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Target Detection Using Oblique Hyperspectral Imagery: A Domain Trade Study

by

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

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M.S. DEGREE THESIS

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Target Detection Using Oblique Hyperspectral Imagery: A Domain Trade Study

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Submitted to the
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Abstract

Hyperspectral imagery (HSI) has proven to be a useful tool when considering the task of target detection. Various processes have been developed that manipulate HSI data in different ways in order to render the data usable for target detection activities. A fundamental initial step in each of these processes is ensuring that the HSI data set obtained is in the same domain as the target’s spectral signature. In general, remotely sensed HSI is collected in terms of digital counts which are calibrated to units of radiance, whereas spectral target signatures are normally available in units of reflectance.

This work investigates target detection using simulated hyperspectral imagery captured from highly oblique angles. Specifically, this thesis seeks to determine which domain, radiance or reflectance, is more appropriate for the off-nadir case. An oblique atmospheric compensation technique based on the empirical line method (ELM) is presented and used to compensate the simulated data used in this study. The resulting reflectance cubes are subjected to a variety of standard target detection processes. A forward modeling technique that is appropriate for use on oblique hyperspectral data is
also presented. This forward modeling process allows for standard target detection techniques to be applied in the radiance domain.

Results obtained from the radiance and reflectance domains are comparable. Under ideal circumstances, however, the radiance domain results observed tend to be superior compared to results observed in the reflectance domain. These somewhat favorable results observed in the radiance domain, considered with the practicality and potential operational applicability of the forward modeling technique presented, suggest that the radiance domain is an attractive option for oblique hyperspectral target detection.
1. INTRODUCTION

In general, remotely sensed HSI is collected in terms of digital counts (DC) which are calibrated to units of radiance, whereas spectral target signatures are normally available in units of reflectance (Ientilucci, 2005). An essential preliminary step in any target detection process is ensuring that the domain in which the spectral imagery of the scene has been measured is the same as that of the spectral target signature of interest (Foster, 2007). Atmospheric compensation techniques seek to transform the measured scene radiance of an image to units of reflectance. Detection is then performed in the reflectance domain. Forward modeling seeks to predict the sensor-reaching radiance of the target as if it were present in the scene; detection is then performed in the radiance domain (Ientilucci, 2005).

Compensation and reflectance domain processing is the traditional way of processing HSI and performing target detection and is a fixture in the remote sensing community. It is popular since it attempts to arrange the hyperspectral data in terms of standard physical units (i.e., reflectance units). There are several proven methods of compensation that all attempt to assign estimated reflectance values to the hyperspectral data. These methods generally either predict the reflectance of the imaged scene based on ground truth measurements or atmospheric measurements taken at the time of data collection. In this thesis the ground truth based empirical line method (ELM) is used for compensation purposes.

Forward modeling, originally presented by Healey and Slater (1999), is advantageous since it seeks to account for various factors that are not constant in an imaged scene. For
example, target surfaces may be orientated in different positions and may be illuminated differently and atmospheric conditions can vary within a certain range.

This domain trade study seeks to determine which processing domain is more beneficial for target detection when dealing with HSI that has been collected from off-nadir viewing angles. Standard atmospheric compensation and forward modeling techniques have been developed based on the assumption that the sensor is approximately directly overhead of the scene at the time of image acquisition and do not necessarily account for additional challenges present in the oblique case. Additional challenges include longer and varying slant ranges across an oblique field of view (FOV). Geometrical challenges include changes in ground pixel size and expanded range of target surface orientations. The non-Lambertian properties of real materials pose an additional challenge since non-Lambertian effects are sometimes most noticeable at oblique angles.

A forward modeling technique that is applicable in the oblique case is presented here. This forward modeling process is an intuitive extension to Lentilucci’s Physics-Based Forward Modeling (PBFM) (Lentilucci, 2005). This intuitive extension to PBFM is an attractive option since it can seemingly be employed in both research and operational scenarios, and can address the additional challenges presented by the oblique case. A method to accurately compensate oblique HSI is also presented in this thesis. This technique, based on ELM, uses ground truth points to compensate oblique HSI. As with ELM it is not necessarily applicable in all operational settings, however it also addresses the challenges of the oblique case.
The oblique forward modeling process and oblique compensation technique are initial steps to radiance domain and reflectance domain detection processes respectively. Popular target detection processes are applied in each domain. Results from each domain are observed and compared in the form of receiver operator characteristic (ROC) curves and their associated average false alarm rates (AFAR) (Bajorski et al., 2004). By using an ELM-based compensation method and striving to achieve an ideal situation in the radiance domain a “best case scenario” in both domains is achieved, making the comparison between results from each domain meaningful.

This thesis also investigates how radiance domain results degrade under less than ideal circumstances. Also, this thesis investigates how results in the radiance domain change when local areas in an image are considered individually.

This study takes advantage of simulated oblique HSI rendered using the Digital Imaging and Remote Sensing Image Generation (DIRSIG) model (Schott et al., 1999). An empirical approach is taken. That is to say, results using a variety of standard detection processes are considered for multiple target types. This ensures that results are not limited to a specific set of circumstances, and conclusions can be made based on observations from several different scenarios.

