel was calculated for each band. The results
Figure A.34: Bad pixel map from one scan of the HST-3 over the HYMNS-P scene. The black points represent bad pixels for a particular scan.

are shown in Figure A.35 where each graph represents the digital count magnitude versus pixel number. Note that the pixel number along the x-axis in Figure A.35 corresponds to the row where the pixel was located in Figure A.31 since the HST-3 was a whisk-broom type scanner. The four bands graphed along the first row of Figure A.35 were counted as good bands because they showed lower noise characteristics in Figure A.31. They were included in Figure A.35 as a reference for the other bands in question and illustrate a fairly consistent standard deviation across pixels. The remaining sixteen graphs plot the digital count magnitude versus pixel location of the suspect bands. The title of each graph shows the band number as well as the corresponding wavelength of that band. By inspection, there are a few pixels in the suspect bands which show a particularly high digital count standard deviation value for the few images. Given the ranges, it would explain the reason for the suspect SNR in those bands.

Further analysis could be done to identify suspect pixels and measure the statistical significance of suspect pixels using F- or t- tests to compare variances or means, respectively [66]. With that information, the detection process could take into account the likelihood of a target existing within one of the suspect pixels and attach a confidence to the detection probability. However, for the
Figure A.35: Distribution of sample pixel digital count magnitude versus pixel sample location for pixels outlined in flat-field sample area shown in Figure A.31. The four graphs across the top row were bands that did not exhibit the same random large standard deviation as the sixteen bands in question. The remaining sixteen bands are shown below with specific band numbers given as the title for each axis.

purposes of this research it was deemed unnecessary. This exercise simply illustrates that certain anticipated good bands for feature extraction may not be available depending on the condition of the imager used. Since one of the assumptions of this phenomenology study was that feature extraction could be accomplished at the time of image capture, we will add these 16 bands to the bad bands list and limit the feature analysis to the remaining 152 bands.
Table A.4: Table of final bad bands list and corresponding wavelength regions used for the HYMNS-P data. Bad bands selected based on inspection of Figure A.33 and the noisy pixel analysis.

<table>
<thead>
<tr>
<th>Band Number</th>
<th>Wavelength (nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - 3</td>
<td>449.3 - 472.1</td>
</tr>
<tr>
<td>39 - 47</td>
<td>899.3 - 964.1</td>
</tr>
<tr>
<td>67 - 70</td>
<td>1127.1 - 1151.7</td>
</tr>
<tr>
<td>94 - 113</td>
<td>1348.7 - 1503.6</td>
</tr>
<tr>
<td>135 - 138</td>
<td>1686.2 - 1711.0</td>
</tr>
<tr>
<td>145 - 167</td>
<td>1768.7 - 1950.4</td>
</tr>
<tr>
<td>170</td>
<td>1975.1</td>
</tr>
<tr>
<td>173</td>
<td>1991.7</td>
</tr>
<tr>
<td>189</td>
<td>2132.2</td>
</tr>
<tr>
<td>192</td>
<td>2156.8</td>
</tr>
<tr>
<td>195</td>
<td>2181.4</td>
</tr>
<tr>
<td>197</td>
<td>2197.7</td>
</tr>
<tr>
<td>223 - 227</td>
<td>2413.2 - 2446.3</td>
</tr>
</tbody>
</table>
Appendix B

Comparing Field Contact Probe to Diffuse Hemispherical Reflectance Measurements

B.1 Overview

As mentioned in Appendix A.2.3, a custom built contact probe was used for several spectral ground truth measurements. Due to the design of the probe, there was concern as to how close the measurements compared with a true diffuse hemispherical reflectance (DHR) measurement. This appendix reports on the comparison between material reflectance measurements collected using the contact probe and a Datacolor Spectraflash 600 instrument.

B.2 DHR Instrument

The Spectraflash 600 instrument by Datacolor is a bench top spectrophotometer for color reflectance measurements [67]. The instrument houses a six-inch integrating sphere with ports for the illumination source, sample, specular reflection, and measurement detector. The source is a
xenon flash lamp filtered to D65 illumination. The detectors measure 360 - 750 nm with a 5 or 10 nm spectral resolution, configurable in software. An example of the instrument with fabric sample over measurement port is shown in Figure B.1.

Figure B.1: Datacolor SpectraFlash 600 instrument with blue felt fabric sample ready for measurement.

**B.2.1 Method**

For this comparison study, four fabric samples were measured using both the custom contact probe and the Datacolor SpectraFlash 600 instrument. These samples were squares of red cotton broad cloth, yellow T-Shirt, red felt, and blue felt as shown in Figure B.2. The broad cloth and yellow T-shirt were made of 100% cotton and the felt samples were 100% poyester. They were chosen since they were samples of targets used in another data collection campaign and were extensively characterized as part of the ground truth effort [68].

The samples were measured using both the custom contact probe shown in Figure A.23 and on
the SpectraFlash 600 instrument as shown in Figure B.1. The fabric was transmissive so Spectralon was used as a backing material to improve contrast of spectral features of the materials. The SpectraFlash was configured to collect from 400 - 700 nm with a spectral resolution of 10 nm. It also sampled the spectrum in 10 nm increments. The ASD FieldSpec Pro FR was set to measure from 400 - 2500 nm in 1 nm increments with a set spectral resolution of 3 - 12 nm, where higher resolutions were realized in the visible spectrum. The spectra measured with the ASD was down sampled to a 10 nm increment interval and limited to the 400 - 700 nm region for comparison.

Figure B.2: Showing the fabric samples used for the DHR measurement comparison. Left to right they are red felt, red cotton broad cloth, blue felt, and yellow cotton t-shirt. The numbers from the samples were used for orientation identifiers from another study.

B.2.2 Comparison of Results and Discussion

The spectral comparison plots for each of the four materials are shown in Figure B.3. By inspection, it can be seen that the spectral curves for the red and blue felt as well as the red cotton have almost exactly the same curves. The red felt and red cotton have a maximum deviation of 3.5% at 700 nm. The yellow cotton did not overlay exactly and had a deviation ranging 1 - 4% along the curve. It should be noted that the ASD FieldSpecPro has a published repeatability of 5% for measurements, so it was determined that the yellow cotton measurements fell within the measurement error. Given these results, the spectral reflectance measurements from the custom contact probe were treated as sufficiently representing a DHR measurement.
Figure B.3: Spectral comparison plots for the ASD FieldSpec Pro versus SpectraFlash 600 reflectance measurements. The differences between the measurements were 4% or less for all curves.
Appendix C

Synthetic Scene Generation with MODTRAN and DIRSIG

C.1 Overview

The extensive ground truth that was collected during the HYMNS-P data collection campaign discussed in Appendix A was used to simulate a similar scene synthetically using DIRSIG. The synthetic scenes were necessary due to the limited duration of the outdoor HYMNS-P data collection campaign caused by weather and volunteer pedestrian availability. In the real-world data only a limited number of sun angles were realized for the pedestrians during the data collection. In order to overcome this limitation, a scene with similar physical geometry was created for use with the Digital Imaging and Remote Sensing Image Generation (DIRSIG) tool. DIRSIG is a first principles simulation tool for generating radiometrically correct synthetic imagery [53]. In order to ensure an accurate representation of the real-world scene, first the atmosphere was modeled using the Moderate Resolution Atmospheric Transmission (MODTRAN) tool [69] to ensure the appropriate settings were chosen. Then the scene was modeled in DIRSIG.
C.2 Modeling Atmosphere with MODTRAN

The first step in modeling the HYMNS-P scene was to determine the appropriate settings for modeling the atmosphere using the Moderate Resolution Atmospheric Transmission (MODTRAN) tool. MODTRAN is a radiative transfer modeling tool developed by the United States Air Force Research Laboratory [69] for calculating photometric absorption and scattering through the atmosphere. There are several parameters which can be set related to the atmospheric conditions with respect to temperature, environmental, and constituent particulate. Additionally the time of day, day of year, and target-sensor geometries are set. All of these settings are necessary to appropriately account for the path losses as the exoatmospheric irradiance passes through the atmosphere onto the target and then back up toward the sensor.

To assess the closeness of fit between the modeled atmosphere and the real-world data, samples of the sensor reaching radiance for pixels subtending a view of concrete and asphalt were used. Figure C.1 shows the approximate pixel locations that were used for this analysis. The corresponding reflectance curves for the asphalt and concrete samples, respectively, are shown in Figure C.2.

![Figure C.1: Scene 1, pose 1 from the HYMNS-P dataset with the approximate location of the pixels used for the radiance match analysis.](image)

The atmospheric settings used for the modeled HYMNS-P scene are outlined in Table C.1. There were additional parameters for other cards which could be used, but DIRSIG only takes
**APPENDIX C. SYNTHETIC SCENE GENERATION**

181

(a)

(b)

Figure C.2: Reflectance curves for (a) asphalt and (b) concrete. Note that more than one sample was captured for each material so an average was calculated which was used for subsequent radiance matching.

The HYMNS-P scene shown in Figure C.1 was modeled in DIRSIG using the ground truth reflectance measurements described in Appendix A. There were 17 unique individuals modeled using the subregion constituent material relative reflectance measurements collected during the HYMNS-
Table C.1: Final parameter setting for the MODTRAN generated simulated atmosphere of the HYMNS-P dataset. Note that other parameters not listed were set to default in MODTRAN. Abbreviations can be referenced in the MODTRAN4 User’s Manual [69].

<table>
<thead>
<tr>
<th>Card</th>
<th>Parameter</th>
<th>Setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>MODTRN</td>
<td>T</td>
</tr>
<tr>
<td>1</td>
<td>SPEED</td>
<td>S</td>
</tr>
<tr>
<td>1</td>
<td>MODEL</td>
<td>2 - Mid-Latitude Summer</td>
</tr>
<tr>
<td>1</td>
<td>ITYPE</td>
<td>2 - Slant path between two altitudes</td>
</tr>
<tr>
<td>1</td>
<td>IEMSCT</td>
<td>2 - Thermal &amp; Solar/Lunar Irradiance</td>
</tr>
<tr>
<td>1</td>
<td>IMULT</td>
<td>1 - Scattering at H1</td>
</tr>
<tr>
<td>1</td>
<td>M1-M6</td>
<td>0 - Standard pressures and temperatures for MODEL</td>
</tr>
<tr>
<td>1</td>
<td>MDEF</td>
<td>0 - Default to MODEL for minor species</td>
</tr>
<tr>
<td>1</td>
<td>SALB</td>
<td>1.00 - Perfect reflector</td>
</tr>
<tr>
<td>1A</td>
<td>DIS</td>
<td>t - True for DISORT</td>
</tr>
<tr>
<td>1A</td>
<td>DISAZM</td>
<td>F - no azimuth dependence</td>
</tr>
<tr>
<td>1A</td>
<td>NSTR</td>
<td>8</td>
</tr>
<tr>
<td>1A</td>
<td>LSUN</td>
<td>T</td>
</tr>
<tr>
<td>1A</td>
<td>LSUN</td>
<td>0</td>
</tr>
<tr>
<td>1A</td>
<td>CO2MX</td>
<td>360.0</td>
</tr>
<tr>
<td>2</td>
<td>APLUS</td>
<td>Blank - Not used</td>
</tr>
<tr>
<td>2</td>
<td>IHAZE</td>
<td>2 - Rural/5km vis</td>
</tr>
<tr>
<td>2</td>
<td>ISEASON</td>
<td>1 - Spring-Summer</td>
</tr>
<tr>
<td>2</td>
<td>IVULCN</td>
<td>0 - Background Stratospheric</td>
</tr>
<tr>
<td>2</td>
<td>ICSTL</td>
<td>0 - Open ocean</td>
</tr>
<tr>
<td>2</td>
<td>ICLD</td>
<td>0 - No clouds</td>
</tr>
<tr>
<td>2</td>
<td>GNDALT</td>
<td>0.228 km</td>
</tr>
</tbody>
</table>

P data collect. Each of these individuals maintained the respective subregion reflectance samples of their real-world counterparts so there was not any exchanging of subregion samples between modeled pedestrians.

Several images were generated for the times 0900, 1100, 1300, 1500, and 1700 hours local to the scene to get a varied sun angle. Scenes for those times, with pedestrians in a particular pose are shown in Figure C.4.

C.4 Adding Noise to DIRSIG Imagery

In order to utilize the synthetic imagery for subregion detection analysis, it was necessary to add appropriate noise to the DIRSIG imagery. This section outlines the steps that were taken to
evaluate three methods of adding noise to the DIRSIG imagery.

C.4.1 Approaches to Adding Noise

There are three possible approaches to adding noise. These include adding noise based on a flat Signal-to-Noise Ratio (SNR) to all bands, calculating the spectral SNR for each band of the sensor, or using the correlated noise calculated from a dark frame image to achieve the desired noise characteristics.

Adding Noise Based on Flat SNR

It is well documented that the SNR of an image can be computed from the mean divided by the standard deviation such that [13]

\[ SNR(\lambda) = \frac{\bar{x}(\lambda)}{\sigma_x(\lambda)} \]  

(C.1)

where \( \bar{x} \) is the mean spectral vector and \( \sigma_x \) is the standard deviation spectral vector of an image. The division in Equation C.1 is element by element so \( SNR \) is a vector with the same spectral dimension as \( x \). *Additive White Gaussian Noise* (AWGN) with a desired standard deviation can...
APPENDIX C. SYNTHETIC SCENE GENERATION

Figure C.4: Illustrating the synthetic scenes generated in DIRSIG for pedestrians when the sun is at different solar zenith angles for (a) 0900, (b) 1100, (c) 1300, (d) 1500, and (e) 1700 hours local time.

be added to each pixel in the \((i, j)^{th}\) location of an image such that

\[
\hat{x}_{i,j} = x_{i,j} + \sigma_x \mathcal{N}(\vec{0}, I) \tag{C.2}
\]

where \(\mathcal{N}(\vec{0}, I)\) is a vector of random samples from the Normal distribution with the same dimension as \(x\) and \(I\) is the identity matrix. Solving Equation C.1 for \(\sigma_x\) and substituting into Equation C.2 we have

\[
x_{i,j} = \hat{x}_{i,j} + \frac{\hat{x}_{i,j}}{SNR} \mathcal{N}(\vec{0}, I) \tag{C.3}
\]
where the discrete pixel spectral vector served as its own localized mean. If we assume a standard value for the SNR in Equation C.3, white noise will be added to every band of an image with a fixed noise characteristic.

Adding Band Specific Sensor Noise

Noting that there is detector to detector variability, the SNR may not be consistent among all the bands. In order to account for this, the SNR for a sensor can be calculated by capturing a dark frame image (shutter closed) and computing the variance among the samples. The detectors can also be pointed at a broad band illumination source for a white point image. Then using equation C.1, the spectral dependent SNR can be calculated. Now Equation C.3 will require an element by element divide of the SNR vector with the spectral pixel vector. This will yield an image with noise characteristics of the spectral detectors. However, the noise will be uncorrelated among the bands.