To summarize, this thesis consists of a few steps that aim to determine which domain, reflectance or radiance, is more appropriate for processing oblique HSI. The first step is to define and obtain appropriate datasets that can be used. As mentioned in this case, datasets are created synthetically. The next step is to design and employ a compensation routine that is appropriate for oblique imagery. As mentioned a method based on ELM is developed in this thesis. In parallel an appropriate forward modeling technique is
designed and employed that is based on PBFM. Standard target detection algorithms can then be applied to the radiance and reflectance cubes. Detection results from each domain can then be compared using ROC curves and AFAR summary metrics. This high-level process is presented in Figure 1.0-1.

**Reflectance Domain**

![Diagram of Reflectance Domain Process]

**Radiance Domain**

![Diagram of Radiance Domain Process]

*Figure 1.0-1: High-level diagram of thesis work-flow.*
2. THEORY & APPLICATION

2.1 Remote Sensing Fundamentals and the Governing Equation

There are four main components to consider when dealing with hyperspectral remote sensing: the illuminating source, the atmospheric path, the imaged surface and the sensor as illustrated in Figure 2.1-1. The sun acts as the radiating source when considering passive remote sensing in the reflective region of the spectrum. It emits a level of electromagnetic energy at each wavelength which propagates through the atmosphere. At each wavelength the solar energy is transmitted, reflected and absorbed by the atmosphere at different rates. Every material absorbs, reflects and transmits the surface-reaching solar energy differently at each wavelength. The reflected energy from a material’s surface then travels through the atmosphere to a sensor where it can be measured. This second path through the atmosphere is known as the target-sensor or ground-sensor path. The sensor-measured radiance depends not only on the sensor-reaching radiance but also on the specific characteristics of the sensor itself. The material being imaged can therefore be identified if the effects of the sensor, atmosphere and illumination are taken into consideration and dealt with appropriately (Manolakis et al., 2003).

Figure 2.1-1: Components to consider in passive remote sensing in the reflective region.
The relationship between the illuminating source, atmosphere, and material being imaged in the visible region and near infrared portion of the spectrum can be accurately described by the remote sensing governing equation as presented by Schott (2007) as follows,

$$L_s(\lambda) = [E_s(\lambda)\tau_1(\lambda)\cos\theta \frac{r(\lambda)}{\pi} + FE_d(\lambda) \frac{r_d(\lambda)}{\pi} + (1 - F)L_{bavg}(\lambda) r_d(\lambda)]\tau_2(\lambda) + L_u(\lambda) + L_a(\lambda) \quad . \quad (2.2.1)$$

Here, $L_s(\lambda)$ is the sensor-reaching radiance, $E_s(\lambda)$ is the solar irradiance at the top of the atmosphere (the solar spectrum), $\theta$ is the solar declination angle, $\tau_1(\lambda)$ is the atmospheric transmission from the top of the atmosphere to the surface being imaged, $r(\lambda)$ is the target reflectance spectrum, $F$ is the shape factor or amount of exposed sky, $E_d(\lambda)$ is the downwelled irradiance from the sky dome, $r_d(\lambda)$ is the diffuse target reflectance, $L_{bavg}(\lambda)$ is the average reflected background radiance, $\tau_2(\lambda)$ is the atmospheric transmission from the ground-sensor path, $L_u(\lambda)$ is the atmospheric upwelled radiance scattered into the sensor’s line of sight by the atmosphere and $L_a(\lambda)$ is the radiance reflected from adjacent surroundings that is scattered by the atmosphere towards the sensor. For a fully exposed surface (i.e. $F=1$) this governing equation reduces to

$$L_s(\lambda) = [E_s(\lambda)\cos\theta \tau_1(\lambda) \frac{r(\lambda)}{\pi} + E_d(\lambda) \frac{r_d(\lambda)}{\pi}]\tau_2(\lambda) + L_u(\lambda) + L_a(\lambda) \quad . \quad (2.2.2)$$

This describes the sensor reaching radiance in terms of the direct, downwelled, upwelled and adjacent terms (Schott, 2007). The components of this model are illustrated in Figure 2.1.2. It should be noted that the upwelled term, $L_u(\lambda)$, and adjacent term, $L_a(\lambda)$, presented in these equations are sometimes combined into one path radiance term since both of these components are resulting from photons that are scattered towards the sensor from sources other than the target.
In summary Section 2.1 has introduced some fundamental concepts that are critical in the field of passive hyperspectral remote sensing. The basic concepts summarized here provide a base on which the ideas presented in this thesis are built.

### 2.2 The Oblique Case

Hyperspectral imaging systems flown on aircraft and satellites are presently used in a wide variety of remote sensing applications. Nadir viewing angles are used in the majority of these applications, and applicable processing techniques have been developed for these nadir viewing geometries (Adler-Golden et al., 2007).