Adding Correlated Noise

A third alternative for adding noise accounts for the likelihood of noise correlation among the bands. In this case, instead of computing the spectral SNR, the noise covariance of the dark frame image is computed. It is then substituted for the $\sigma_x$ in Equation C.2 such that

$$\hat{x} = \bar{x} + (E^T \Lambda^{1/2})\mathbf{N}(\bar{0}, I)$$

(C.4)

where $E$ is the matrix of eigenvectors from the desired noise covariance matrix, and $\Lambda$ is the diagonal matrix of eigenvalues corresponding to the respective eigenvectors in $E$. The superscript $T$ denotes the transpose. This results in an image with correlated noise added among the bands. It should be pointed out that Peterson [70] used a modification of the Noise Adjusted Principal Components process to add noise, but that required a two step principal component transformation of the entire image. Equation C.4 achieves the same result which only requires the transformation of the noise covariance matrix.
C.4.2 Calculating Noise from Real-World Data

Calculating the noise statistics for the HYMNS-P data was performed using two different methods. First, the end of scan calibration frames for were used. Second, a dark frame was computed from the calibrated radiance imagery. The two steps were necessary since the raw imagery was in sensor digital counts and could be used to calculate the sensor SNR. However, the calibration file which maps the digital counts to calibrated radiance was not available, so the dark frame covariance had to be calculated from the calibrated radiance imagery using the difference image approach.

Calculating SNR using Raw Calibration Frames

The raw image data contains the calibration frames where the end of scan dark and white frames can be extracted. The dark frame is captured by closing the shutter and the white frame was captured by pointing the detector array at an on-board light source. An example raw image is shown in Figure C.5. The sensor was configured to scan the scene from right to left and capture the calibration frames at the end of the scan. The dark and white frames are on the right hand side and the image is reversed due to the sensor storing the data in the order it was captured. The image direction is corrected in post processing. Note that the HYMNS-P sensor is a push-broom system with a square focal plane array. There are 256 elements in the across track (vertical dimension of Figure C.5) and 256 elements in the spectral dimension [51].

Figure C.5: Raw false color image of the HYMNS-P scene as captured by the HST3 sensor [51]. The image is reversed due to the data storage scheme and the dark and white calibration frames are seen on the right hand side of the image.

Given there are 256 spatial samples, we were only interested in the SNR for one spatial detector since most systems are calibrated with one detector set as the reference standard [13]. As such,
the spectral detectors approximately in the middle of the focal plane (i.e., half way down the image in the vertical direction of Figure C.5) were sampled. Spectral plots of the samples for the dark and white frames are shown in Figure C.6. Notice there isn’t much variation among the spectral samples, however there are two noticeable detectors around 1920 and 2300 nm which were anomalous to their neighbors. The mean, standard deviation and resulting SNR for the White point signal is shown in Figure C.7.

Calculating Correlated Noise Using Difference Image Method

The process shown in Section C.4.2 was useful for computing the SNR among the bands of the HST3 sensor. However, in order to apply the noise covariance in Equation C.4 the radiance calibration file was needed so the covariance of the dark frames could be converted to the proper radiance units. We did not have access to the calibration file, so the noise was calculated using a difference image [13]. This procedure uses a homogeneous region of the scene where a constant reflectance is assumed. An example area is shown in Figure C.8 where a red box encompasses a region of asphalt. It was assumed that the asphalt was of constant reflectance. However, noting that the HST3 had variability among the detectors, only the asphalt pixels from the same detector were considered. These are denoted by the heavy black line across the middle of the red box. There were 95 unique samples collected. The difference between adjacent spatial samples was computed for each band. Then the covariance was calculated for this difference image. According to Schott [13], the noise covariance of the difference image is approximately $1/2\Sigma\Delta n$. The resulting covariance matrix, after applying the $1/2$ bias, was then applied to the DIRSIG Ped Scene spectral pixel vectors according to Equation C.4. It should be pointed out that the covariance matrix was not the best estimation since there were only 95 unique samples to estimate the covariance among the 227 unique spectral bands.
Figure C.6: Spectral plots for the (a) dark samples and the (b) white samples.
APPENDIX C. SYNTHETIC SCENE GENERATION

Figure C.7: Spectral plots for the (a) mean, (b) standard deviation, and the (c) resulting SNR of the signal from the white samples.

Figure C.8: Image of the calibrated radiance image from the HST3 for one of the HYMNS-P scenes. The red box denotes a region of homogeneous reflectance. The heavy black line in the red box denotes pixels captured using the same spatial detector set.
C.4.3 Comparing Resulting Imagery of Additive Noise Methods

One method for comparing the imagery after applying noise is to look at the spectral sample mean and the principal component dimensionality. The spectral mean and the resulting dimensionality for all the images are compared in Figure C.9. The sample mean appears to be consistent among all the DIRSIG images before and after noise is added, as expected. The difference between the real-world imagery and the DIRSIG synthetic imagery in the visible was due to a poor estimation of the atmospheric scattering for the day of the data collection as discussed in Section C.2. Inspecting the dimensionality in Figure C.9(b) indicates that there is little difference between applying a flat SNR for all bands versus calculating the sensor specific SNR per band. Also, it appears the added correlated noise causes the dimensionality of the synthetic image to follow a similar trend as the flat SNR approach. As such, a flat SNR was applied to the synthetic imagery based on the average HST3 sensor spectral SNR values.

Figure C.9: Spectral plots for the (a) spectral sample mean and the (b) principal component dimensionality.
Appendix D

BRDF Models of Pedestrian Subregions

D.1 Overview

One of the original aspects of this research was to look at the bidirectional reflectance characteristics of the pedestrian. Due to available resources and time constraints, that research was not able to be accomplished within this study. However, an extensive background study was conducted in pursuit of the pedestrian BRDF. Portions of that research is included here for completeness and to enable future research in this area.

D.2 General BRDF Model

Most surfaces contain a certain texture which causes them to neither be perfectly diffuse (reflecting light equally in all directions in the hemisphere above the surface) or perfectly specular (such as a mirror). As such, consider the geometry depicted in Figure D.1 illustrating the incident and reflected light of a non-descript medium with reflectance $\rho$. The angle $\theta_i$ is the angle between the vector from the incident irradiance and zenith. Likewise, the angle $\theta_r$ is the angle between...
the zenith vector and the reflected radiance vector toward the observation point. For convenience and simplicity of illustration, the plane of incidence is oriented along the x-axis. The angle $\phi_r$ is the azimuthal angle between the plane of reflection and the plane of incidence. The vector $\mathbf{n}'$ is the local surface normal of a roughened surface facet. The local surface facet can be defined in terms of the declination from the zenith and the projected angle of incidence or projected angle of reflectance, denoted as $\beta$.

![Figure D.1: Simplified model illustrating the geometry for the BRDF of a surface with reflectance, $\rho$.](image)

The reflectance can be defined as the ratio of the reflected radiance to the incident irradiance with respect to the reflected and incident geometry such that [13]

$$\rho(\theta_i, \phi_i; \theta_r, \phi_r | \lambda) = \frac{L(\theta_r, \phi_r | \lambda)}{E(\theta_i, \phi_i | \lambda)} [sr^{-1}]$$

(D.1)

where $L(\theta_r, \phi_r | \lambda)$ is the spectral reflected radiance per wavelength, $\lambda$, and $E(\theta_i, \phi_i | \lambda)$ is the incident spectral irradiance. Note that the angles have a range of $0 \leq \theta_i, \theta_r \leq \pi/2$ and $0 \leq \phi_i, \phi_r \leq 2\pi$. The normalized total sum of combinations for all reflectance angles in Equation D.1 is referred to as the bidirectional reflectance distribution function (BRDF).
Several models exist for the BRDF of different material types. The model illustrated in Figure D.1 was derived by Torrence and Sparrow using geometric optics for rough surfaces where the surface roughness is large compared to wavelength [71]. The Torrence and Sparrow model assumes the spectral reflectance is based on a linear combination of diffuse and specular components using the complex optical properties such that

$$\rho_{BRDF}(\theta_i, \phi_i; \theta_r, \phi_r| \lambda) = \frac{\rho_d(\lambda)}{\cos(\theta_i)} + \frac{\rho_s(\lambda)R(\beta, \eta(\lambda))G(\theta_{ip}, \theta_{rp})P(\theta_h, \alpha)}{4 \cos(\theta_i) \cos(\theta_r)}$$  \hspace{1cm} (D.2)

where $\rho_d$ is the hemispheric diffuse reflectance, $\rho_s$ is the specular reflectance, $R(\beta, \eta(\lambda))$ is the Fresnel reflectance factor, $\beta$ is the angle of incidence onto the microfacet, $\eta(\lambda)$ is the spectral complex index of refraction, $G(\theta_{ip}, \theta_{ip})$ is geometric attenuation factor due to shadowing and masking where $(\theta_{ip} \text{ and } \theta_{rp})$ are the projections of the incident and reflection angles on the microfacet plane, and $P(\theta_h, \alpha)$ is the probability of distribution for micro facet normals lying in the direction of the half-angle vector with $\alpha$ being the RMS of the standard deviation of slopes. The Fresnel reflectance factor for unpolarized light with the spectral dependence on the index of refraction implied is defined as [72]

$$R(\beta, \eta|\lambda) = \frac{1}{2} \left[ \frac{\eta_1 \cos(\beta) - \eta_2 \sqrt{1 - \left( \frac{\eta_1}{\eta_2} \sin(\beta) \right)^2}}{\eta_1 \cos(\beta) + \eta_2 \sqrt{1 - \left( \frac{\eta_1}{\eta_2} \sin(\beta) \right)^2}} + \frac{\eta_1 \sqrt{1 - \left( \frac{\eta_1}{\eta_2} \sin(\beta) \right)^2} \eta_2 \cos(\beta)}{\eta_1 \sqrt{1 - \left( \frac{\eta_1}{\eta_2} \sin(\beta) \right)^2} \eta_2 \cos(\beta)} \right],$$  \hspace{1cm} (D.3)

The angle of incidence $\beta$ onto the microfacet, microfacet declination angle $\theta_h$, and projected angles $(\theta_{ip} \text{ and } \theta_{rp})$ are related to the source and reflection angles, $\theta_i, \theta_r$, using spherical trigonometry such that [71]

$$\beta = \cos^{-1} \left[ \cos(\theta_i) \cos(\theta_r) + \sin(\theta_i) \sin(\theta_r) \cos(\phi_r) \right],$$  \hspace{1cm} (D.4)

$$\theta_h = \cos^{-1} \left[ \cos(\theta_i) \cos(\beta) + \sin(\theta_i) \sin(\beta) \cos(\beta_1) \right],$$  \hspace{1cm} (D.5)

$$\theta_{ip} = \tan^{-1} \left[ \cos(\beta_2) \tan(\theta_i) \right],$$  \hspace{1cm} (D.6)

$$\theta_{rp} = \theta_{ip} + 2\theta_h.$$  \hspace{1cm} (D.7)
where

\[ \beta_1 = \sin^{-1} \left[ \frac{\sin(\phi_r) \sin(\theta_r)}{\sin(2\beta)} \right], \quad (D.8) \]

\[ \beta_2 = \pi - \sin^{-1} \left[ \frac{\sin(\beta_1) \sin(\beta)}{\sin(\theta_h)} \right]. \quad (D.9) \]

Torrence and Sparrow used a Gaussian distribution for \( P(\theta_h, \alpha) \) in their model. The shadowing and masking term can also be modeled as a Gaussian or another suitable model which may or may not be based on the projected angles (\( \theta_{ip} \) and \( \theta_{ip} \)) which Torrence and Sparrow derived geometrically for certain cases. In a later paper, Cook and Torrence [73] discussed a shadowing and masking term for rougher surface texture. It should be noted that the diffuse term shown in Equation D.2 assumes all incident light gets reflected from the material. Therefore, to account for the possibility of transmission, the Fresnel transmission factor can be included in the diffuse term. The transmission factor can be denoted as \( T(\theta_i, \theta_h, \eta(\lambda)) = 1 - R(\theta_i, \theta_r, \eta(\lambda)) \) by way of conservation of energy and neglecting absorption [13]. Additionally, if we use the Lambertian approximation for a perfectly diffuse surface, and include the Fresnel transmission factor, Equation D.2 becomes

\[ \rho_{BRDF}(\theta_i, \phi_i; \theta_r, \phi_r | \lambda) = \frac{\rho_d}{\pi} T(\theta_i, \theta_h, \eta(\lambda)) + \frac{\rho_s R(\theta_h, \eta(\lambda)) G(\theta_{ip}, \theta_{rp}) P(\theta_h, \alpha)}{4 \cos(\theta_i) \cos(\theta_r)} \quad (D.10) \]

\section*{D.3 BRDF of Pedestrian}

In this research, we are concerned with the appearance of a pedestrian in hyperspectral imagery. As such, the BRDF effects to the pedestrian’s spectral signature for each of the materials unique to the subregions should be investigated. The BRDF models for the skin, fabric, and hair, which are derived from the basic form in Equation D.2, are presented here with their modifications due to material type. Unless otherwise noted, the geometry notation referenced is as depicted in Figure D.1.

\subsection*{D.3.1 Skin BRDF}

The BRDF of skin has been studied for several different applications [35, 52, 74]. Generally the research has focused on the visible spectrum for use in the computer graphics industry. However,
Koch [74] extended the skin BRDF model to include the short wave infrared spectrum. For that research, the skin BRDF model used was

\[ \rho_{\text{skin}}(\theta_i, \theta_r, \phi_r | \lambda) = (1 - \rho_{\text{Schlick}}(\rho_o(\lambda), \beta)) \frac{\rho_d(\lambda)}{\pi} + \frac{\rho_{\text{Schlick}}(\rho_o(\lambda), \beta) e^{-\frac{\tan^2(\theta(\theta_i, \theta_r, \phi_r))}{2ax^2(\lambda)}}}{8\pi a^2(\lambda) \cos^4(\theta(\theta_i, \theta_r, \phi_r)) \cos(\theta_i) \cos(\theta_r)} \]  

\( \text{(D.11)} \)

where symbol definitions are as defined in the Torrance-Sparrow BRDF model with the following additions. The specular reflectance and Fresnel reflectance coefficient for the air/skin interface was approximated using Schlick’s method [75] such that

\[ \rho_{\text{schlick}}(\rho_o(\lambda), \beta) = \rho_o + (1 - \rho_o)(1 - \cos(\beta))^5, \]  

\( \text{(D.12)} \)

\( \rho_o \) is calculated from Equation D.3 for normal incidence using the complex index of refraction for skin, \( \eta_{\text{skin}}(\lambda) \), and air, \( \eta_{\text{air}}(\lambda) \), such that

\[ \rho_o(\lambda) = \left( \frac{\eta_{\text{skin}}(\lambda) - \eta_{\text{air}}(\lambda)}{\eta_{\text{skin}}(\lambda) + \eta_{\text{air}}(\lambda)} \right)^2, \]  

\( \text{(D.13)} \)

and the surface slope, \( \theta(\theta_i, \theta_r, \phi_r) \) is

\[ \theta(\theta_i, \theta_r, \phi_r) = \cos^{-1} \left( \frac{\cos(\theta_i) + \cos(\theta_r)}{2 \cos(\beta)} \right). \]  

\( \text{(D.14)} \)

A few things to note about Equation D.11. First, Schlick’s approximation in Equation D.12 was originally developed to reduce computation time for the specular surface reflectance in graphical rendering programs. Koch showed how it was a close approximation for Fresnel calculated surface reflectance. Secondly, due to the generally smooth nature of skin, the scattering was treated as isotropic such that \( \alpha_x = \alpha_y = \alpha \). Finally, Koch empirically determined the index of refraction in Equation D.13 varied from 1.42 in the visible to 1.54 in the SWIR. His measurements of the index of refraction matched those reported by Bolin, et al., for the visible spectrum [76]. Both Koch and Bolin showed a downward trend of the index of refraction for the skin in the visible spectrum as wavelength increases from approximately 400 - 700 nm. Koch did not reference Bolin’s work.
though he may have been unaware. What is interesting though is that Koch found the index of refraction to increase again in the near infrared to 1.54 and then continued a downward trend as wavelength increased. For our purposes here, we simply point this finding out, but a detailed pursuit of the physical basis for this finding is beyond the scope of this work. It is left for future work in studying and characterizing the optical properties of skin in the near and short-wave infrared.