The advantages and potential applications of oblique hyperspectral imaging are numerous. Off-nadir viewing provides for increased area coverage and reduced revisit times. It also allows for the remote sensing of areas where sensors are unavailable directly over the geographic area of interest (Adler-Golden et al., 2007). It is easy to imagine scenarios where aircraft are unable to access airspace directly over areas of interest, or when an area of interest is not located near the ground track of an orbiting satellite, making traditional nadir remote sensing impossible.

Despite the advantages and utility, relatively few publications exist that investigate off-nadir hyperspectral remote sensing. This is potentially in part due to the additional
factors requiring consideration for the oblique case. Data analysis and target detection in the off-nadir-case is more difficult for several reasons as described in the following sections.

2.2.1 Increased Ground-Sensor Path Distance

Perhaps the most notable additional radiometric challenge presented by an oblique collection angle is the increased ground-sensor or target-sensor path distance through the atmosphere. The associated increase in optical thickness of the atmosphere is responsible for a decrease in atmospheric transmission and increase in atmospheric attenuation (Leathers et al., 2006). The associated increase in scattered upwelled path radiance is responsible for increased atmospheric interference (Adler-Golden et al., 2007). These effects reduce the spectral contrast between materials in obliquely captured imagery (Suen et al., 2001).

Let us first consider these issues by considering the governing equation introduced in Section 2.1 presented here again for convenience

\[ L_1(\lambda) = \left[ E_1(\lambda) \cos \theta \tau_1(\lambda) \frac{r(\lambda)}{\pi} + E_0(\lambda) \frac{r_d(\lambda)}{\pi} \right] \tau_2(\lambda) + L_{\text{path}}(\lambda) \quad (2.2.1) \]

where \( L_{\text{path}} \) is the summation of \( L_{\text{u}} \) and \( L_{\text{a}} \) and can be considered the radiance that is scattered towards the sensor from objects other than the target. In the oblique case, the increased target-sensor path length directly affects two components in Eq. (2.2.1), \( \tau_2(\lambda) \) and \( L_{\text{path}}(\lambda) \).

Transmission can be defined using Lambert’s law as

\[ \tau = \frac{\Phi}{\Phi_0} = e^{-\beta_z \int_0^z dz} = e^{-\beta_z z} \quad (2.2.2) \]
where $\Phi$ is the flux observed at a given position, $z$ is the distance traveled through the atmosphere (from position 0 to position $z$), and $\beta_a$ is the absorption coefficient for the particular atmosphere (Schott, 2007). In the case of $\tau_2(\lambda)$, $z$ is the target-sensor path distance. It follows that for the oblique case where $z$ is increased, $\tau_2(\lambda)$ is decreased according to Eq. (2.2.2). As dictated by the governing equation, the decrease in $\tau_2(\lambda)$ diminishes the contribution of the direct and downwelled terms to the overall sensor reaching radiance.

The increased path distance diminishes the contribution of the ground-leaving terms since $\tau_2(\lambda)$ is decreased, but it is also responsible for increasing $L_{\text{path}}(\lambda)$. As mentioned $L_{\text{path}}(\lambda)$ can be defined as

$$L_{\text{path}}(\lambda) = L_u(\lambda) + L_a(\lambda) .$$

(2.2.3)

The governing equation for $L_u(\lambda)$, as described by Schott is

$$L_u(\lambda) = E_s(\lambda) \int \tau_1(\lambda) \tau_2(\lambda) \beta_{\text{sca}}(\lambda, \theta) dz ,$$

(2.2.4)

where $\beta_{\text{sca}}(\lambda, \theta)$ is the angular scattering function associated with the atmosphere. Schott (2007) notes that analysis of Eq. (2.2.4) shows that path radiance will monotonically increase with an increase in path length for any particular line of sight. However, the variation of $L_u(\lambda)$ with view angle is not as straightforward due to the nature of the angular scattering phase function which plays an important role in determining how upwelled radiance changes with view angle. Since $\beta_{\text{sca}}(\lambda, \theta)$ is unique for each atmosphere, we can only generalize that $L_u(\lambda)$ will usually increase at oblique view angles due to the associated increase in target-sensor path distance. That is to say, in general, path radiance will tend to increase as view angle becomes less nadir, though the minimum upwelled radiance will not necessarily occur at nadir (Schott, 2007).
Similarly, $L_\alpha(\lambda)$ tends to increase as target-sensor path length increases. Since the path length at oblique angles is longer there is a greater chance of adjacent photons from surrounding surfaces to be scattered into the path towards the sensor (Leathers et al., 2006).

Ientilucci et al., (2008) provide empirical data that demonstrates how sensor reaching radiance changes as a function of sensor view angle for a given target, background and atmosphere. Figure 2.2-1 illustrates the three different viewing geometries that were studied.