D.3.2 Fabric BRDF

Next we will discuss the BRDF model for fabric. Fabric is manufactured by one of two processes, either weaving fibers together or matting them as seen in felt. For convenience we will limit the discussion to woven fabrics. Figure D.2 illustrates a plain weave pattern and shows the warp (vertical strands) and weft (horizontal strands) yarns that make the fabric [77]. For ease of illustration, the strands in each direction are of different diameters, though they do not always have to be this way. Also note that the weft strands are characterized by their bends on each end while the warp does not change direction. The weft strands bind the warp strands together [78]. The plain weave is characterized by the warp strands alternating above and below each of the weft strands. Other types of weaves can be used for textiles such as a twill weave, satin weave, or more complex weaves. For simplicity, we will limit fabric BRDF characteristics to the plain weave.

Figure D.2: Illustration of the plain weave pattern with the warp and weft strands identified [77].
Several groups have looked at characterizing the BRDF of fabric for rendering in computer graphics [36, 79-83]. The approaches have included looking at the first surface and sub-surface scattering as well as fabric weave density and their impacts to the BRDF. While the several approaches offer different levels of fidelity for the scattering due to fabric texture, for our purposes here a more simplified Gaussian model of the geometric shadowing over the rough cloth surface will be used [84]. For this model, the probability of a microfacet being illuminated, independent of micro surface height and orientation, is defined as

\[ S(\theta_{i,r}) = \frac{1 - \frac{1}{2}\text{erfc}(\mu/\sqrt{2}\alpha)}{\Lambda(\mu) + 1} \]  

(D.15)

where \( \text{erfc}(\cdot) \) is the compliment of the error function, \( \theta_{i,r} \) is either the angle of incidence or reflection, \( \mu = \cot(\theta_{i,r}) \), \( \alpha \) is the RMS of the surface slope, and \( \Lambda(\mu) \) is defined as

\[ \Lambda(\mu) = \frac{1}{2} \left[ \left( \frac{2}{\pi} \right)^{1/2} \frac{\alpha}{\mu} e^{-\mu^2/2\alpha^2} - \text{erfc}(\mu/\sqrt{2}\alpha) \right] . \]  

(D.16)

Equation D.15 is defined for both the incident and observation (reflected) directions since an area that is illuminated may be obscured to the observer, or vice versa.

For the microfacet normals probability distribution, Adabala, et al., in [80], proposed the model as a linear combination of the fabric structure due to the warp and weft threads such that

\[ P(\theta_h, \alpha) = f_{\text{warp}} p_{\text{warp}}(\theta_h, \alpha) + f_{\text{weft}} p_{\text{weft}}(\theta_h, \alpha) \]  

(D.17)

where \( f_{\text{warp}} \) and \( f_{\text{weft}} \) are the fractional areas of the warp and weft threads exposed. The probability distributions, \( p_{\text{warp}}(\theta_h, \alpha) \) and \( p_{\text{weft}}(\theta_h, \alpha) \), were anisotropic Gaussian of the form

\[ p_{\text{warp,weft}}(\theta_h, \alpha) = \frac{1}{4\pi\alpha_x\alpha_y} \exp\left[ -\tan^2 \theta_h (\cos^2(\phi_h)/\alpha_x^2 + \sin^2(\phi_h)/\alpha_y^2) \right] \]  

(D.18)

where the RMS surface slope \( \alpha \) was the thread thickness used in the fabric weave. If we assume that the warp and weft threads are approximately equal in size and a plain weave pattern is used,
then Equation D.17 can be simplified to be

\[ P(\theta_h, \alpha) = \frac{1}{2} f_{\text{warp}}(\theta_h, \alpha) = \frac{f}{4\pi\alpha} \exp[-(\tan(\theta_h)/\alpha)^2]. \]  \hfill (D.19)

In Equation D.19, \( f \) is simply the cover factor, or fabric density per unit area [46].

Now we can substitute the approximations from equations D.15 and D.19 into Equation D.10 and the fabric BRDF becomes

\[ \rho_{\text{fabric}}(\theta_i, \phi_i; \theta_r, \phi_r) = \rho_d(\lambda) \frac{T(\theta_i, \theta_r, \eta(\lambda))}{\pi} + \frac{\rho_s(\lambda) S(\theta_i) S(\theta_r)}{8\pi\alpha^2 \cos(\theta_i) \cos(\theta_r)} \exp[-(\tan(\theta_h)/\alpha)^2] \hfill (D.20) \]

where the geometric shadowing, \( G(\theta_i, \theta_r) = S(\theta_i)S(\theta_r) \), accounts for the shadowing due to incident illumination orientation as well as the observation orientation.

### D.3.3 Hair BRDF

As with other materials, several scattering models exist to account for the appearance of hair in visible imagery [85]. While each model attempts to characterize different levels of fidelity for the structure and texture of hair, as well as artificial styling, most of the models are targeting high resolution graphical rendering of individual hair strands as well as hair fiber bundles. Within the scope of our research here, remote sensed imagery is typically a lower resolution and only the bulk reflectance is of primary concern. Additionally, the scattering due to unbounded hair (hair that is not restrained in some way) is better modeled as scattering from fibers rather than a contiguous or continuous surface. With this in mind, the simplified scattering model by Kajiya and Kay [86] is sufficient to assess the BRDF effects of scalp hair on the pedestrian as it captures the most obvious features, namely the linear highlight [26]. It should be pointed out that the hair being considered is hair on the scalp and as such it rests against skin which does in fact contribute to the appearance of hair depending on the thickness, length, and quantity. However, developing a full BRDF model with the underlayerment of skin is beyond the scope of this work.

Kajiya and Kay’s model was originally developed for graphically rendering fur, and includes
a diffuse and a specular component similar to Equation D.10. Due to the nature of hair, the geometry has some slight modifications over that shown in Figure D.1. The hair shaft is oriented along the zenith direction and is referred to as the tangential direction of the hair. The angle of incidence is measured from the tangential direction to the vector pointing at the source from a given point on the hair shaft. Thus the diffuse component is defined as

$$k_d = 2\rho_d r \sin(\theta_i)$$

(D.21)

where, \( r \) is the diameter of hair. The \( r \) dependence accounts for the observation that thicker hair tends to have a stronger highlight due to increased surface area. Note that \( \theta_i \) is only defined for \( 0 \leq \theta_i \leq \pi/2 \) which prevents the impossible case of a negative reflectance. However, this model does allow for the diffuse component to be non-Lambertian which is different from the previous models used for fabric and skin. Kajiya and Kay point out that a hair shaft, when viewed perpendicular to the tangential direction, will show the color of the hair while when approaching the tangential direction the hair looks optically darker.

The specular component does not maintain the distributions defined in Equation D.10 and rather is only dependent on the geometric orientations of the illuminant and observation directions. Kajiya and Kay noted a preferential conical orientation of the specular reflection where the cone is oriented with the opening away from the follicle. This is due to the cuticle scales on the surface of the hair. As such, the model relies on the viewpoint existing within the conical cone or beyond it. Kajiya and Kay derived the specular model with respect to the viewing vectors and it was later simplified in [85] to be

$$k_s = \rho_s \frac{\cos^p(\theta_r + \theta_i)}{\cos(\theta_i)}$$

(D.22)

where \( p \) is the Phong exponent for the highlight related to the apparent smoothness of the hair surface which is user defined. As the bulk of hair is more aligned with a given length, then the highlight is sharper while mussed hair tends to have less of a highlight. The rate of roll-off for the highlight is governed by the Phong exponent. Kajiya and Kay limited their hair scattering model derivation to the geometric setting of hair and they did not delve into the optical properties of hair.
For convenience, we will use the Schlick reflection approximation in Equation D.12 for the specular reflectance function. Marschner, et al. [26], proposed a complete, physically-based hair scattering model which accounts for the sub-surface scattering and complex highlighting observable with hair. However, that model maintains parameters which are beyond the scope of this particular study. Combining equations D.21 and D.22, the hair BRDF is defined as

\[
\rho_{\text{hair}}(\theta_i, \phi_i, \theta_r, \phi_r) = k_d + k_s
\]

\[
= 2\rho_d r \sin(\tilde{v}_i, \tilde{v}_l) + \rho_{\text{Schlick}} \frac{\cos^p(\theta_r + \theta_i)}{\cos(\theta_i)}.
\]

(D.23)

## D.4 Next Steps in Pedestrian Subregion BRDF Modeling

The foregoing subregion BRDF model descriptions were derived from extensive research in the computer vision and machine learning communities. As was stated in Chapter 1, most of this research has focused on the visible spectrum and studies were nominally limited to 400 - 700 nm. Some studies, such as the skin BRDF model proposed by Koch [74] did, in fact, seek to extend into the infrared portion of the spectrum, but even there only the groundwork for future work was established. It was determined that insufficient data existed to make scientific conclusions about the nature of the BRDF in each of the pedestrian subregions. This data was necessary for determining the factors of surface roughness, optical transmission, indices of refraction and scattering effects as wavelength increases to 2500 nm. As such, further development in this area is needed to further refine these models and prove, with robust certainty, the pedestrian subregion BRDF effects on detectability.
Appendix E

Subregion Probability of Error Results by Pedestrian

E.1 Overview

This chapter contains the several probability of error plots for the binary classification of each pedestrian as the POI. Each plot shows the subregion probability of error per pedestrian for the images and spectral ranges indicated. The results of these probability of error scores were averaged and tabulated in the sections indicated.

E.2 Source Data for Table 5.2

The plots below correspond with the results shown in Table 5.2.
APPENDIX E. SUBREGION PROBABILITY OF ERROR PER PEDESTRIAN

Figure E.1: Graphically showing the probability of error for each pedestrian according to subregion using the full spectral range. This was for the first HSI image shown in Figure 5.13.

Figure E.2: Graphically showing the probability of error for each pedestrian according to subregion using the 3-band visible spectrum. This was for the first HSI image shown in Figure 5.13.
Figure E.3: Graphically showing the probability of error for each pedestrian according to subregion using the 22-band visible spectrum. This was for the first HSI image shown in Figure 5.13.

Figure E.4: Graphically showing the probability of error for each pedestrian according to subregion using the 39-band VNIR spectrum. This was for the first HSI image shown in Figure 5.13.
Figure E.5: Graphically showing the probability of error for each pedestrian according to subregion using the 66-band SWIR1 spectrum. This was for the first HSI image shown in Figure 5.13.

Figure E.6: Graphically showing the probability of error for each pedestrian according to subregion using the 48-band SWIR2 spectrum. This was for the first HSI image shown in Figure 5.13.
E.3 Source Data for Table 5.3

The results below correspond with the results shown in Table 5.3.

Figure E.7: Graphically showing the probability of error for each pedestrian according to subregion using the full spectral range. This was for the second HSI image shown in Figure 5.14.
APPENDIX E. SUBREGION PROBABILITY OF ERROR PER PEDESTRIAN

Figure E.8: Graphically showing the probability of error for each pedestrian according to subregion using the 3-band visible spectrum. This was for the second HSI image shown in Figure 5.14.

Figure E.9: Graphically showing the probability of error for each pedestrian according to subregion using the 22-band visible spectrum. This was for the second HSI image shown in Figure 5.14.
Figure E.10: Graphically showing the probability of error for each pedestrian according to subregion using the 39-band VNIR spectrum. This was for the first HSI image shown in Figure 5.14.

Figure E.11: Graphically showing the probability of error for each pedestrian according to subregion using the 66-band SWIR1 spectrum. This was for the second HSI image shown in Figure 5.14.
Figure E.12: Graphically showing the probability of error for each pedestrian according to subregion using the 48-band SWIR2 spectrum. This was for the second HSI image shown in Figure 5.14.
E.4 Source Data for Table 5.4

The results below correspond with the results shown in Table 5.4.

Figure E.13: Graphically showing the probability of error for each pedestrian according to subregion using the full spectral range. This was for the GLHR HSI image 1 shown in Figure 5.15.
Figure E.14: Graphically showing the probability of error for each pedestrian according to subregion using the 3-band visible spectrum. This was for the GLHR HSI image 1 shown in Figure 5.15.

Figure E.15: Graphically showing the probability of error for each pedestrian according to subregion using the 22-band visible spectrum. This was for the GLHR HSI image 1 shown in Figure 5.15.
APPENDIX E. SUBREGION PROBABILITY OF ERROR PER PEDESTRIAN

Figure E.16: Graphically showing the probability of error for each pedestrian according to subregion using the 39-band VNIR spectrum. This was for the GLHR HSI image 1 shown in Figure 5.15.

Figure E.17: Graphically showing the probability of error for each pedestrian according to subregion using the 66-band SWIR1 spectrum. This was for the GLHR HSI image 1 shown in Figure 5.15.
Figure E.18: Graphically showing the probability of error for each pedestrian according to subregion using the 48-band SWIR2 spectrum. This was for the GLHR HSI image 1 shown in Figure 5.15.
E.5 Source Data for Table 5.5

The results below correspond with the results shown in Table 5.5.

Figure E.19: Graphically showing the probability of error for each pedestrian according to subregion using the full spectral range. This was for the GLHR HSI image 2 shown in Figure 5.16.
Figure E.20: Graphically showing the probability of error for each pedestrian according to subregion using the 3-band visible spectrum. This was for the GLHR HSI image 2 shown in Figure 5.16.

Figure E.21: Graphically showing the probability of error for each pedestrian according to subregion using the 22-band visible spectrum. This was for the GLHR HSI image 2 shown in Figure 5.16.
Figure E.22: Graphically showing the probability of error for each pedestrian according to subregion using the 39-band VNIR spectrum. This was for the GLHR HSI image 2 shown in Figure 5.16.

Figure E.23: Graphically showing the probability of error for each pedestrian according to subregion using the 66-band SWIR1 spectrum. This was for the GLHR HSI image 2 shown in Figure 5.16.
Figure E.24: Graphically showing the probability of error for each pedestrian according to subregion using the 48-band SWIR2 spectrum. This was for the GLHR HSI image 2 shown in Figure 5.16.
APPENDIX E. SUBREGION PROBABILITY OF ERROR PER PEDESTRIAN

E.6 Source Data for Table 5.6

The results below correspond with the results shown in Table 5.6.

Figure E.25: Graphically showing the probability of error for each pedestrian according to subregion using the full spectral range. This was for the GLHR HSI image 3 shown in Figure 5.17.
Figure E.26: Graphically showing the probability of error for each pedestrian according to subregion using the 3-band visible spectrum. This was for the GLHR HSI image 3 shown in Figure 5.17.

Figure E.27: Graphically showing the probability of error for each pedestrian according to subregion using the 22-band visible spectrum. This was for the GLHR HSI image 3 shown in Figure 5.17.
APPENDIX E. SUBREGION PROBABILITY OF ERROR PER PEDESTRIAN

Figure E.28: Graphically showing the probability of error for each pedestrian according to subregion using the 39-band VNIR spectrum. This was for the GLHR HSI image 3 shown in Figure 5.17.