![Figure 2.2-1: Viewing geometries considered by Ientilucci et al. (2008).](image)

The atmosphere modeled using MODTRAN can be described by the input variables summarized in Table 2.2-1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerosol Model</td>
<td>Rural</td>
</tr>
<tr>
<td>Multiple Scattering</td>
<td>DISORT</td>
</tr>
<tr>
<td>Sensor Altitude</td>
<td>12,000 ft = 3.6 km</td>
</tr>
<tr>
<td>Latt / Long</td>
<td>Washington, DC, Latt=38.5, Long=-77.0</td>
</tr>
<tr>
<td>Elevation</td>
<td>262 ft = 0.08 km</td>
</tr>
<tr>
<td>Date</td>
<td>July 1, 2007</td>
</tr>
<tr>
<td>TOD</td>
<td>10am EST = 1500 GMT</td>
</tr>
<tr>
<td>Sun Location</td>
<td>ALT=57.9, AZ=109.7 deg</td>
</tr>
<tr>
<td>Wavelength Region</td>
<td>0.380 to 2.510 um</td>
</tr>
<tr>
<td>FWHM</td>
<td>0.010 um (213 data points)</td>
</tr>
</tbody>
</table>

Table 2.2-1: Atmospheric parameters defined by MODTRAN for this simulation.

Figure 2.2-2 shows the resulting radiance curves associated with each viewing geometry presented in Figure 2.2-1. The target reflectance was a flat 30% reflector for this
simulation. As slant range is varied, the associated change in $\tau_2(\lambda)$ and $L_{path}(\lambda)$ greatly effect the components of the governing equation that make up sensor reaching radiance. The total sensor reaching radiance is represented by the black curve (TOTAL_RAD) in the following figures. Sensor-reaching path radiance is represented by the blue curves (SOL_SCAT). Sensor reaching radiance attributed to the direct term is represented by the green curves (DRCT_RFLT) and the sensor-reaching ground leaving radiance (sensor-reaching reflected direct term plus the sensor reaching reflected downwelled term) is represented with the red curves (GRND_RFLT).

![Figure 2.2-2](image)

**Figure 2.2-2:** Sensor-reaching radiance curves observed for each viewing geometry considered by Ientilucci et al. (2008). Total sensor-reaching radiance is displayed along with individual contributing components.

As predicted by the theory presented in this section, Figure 2.2-2 confirms that as look angle moves away from nadir, the sensor-reaching path radiance term becomes more significant. Also, the ground reflected component becomes less significant as look angle moves away from nadir due to the decrease in $\tau_2(\lambda)$ caused by the increased path length. Ientilucci et al., (2008) show that the increase in path radiance and decrease in the sensor-reaching ground leaving component is apparent for various atmospheres and target reflectance values. Additional information from Ientilucci et al. is presented in Appendix A.

In a sense, as the path length is increased at oblique angles the contradicting effects on $\tau_2(\lambda)$ and $L_{path}(\lambda)$ play out against one another to determine the final value of $L_s(\lambda)$. An
observation that is made time and again when dealing with oblique versus nadir imagery is that the increase in $L_{\text{path}}(\lambda)$ at oblique angles is most apparent in the shorter “blue” and ultra-violet wavelengths near 0.4 microns, due to the high Rayleigh scattering associated with these shorter wavelengths (Schott, 2007). At longer wavelengths it becomes less of a factor. At these longer wavelengths in the short-wave infrared (SWIR) the decrease in target-sensor path transmission at oblique angles is therefore more apparent. Thus as viewing angle becomes more oblique, generally the result is higher sensor-reaching radiance in the shorter wavelengths, and lower sensor-reaching radiance in the longer wavelengths.

Ientilucci et al., (2008) also show qualitatively that the increase in $L_{\text{path}}(\lambda)$ as view angle becomes more oblique, is mainly due to the increase in $L_u(\lambda)$ as $L_a(\lambda)$ remains relatively constant. That is to say, $L_a(\lambda)$ increases as sensor view angle increases but not at the same rate as $L_u(\lambda)$. Figure 2.2-3 taken from Ientilucci et al. (2008) illustrates this phenomenon for a given atmosphere and a 15% albedo background. The Figure shows how the $L_u(\lambda)$ curves for both the nadir and oblique cases are relatively constant compared to the large increase in $L_u(\lambda)$ for the oblique case over the nadir case.

Figure 2.2-3: Upwelled, path and adjacent terms as a function of look angle. Adapted from Ientilucci et al. (2008)
This qualitative demonstration however, was only performed for one background type- an estimated surrounding background albedo of 15%. Since intuitively, $L_a(\lambda)$ should be greatly effected by the background albedo two additional MODTRAN simulations were performed.

The first simulation was similar to that performed by Ientilucci et al. (2008). A clearer atmosphere was used in the simulation and a 10% earth albedo was used in place of 15%. Results are presented in Figure 2.2-4. This control experiment yielded results that were qualitatively similar to those presented in Figure 2.2-3 in that $L_a(\lambda)$ remained relatively constant compared to $L_u(\lambda)$. Figure 2.2-4 shows that the clearer atmosphere yields lower values for all components and that the lower background earth albedo results in lower $L_a(\lambda)$ values.