Figure E.29: Graphically showing the probability of error for each pedestrian according to subregion using the 66-band SWIR1 spectrum. This was for the GLHR HSI image 3 shown in Figure 5.17.
Figure E.30: Graphically showing the probability of error for each pedestrian according to subregion using the 48-band SWIR2 spectrum. This was for the GLHR HSI image 3 shown in Figure 5.17.
E.7 Source Data for Table 5.8

The results below correspond with the results shown in Table 5.8.

Figure E.31: Graphically showing the probability of error for each pedestrian according to subregion using the full spectral range. This was for the HSI image shown in Figure 5.14 as the source.
Figure E.32: Graphically showing the probability of error for each pedestrian according to subregion using the 3-band visible spectrum. This was for the HSI image shown in Figure 5.14 as the source.

Figure E.33: Graphically showing the probability of error for each pedestrian according to subregion using the 22-band visible spectrum. This was for the HSI image shown in Figure 5.14 as the source.
APPENDIX E. SUBREGION PROBABILITY OF ERROR PER PEDESTRIAN

Figure E.34: Graphically showing the probability of error for each pedestrian according to subregion using the 39-band VNIR spectrum. This was for the HSI image shown in Figure 5.14 as the source.

Figure E.35: Graphically showing the probability of error for each pedestrian according to subregion using the 66-band SWIR1 spectrum. This was for the HSI image shown in Figure 5.14 as the source.
Figure E.36: Graphically showing the probability of error for each pedestrian according to subregion using the 48-band SWIR2 spectrum. This was for the HSI image shown in Figure 5.14 as the source.
E.8 Source Data for Table 5.9

The results below correspond with the results shown in Table 5.9.

Figure E.37: Graphically showing the probability of error for each pedestrian according to subregion using the full spectral range. This was for the HSI image shown in Figure 5.13 as the target image.
Figure E.38: Graphically showing the probability of error for each pedestrian according to subregion using the 3-band visible spectrum. This was for the HSI image shown in Figure 5.13 as the target image.
Figure E.39: Graphically showing the probability of error for each pedestrian according to subregion using the 22-band visible spectrum. This was for the HSI image shown in Figure 5.14 as the target image.
Figure E.40: Graphically showing the probability of error for each pedestrian according to subregion using the 39-band VNIR spectrum. This was for the HSI image shown in Figure 5.14 as the target image.
Figure E.41: Graphically showing the probability of error for each pedestrian according to subregion using the 66-band SWIR1 spectrum. This was for the HSI image shown in Figure 5.14 as the target image.
Figure E.42: Graphically showing the probability of error for each pedestrian according to subregion using the 48-band SWIR2 spectrum. This was for the HSI image shown in Figure 5.14 as the target image.
E.9 Source Data for Table 5.10

The results below correspond with the results shown in Table 5.10.

Figure E.43: Graphically showing the probability of error for each pedestrian according to subregion combination Hair-Skin. Each spectral range used is shown. This was for the first HSI image shown in Figure 5.13.
APPENDIX E. SUBREGION PROBABILITY OF ERROR PER PEDESTRIAN

Figure E.44: Graphically showing the probability of error for each pedestrian according to subregion combination Hair-Torso. Each spectral range used is shown. This was for the first HSI image shown in Figure 5.13.

Figure E.45: Graphically showing the probability of error for each pedestrian according to subregion combination Hair-Trousers. Each spectral range used is shown. This was for the first HSI image shown in Figure 5.13.
APPENDIX E. SUBREGION PROBABILITY OF ERROR PER PEDESTRIAN

Figure E.46: Graphically showing the probability of error for each pedestrian according to subregion combination Skin-Torso. Each spectral range used is shown. This was for the first HSI image shown in Figure 5.13.

Figure E.47: Graphically showing the probability of error for each pedestrian according to subregion combination Skin-Trousers. Each spectral range used is shown. This was for the first HSI image shown in Figure 5.13.
APPENDIX E. SUBREGION PROBABILITY OF ERROR PER PEDESTRIAN

Figure E.48: Graphically showing the probability of error for each pedestrian according to subregion combination Torso-Trousers. Each spectral range used is shown. This was for the first HSI image shown in Figure 5.13.

Figure E.49: Graphically showing the probability of error for each pedestrian according to subregion combination Hair-Skin-Torso. Each spectral range used is shown. This was for the first HSI image shown in Figure 5.13.
APPENDIX E. SUBREGION PROBABILITY OF ERROR PER PEDESTRIAN

Figure E.50: Graphically showing the probability of error for each pedestrian according to subregion combination Hair-Skin-Trousers. Each spectral range used is shown. This was for the first HSI image shown in Figure 5.13.

Figure E.51: Graphically showing the probability of error for each pedestrian according to subregion combination Hair-Torso-Trousers. Each spectral range used is shown. This was for the first HSI image shown in Figure 5.13.
Figure E.52: Graphically showing the probability of error for each pedestrian according to subregion combination Skin-Torso-Trousers. Each spectral range used is shown. This was for the first HSI image shown in Figure 5.13.

Figure E.53: Graphically showing the probability of error for each pedestrian according to subregion combination Hair-Skin-Torso-Trousers. Each spectral range used is shown. This was for the first HSI image shown in Figure 5.13.
E.10 Source Data for Table 5.11

The results below correspond with the results shown in Table 5.11.

Figure E.54: Graphically showing the probability of error for each pedestrian according to subregion combination Hair-Skin. Each spectral range used is shown. This was for the second HSI image shown in Figure 5.14.
Figure E.55: Graphically showing the probability of error for each pedestrian according to subregion combination Hair-Torso. Each spectral range used is shown. This was for the second HSI image shown in Figure 5.14.

Figure E.56: Graphically showing the probability of error for each pedestrian according to subregion combination Hair-Trousers. Each spectral range used is shown. This was for the second HSI image shown in Figure 5.14.
APPENDIX E. SUBREGION PROBABILITY OF ERROR PER PEDESTRIAN

Figure E.57: Graphically showing the probability of error for each pedestrian according to subregion combination Skin-Torso. Each spectral range used is shown. This was for the second HSI image shown in Figure 5.14.

Figure E.58: Graphically showing the probability of error for each pedestrian according to subregion combination Skin-Trousers. Each spectral range used is shown. This was for the second HSI image shown in Figure 5.14.
Figure E.59: Graphically showing the probability of error for each pedestrian according to subregion combination Torso-Trousers. Each spectral range used is shown. This was for the second HSI image shown in Figure 5.14.

Figure E.60: Graphically showing the probability of error for each pedestrian according to subregion combination Hair-Skin-Torso. Each spectral range used is shown. This was for the second HSI image shown in Figure 5.14.
Appendix E. Subregion Probability of Error Per Pedestrian

Figure E.61: Graphically showing the probability of error for each pedestrian according to subregion combination Hair-Skin-Trousers. Each spectral range used is shown. This was for the second HSI image shown in Figure 5.14.

Figure E.62: Graphically showing the probability of error for each pedestrian according to subregion combination Hair-Torso-Trousers. Each spectral range used is shown. This was for the second HSI image shown in Figure 5.14.
Figure E.63: Graphically showing the probability of error for each pedestrian according to subregion combination Skin-Torso-Trousers. Each spectral range used is shown. This was for the second HSI image shown in Figure 5.14.

Figure E.64: Graphically showing the probability of error for each pedestrian according to subregion combination Hair-Skin-Torso-Trousers. Each spectral range used is shown. This was for the first HSI image shown in Figure 5.14.
E.11 Source Data for Table 5.12

The results below correspond with the results shown in Table 5.12.

Figure E.65: Graphically showing the probability of error for each pedestrian according to subregion using the full spectral range. This was for the synthetic HSI image 1 with direct illumination shown in Figure 4.15(c).
Figure E.66: Graphically showing the probability of error for each pedestrian according to subregion using the 3-band visible spectrum. This was for the synthetic HSI image 1 with direct illumination shown in Figure 4.15(c).