A second situation was simulated where the background was set to grassland. The reflectance spectrum of the background is presented in Figure 2.2-5.
As one would expect, the spectral character of the background was manifested in $L_a(\lambda)$ and as an extension in $L_{path}(\lambda)$ in both the nadir and oblique simulations as shown in Figure 2.2-6.

![Figure 2.2-6](image)

**Figure 2.2-6:** Control experiment using same viewing geometry as used in Figure 2.2.4 with background albedo set to grassland spectrum vice 10%.

Qualitatively it appeared that, in the second simulation with a grassland background, $L_a(\lambda)$ became a bigger contributor to $L_{path}(\lambda)$ in the oblique case compared to the nadir case. When quantitative analysis was performed, it was shown that for both backgrounds $L_a(\lambda)$ was in fact more of a factor in $L_{path}(\lambda)$ in the nadir case than it was in the oblique case in terms of percent ratio. The contribution of $L_a(\lambda)$ to $L_{path}(\lambda)$ as a function of look angle was calculated in terms of a percent ratio as follows

$$P = \frac{L_a}{L_a + L_u} \times 100\% = \frac{L_a}{L_{path}} \times 100\% .$$

(2.2.5)

The results of this operation are presented in Figure 2.2-7. These results indicate that in terms of % ratio, $L_a(\lambda)$ contributes more to $L_{path}(\lambda)$ at nadir view angles compared to oblique angles. Another conclusion that can be drawn from Figure 2.2-7 is that $L_a(\lambda)$ associated with the Grassland contributes more than $L_a(\lambda)$ associated with the 10% reflector background. This is expected considering the spectral curve presented in Figure 2.2-5.
This study confirmed that $L_a(\lambda)$ indeed increases as viewing angle becomes more oblique. It also confirms what one would intuitively expect, that $L_a(\lambda)$ depends primarily on the reflectance value of the surrounding background. It also demonstrates that though the raw value of $L_a(\lambda)$ increases as viewing angle becomes more oblique, it does not increase as fast as $L_u(\lambda)$. That is to say, as $L_{path}(\lambda)$ increases due to sensor view angle the contribution from $L_a(\lambda)$ increases faster than the contribution of $L_u(\lambda)$. Therefore from the point of view of the composition of $L_{path}(\lambda)$, $L_a(\lambda)$ is less of a factor at oblique angles as it is at nadir.

In summary, this section has identified that increased path lengths are associated with oblique viewing angles. These increased path lengths decrease the contribution of the sensor-reaching ground leaving radiance due to a decrease in $\tau_2(\lambda)$, and increase the contribution of $L_{path}(\lambda)$ due to the additional scatterers present in the longer path length. It was also shown that the increase in $L_{path}(\lambda)$ is due more so to the increase in $L_u(\lambda)$ than the increase in $L_a(\lambda)$.
Despite these effects and the associated decreased contrast (Ientilucci et al., 2008), studies have shown (Suen et al., 2001; Leathers et al., 2006; Adler-Golden et al., 2007) that processing oblique HSI is possible.

### 2.2.2 Change in Ground-Sensor Path Distance

Related to the increased target-sensor path distance challenge is the fact that in a highly oblique situation the target-sensor path distance through the atmosphere can not be necessarily approximated as constant, as it is for nadir viewing angles. This notion is illustrated in Figure 2.2-8. This approximation becomes less valid the more oblique the view angle and the greater the field of view (FOV) of the sensor is.

**Figure 2.2-8: Nadir case and oblique case for a sensor with the same FOV.**

The examples illustrated in Figure 2.2-1 and Figure 2.2-2 can be used here for illustrative purposes. Imagine that the sensor used in the example had a view angle of 21 degrees below the horizontal and a FOV of 18 degrees. The extreme edges of the FOV would therefore correspond to 12 and 30 degree depression angles, viewing geometry (c) and viewing geometry (b) from Figure 2.2-1. This scenario is illustrated in Figure 2.2-9.
The radiance curves presented in Figure 2.2-2 (b) & (c) for depression angles of 12 and 30 degrees would represent the radiance curves associated with the edges of the FOV of the sensor. This example demonstrates that for the oblique case, the ground-sensor path distance can not be assumed constant as in the nadir case. The example demonstrates that two targets with exactly the same optical properties will produce different sensor reaching radiance curves depending on where they are captured in the sensor FOV. That is to say, when viewing the resulting imagery, materials with the same reflectance curves will appear different depending on where they are located in the image. Typical, atmospheric compensation techniques and forward modeling techniques designed for use on nadir imagery do not account for this varying target-sensor path distance and its effects. This issue will be addressed in future sections of this chapter.

2.2.3 Additional Considerations for the oblique case

Other factors, though not exclusive to the oblique case, are arguably more important in the off-nadir case. These factors include variation in illumination angle, bidirectional reflectance distribution function (BRDF), and spatial considerations.

Spatial effects include decreased spatial resolution caused by increased ground sample distances (Adler-Golden et al., 2007). This results in having less pixels per target due to the farther standoff range. Additionally, in the oblique case, varying
ground pixel sizes exist due to the varying slant-range distance across an FOV (Leathers et al., 2006). These spatial effects as well as aspect ratio can be assessed from the geometrical properties of the sensor, terrain and surface objects and do not necessarily cause problems when processing spectral data (Adler-Golden et al., 2007).

The non-uniformity of a material’s BRDF is not necessarily a problem unique to the oblique case. In the nadir case, however, the target/background materials are often illuminated and observed from an angle approximately normal to the material’s surface, whereas the non-uniformity of a material’s BRDF is often most apparent when it is illuminated and/or viewed from an oblique angle (Schott, 2007). This material dependant factor needs to be noted, and could make oblique HSI more difficult to process than its nadir counterpart. In the case of target detection, a potential solution to this problem is to obtain reflectance measurements of the target under study from a similar viewing geometry that is expected to be used at the time of data collection. That is to say, the BRDF issue could be avoided by measuring the reflectance of the target material from an oblique angle similar to that which will be used at the time of collection.

Another concern is the potential wide range of target illumination angles present in an oblique scene. In an oblique situation viewable target surfaces may include the “top” surface as well as the “side” surface, unlike in the nadir case where it is generally approximated that the viewable target surface is close to parallel to the ground plane. This range of illumination angles, represented by $\theta$ in the governing equation, will be addressed in the following sections of this chapter. Intuitively, this 3D target factor will
have specific tasking implications. The time of day and sensor position must be considered, as in the oblique case it is easy to imagine a scenario where the “side” surfaces of the target are completely in shadow, thus eliminating the direct term from the governing equation.

### 2.2.4 Oblique case summary

Section 2.2 provides information on special considerations that must be made for the oblique case. Considerations must be made for increased ground-sensor path length, which decrease transmission and increases path radiance. The range of path lengths across a given FOV need also be considered, along with a greater range of illumination angles, BRDF and additional spatial considerations. In the following sections methods are presented that address some of these additional challenges, along with results and analysis of these methods.

### 2.3 Forward Modeling

Forward modeling aims to predict the sensor measured radiance of a target pixel if it were present in the captured HSI. This concept is illustrated in Figure 2.3-3.

![Figure 2.3-1: Concept of radiance domain target detection.](image-url)
This requires modeling the propagation of the target reflectance spectrum through the atmosphere to the sensor (Healey and Slater, 1999). The forward modeling process used in this thesis is based on that developed by Ientilucci (2005). The physical model used in this process is based on the governing equation presented in Section 2.1 and can be expressed as

\[
L_p = \int \beta_p(\lambda) \left[ (E_s(\lambda) \tau_1(\lambda) \cos \theta + F E_d(\lambda)) \tau_2(\lambda) \frac{r(\lambda)}{\pi} + L_u(\lambda) \right] d\lambda , \quad (2.3.1)
\]

where \( L_p \) is the spectral radiance in the \( p \)th band, \( E_s(\lambda) \) is the exoatmospheric spectral irradiance from the sun, \( \tau_1(\lambda) \) is the transmission through the atmosphere along the sun-target path, \( \theta \) is the angle from the target surface normal to the sun, \( F \) is the fraction of the spectral downwelled irradiance from the sky \( (E_d(\lambda)) \) incident on the target (i.e., fraction of the sky not blocked by adjacent objects), \( \tau_2(\lambda) \) is the transmission through the atmosphere along the target-sensor path, \( r(\lambda) \) is the spectral reflectance of the target material, \( L_u(\lambda) \) is the spectral upwelled path radiance and \( \beta_p(\lambda) \) is the normalized spectral response of the \( p \)th spectral channel of the sensor used to collect the HSI under study (Ientilucci, 2005). Note that this version of the governing equation not only accounts for sensor reaching radiance by accounting for the direct, downwelled and upwelled radiance reaching the sensor, it also takes into account the sensor response.

The forward modeling process developed by Ientilucci (2005) takes advantage of the MODTRAN radiative transfer code (Berk et al., 1988). Given a set of atmospheric conditions and a target spectral reflectance curve, the MODTRAN radiative transfer code can be used to solve for the other terms in the governing equation including the associated target spectral radiance curve, \( x(\lambda) \), observed by a \( p \)-channel sensor which can be expressed as
In practice, the specific atmospheric conditions over a scene at the time of a collection are not precisely known. A range of atmospheric conditions, however, can be accurately estimated. This range of atmospheric conditions can be input into MODTRAN along with a target spectral reflectance curve. The resulting family of $\mathbf{x}(\lambda)$ vectors can be referred to as a *target space* (Ientilucci, 2005). Some MODTRAN inputs such as atmospheric model, aerosol model, day of year, time of day, and location (Berk et al., 2003) are known or can be accurately estimated at the time of data collection. Input parameters that are not precisely known are varied. The MODTRAN input parameters varied by Ientilucci (2005) are visibility, water vapor and elevation. Other components of the big equation that are not MODTRAN input parameters such as shape factor, $F$, as well as target illumination angle, $\theta$, can also be varied by altering MODTRAN outputs. Shape factor can be treated as a scalar ranging from 0 to 1 that modifies the downwelled term. The variation in target orientation takes into account the possible range of illumination of the target by the direct term by varying the angle of rotation, $\sigma_{\text{rot}}$.

\[
E_{s_{\text{new}}} (\lambda) = \frac{E_s (\lambda)}{\cos \theta} \cos (\theta - \sigma_{\text{rot}}) \quad \text{(Ientilucci, 2005).} \tag{2.3.3}
\]

To summarize, five parameters are varied in order to generate a target space. They are: visibility, water vapor, elevation, shape factor and illumination angle.