Figure E.67: Graphically showing the probability of error for each pedestrian according to subregion using the 22-band visible spectrum. This was for the synthetic HSI image 1 with direct illumination shown in Figure 4.15(c).
Figure E.68: Graphically showing the probability of error for each pedestrian according to subregion using the 39-band VNIR spectrum. This was for the synthetic HSI image 1 with direct illumination shown in Figure 4.15(c).

Figure E.69: Graphically showing the probability of error for each pedestrian according to subregion using the 66-band SWIR1 spectrum. This was for the synthetic HSI image 1 with direct illumination shown in Figure 4.15(c).
Figure E.70: Graphically showing the probability of error for each pedestrian according to sub-region using the 48-band SWIR2 spectrum. This was for the synthetic HSI image 1 with direct illumination shown in Figure 4.15(c).
E.12 Source Data for Table 5.13

The results below correspond with the results shown in Table 5.13.

![Figure E.71: Graphically showing the probability of error for each pedestrian according to subregion using the full spectral range. This was for the synthetic HSI image 2 with partial illumination shown in Figure 4.15(b).](image-url)
APPENDIX E. SUBREGION PROBABILITY OF ERROR PER PEDESTRIAN

Figure E.72: Graphically showing the probability of error for each pedestrian according to subregion using the 3-band visible spectrum. This was for the synthetic HSI image 2 with partial illumination shown in Figure 4.15(b).

Figure E.73: Graphically showing the probability of error for each pedestrian according to subregion using the 22-band visible spectrum. This was for the synthetic HSI image 2 with partial illumination shown in Figure 4.15(b).
APPENDIX E. SUBREGION PROBABILITY OF ERROR PER PEDESTRIAN

Figure E.74: Graphically showing the probability of error for each pedestrian according to subregion using the 39-band VNIR spectrum. This was for the synthetic HSI image 2 with partial illumination shown in Figure 4.15(b).

Figure E.75: Graphically showing the probability of error for each pedestrian according to subregion using the 66-band SWIR1 spectrum. This was for the synthetic HSI image 2 with partial illumination shown in Figure 4.15(b).
Figure E.76: Graphically showing the probability of error for each pedestrian according to sub-region using the 48-band SWIR2 spectrum. This was for the synthetic HSI image 2 with partial illumination shown in Figure 4.15(b).
E.13 Source Data for Table 5.14

The results below correspond with the results shown in Table 5.14.

Figure E.77: Graphically showing the probability of error for each pedestrian according to subregion using the full spectral range. This was for the synthetic HSI image 3 with indirect illumination shown in Figure 4.15(a).
Figure E.78: Graphically showing the probability of error for each pedestrian according to subregion using the 3-band visible spectrum. This was for the synthetic HSI image 3 with indirect illumination shown in Figure 4.15(a).

Figure E.79: Graphically showing the probability of error for each pedestrian according to subregion using the 22-band visible spectrum. This was for the synthetic HSI image 3 with indirect illumination shown in Figure 4.15(a).
Figure E.80: Graphically showing the probability of error for each pedestrian according to sub-region using the 39-band VNIR spectrum. This was for the synthetic HSI image 3 with indirect illumination shown in Figure 4.15(a).

Figure E.81: Graphically showing the probability of error for each pedestrian according to sub-region using the 66-band SWIR1 spectrum. This was for the synthetic HSI image 3 with indirect illumination shown in Figure 4.15(a).
Figure E.82: Graphically showing the probability of error for each pedestrian according to subregion using the 48-band SWIR2 spectrum. This was for the synthetic HSI image 3 with indirect illumination shown in Figure 4.15(a).
Appendix F

Subregion Detection Results

F.1 Overview

This chapter contains several of the raw ROC curves used to assess the subregion detectability in HSI data. These curves were used to compute the AUC metrics tabulated in Section 5.6. They are included here for completeness.

F.2 Detectability with Full Spectral Range
Figure F.1: Showing the subregion detection ROC curves for pedestrian B from the scene shown in Figure 4.8 using the full spectral range. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.2: Showing the subregion detection ROC curves for pedestrian B from the scene shown in Figure 4.9 using the full spectral range. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.3: Showing the subregion detection ROC curves for POIs highlighted in Figure 4.10 using the full spectral range. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.4: Showing the subregion detection ROC curves for POI highlighted in Figure 4.11 using the full spectral range. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.5: Showing the subregion detection ROC curves for POI highlighted in Figure 4.12 using the full spectral range. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
F.3 Detectability in Tricolor Imagery

![Graphs showing subregion detection ROC curves for different subregions.](image)

Figure F.6: Showing the subregion detection ROC curves for POI highlighted in Figure 4.8 when only red, green, blue tri-color imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.7: Showing the subregion detection ROC curves for POI highlighted in Figure 4.9 when only red, green, blue tri-color imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.8: Showing the subregion detection ROC curves for POI highlighted in Figure 4.10 when only red, green, blue tri-color imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.9: Showing the subregion detection ROC curves for POI highlighted in Figure 4.11 when only red, green, blue tri-color imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.10: Showing the subregion detection ROC curves for POI highlighted in Figure 4.12 when only red, green, blue tri-color imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
F.4 Detectability in 22-Band Visible Imagery

Figure F.11: Showing the subregion detection ROC curves for POI highlighted in Figure 4.8 when 22-band visible spectrum imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.12: Showing the subregion detection ROC curves for POI highlighted in Figure 4.9 when 22-band visible spectrum imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.13: Showing the subregion detection ROC curves for POI highlighted in Figure 4.10 when only red, green, blue tri-color imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.14: Showing the subregion detection ROC curves for POI highlighted in Figure 4.11 when only red, green, blue tri-color imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.15: Showing the subregion detection ROC curves for POI highlighted in Figure 4.12 when only red, green, blue tri-color imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
F.5 Detectability in 39-Band VNIR Imagery

Figure F.16: Showing the subregion detection ROC curves for POI highlighted in Figure 4.8 when 39-band visible to near infra-red spectrum imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.17: Showing the subregion detection ROC curves for POI highlighted in Figure 4.9 when 39-band visible to near infra-red spectrum imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.18: Showing the subregion detection ROC curves for POI highlighted in Figure 4.10 when only red, green, blue tri-color imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
APPENDIX F. SUBREGION DETECTION ROC RESULTS

Figure F.19: Showing the subregion detection ROC curves for POI highlighted in Figure 4.11 when only red, green, blue tri-color imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.20: Showing the subregion detection ROC curves for POI highlighted in Figure 4.12 when only red, green, blue tri-color imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
F.6 Detectability in SWIR Imagery

Figure F.21: Showing the subregion detection ROC curves for POI highlighted in Figure 4.8 when 114-band short-wave infra-red spectrum imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.22: Showing the subregion detection ROC curves for POI highlighted in Figure 4.9 when 114-band short-wave infra-red spectrum imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.23: Showing the subregion detection ROC curves for POI highlighted in Figure 4.10 when only red, green, blue tri-color imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.24: Showing the subregion detection ROC curves for POI highlighted in Figure 4.11 when only red, green, blue tri-color imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.25: Showing the subregion detection ROC curves for POI highlighted in Figure 4.12 when only red, green, blue tri-color imagery is used. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
F.7 Detectability Under Differing Illumination Conditions

Figure F.26: Showing the subregion detection ROC curves for POI in DIRSIG imagery for indirect illumination. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.27: Showing the subregion detection ROC curves for POI in DIRSIG imagery for PD illumination. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.28: Showing the subregion detection ROC curves for POI in DIRSIG imagery for FD illumination. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.29: Showing the subregion detection ROC curves for POI in DIRSIG imagery using FD illumination spectral data to detect PD illuminated subregions. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Figure F.30: Showing the subregion detection ROC curves for POI in DIRSIG imagery using FD illumination spectral data to detect indirectly illuminated subregions. The graphs for individual subregions are (a) torso, (b) skin, (c) trousers, and (d) hair.
Bibliography