Once the target space is populated it must be characterized. Ientilucci (2005) shows that collapsing a target space into a single mean vector achieves better detection results than results achieved by characterizing the same target space using *endmembers* (Schott, 2007). This research, therefore, characterizes all target spaces by collapsing them into a
single mean vector. Once a target space is characterized by a single vector, standard detection schemes can be easily applied to the imagery under study.

In theory, an ideal target space would consist of every target spectral radiance vector actually present in the HSI under study and no additional vectors. Though an ideal target space is impractical to achieve in operational setting as it requires \textit{a priori} knowledge of the target’s position and orientation as well as precise knowledge of the atmosphere at the time of the collect, it can be achieved in research situations where this \textit{a priori} knowledge is available. As will become apparent in later sections, this thesis uses ideal target spaces as a “best-case scenario” standard that other results can be compared against. This thesis assumes that though achieving an ideal target space is improbable in an operational setting, achieving a target space that is characterized by a mean vector that is similar to that of an ideal target space is not as unlikely. If this assumption is valid, achieving results close to those achieved in the ideal case is not out of the question, as is shown in later chapters.

2.4 Oblique Extension to PBFM

The PBFM technique described in the previous section, lends itself nicely to the oblique case. The process is inherently capable of addressing the wide variety of target illumination angles in the oblique case. It is also able to take into account the BRDF of a target. Intuitively, instead of providing one target reflectance vector to the process a range of reflectance vectors corresponding to modeled or observed points from the target BRDF could be input into the process. In addition to varying the five original parameters, visibility, water vapor, elevation, shape factor and illumination angle, sensor view angle
can also be varied. By varying sensor view angle appropriately across the sensor FOV, the varying target-sensor path distance can be accounted for.

The example discussed in section 2.2.2 is evidence that this additional parameter should be varied in order to account for the varying slant ranges within an oblique scene. Additional examples are presented here using a smaller FOV and different target reflectance values. The simulated sensor viewing geometry is given in Figure 2.4.1.

These example situations were modeled using standard MODTRAN atmospheric parameters described in table 2.2-1. In each situation, the difference in slant range causes significant differences in sensor reaching radiance, that can be seen in Figures 2.4-2 to 2.4-4.

Figure 2.4-1: Sensor viewing geometry.

Figure 2.4-2: Reflectivity of target 100%.

Figure 2.4-3: Reflectivity of target 30%.
These simulations show how sensor reaching radiance, and its components, can vary across a FOV. Note that for a target with a high reflectivity the sensor-reaching radiance is diminished as the sensor view angle becomes more oblique. This is because the ground leaving component is more significant and the longer path length diminishes its contribution to total sensor reaching radiance. The opposite is true for targets with low reflectance values. Path radiance is a larger contributor in this case, and as the path length becomes longer this component is increased.

So far it has been reasoned and shown in example situations that a difference in sensor-reaching radiance values can be attributed to the varying slant ranges across a FOV for an oblique viewing geometry. Is this range in sensor-reaching radiance significant enough to warrant its inclusion in an oblique target space? To answer this, the work of Ientilucci (2005) is again considered. He shows that of the original MODTRAN atmospheric parameters that are varied, visibility is a significant contributor to any given target space. By changing the visibility input parameter the resulting target space vector is qualitatively significantly different. It stands to reason that if the change in sensor reaching radiance due to change in sensor view angle across a FOV is of the same order of magnitude caused by a realistic input range in visibility, the former should indeed be included in the generation of a target space. Figure 2.4-5 shows two target vectors resulting from two different visibilities.
Figure 2.4-5: Control experiments. Change in radiance caused by changing original variable, visibility (left). Change in radiance across a nadir FOV (right), note the curves are nearly identical and essentially plotted on top of each other. The target in these simulations was modeled as a 30% reflector.

This range of visibility is a good example of the extreme ranges of visibility used in creation of a target space. Note the difference in sensor-reaching radiance is of the same magnitude as the results from simulations presented in Figure 2.4-3.

We also ask ourselves the question, how does the change in sensor-reaching radiance vary with the same sensor with a nadir viewing geometry? This simulation is presented in Figure 2.4-5 as well. Here we show the difference between components of the sensor-reaching radiance is negligible at the two points where the difference between path difference is greatest at nadir, at one edge of the sensor’s FOV and at the center the FOV. This control experiment confirms our assumptions drawn from Figure 2.2-8.

To summarize, this section has proposed that the change in sensor-reaching radiance due to varying slant range across an oblique FOV can be accounted for by varying an additional parameter in the target space generation process. This idea was encouraged by confirming that the difference in sensor-reaching radiance across an FOV is much more significant in the oblique case then the nadir case, and the range of $L_s$ across an oblique FOV is of the same order of magnitude of that caused by varying an original parameter across a realistic range.
Traditionally, detection is performed in the reflectance domain. In order to perform target detection the reflectance, \( r(\lambda) \), for each pixel must be estimated from the observed sensor reaching radiance, \( L_s(\lambda) \), so that it can be compared to the known reflectance spectrum of a target. This concept is illustrated in Figure 2.5-1.

The empirical line method (ELM) is a traditional compensation method. It is widely used when possible due to its simplicity and accuracy in estimating \( r(\lambda) \) from \( L_s(\lambda) \). Studies show that ELM routinely outperforms other compensation methods (Grimm, 2005). Due to the superior performance of ELM it was chosen as the base atmospheric compensation method for this thesis. ELM can not be used in all situations since it relies on ground truth measurements, but for most research situations such as this thesis it is applicable.

ELM uses Lambertian ground truth points of known reflectance to atmospherically compensate an image. This approach requires approximating Schott’s governing equation as

\[
L_s(\lambda) = \left[ E_s(\lambda) \tau_1(\lambda) \cos \theta + E_d(\lambda) \right] \frac{r(\lambda)}{\pi} \tau_2(\lambda) + L_{path}(\lambda). \tag{2.5.1}
\]
Compensation of the scene can be accomplished due to the fact that a linear relationship between $r(\lambda)$ and $L_s(\lambda)$ can be approximated, where the slope, $m$, and intercept, $b$, of the linear relationship can be expressed as

$$m = \left[ E' \tau_1(\lambda) \cos \theta + E_d(\lambda) \right] \tau_2 \pi^{-1},$$

$$b = L_{\text{path}}(\lambda).$$

At least two ground truth points are used. Normally one point has a “high” reflectance value and the other has a “low” reflectance value. By knowing each of the reflectance values of the calibration points and corresponding sensor reaching radiance values $m$ and $b$ can be calculated and thus $r(\lambda)$ can be determined for each pixel by rearranging Eq. (2.5.1). This concept is illustrated in Figure 2.5-2.

![Figure 2.5-2: Illustration of ELM for two band case, assuming sensor is calibrated in radiance.](image)

One of the features of ELM is that the sensor used to collect the HSI under study does not need to be properly calibrated to units of radiance in order to estimate reflectance. Compensation can also be accomplished by using units of digital counts measured by the sensor. Note that with ELM the calibration points are assumed to be Lambertian. The atmosphere between the scene and the sensor is also assumed to be constant. That is to say, $L_u(\lambda)$, $\tau_2(\lambda)$, $\tau_1(\lambda)$ are assumed constant throughout the scene (Schott, 2007).
It should be noted that other atmospheric compensation methods exist (Schott, 2007). Other widely used techniques are based on radiative transfer models. These radiative transfer-based atmospheric compensation schemes include Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH), Atmospheric CORrection Now (ACORN), and the ATmospheric REMoval (ATREM) program (Kruse, 2004). Though these software packages are based on different variants of the governing equation presented in section 2.1, they use similar concepts. These techniques essentially seek to estimate reflectance from collected radiance data and atmospheric characteristics such as absorption bands. They do not require any ground truth from the scene. Radiative transfer codes such as MODTRAN (Berk, 2005) are used to predict reflectance based on the observed radiance and estimated atmospheric parameters (Kruse, 2004). For example, FLAASH uses the following variant of the governing equation

\[
L^* = \frac{A\rho}{1-\rho_s S} + \frac{B\rho_e}{1-\rho_e S} + L^*_a, \quad (2.5.4)
\]

Where \( L^* \) is the sensor reaching radiance, \( \rho \) is the pixel surface reflectance, \( \rho_e \) is an average surface reflectance for the surrounding region which is used to account for adjacency effects, \( S \) is the spherical albedo of the atmosphere which accounts for downwelled radiance, and \( L^*_a \) is upwelled radiance. \( A \) and \( B \) are surface independent coefficients that vary with atmospheric and geometric conditions. Each term in the model is implicitly wavelength dependant. MODTRAN is used to empirically determine \( L^*_a, S, A \) and \( B \) on a per pixel basis. FLAASH then solves for the \( \rho_e \) term by finding the average sensor reaching radiance (\( L^*_e \)) and using the same model as in equation (2.3.3) as follows
\[ L_e^* = \frac{(A + B)\rho \varsigma}{1 - \rho S} + L_a^* \] 

Reflectance, \( \rho \) is then solved for in equation (2.5.4) (Berk et al., 2002).

Radiative transfer-based atmospheric compensation schemes will not be used in this body of work in part due to the findings of Grimm (2005) and demonstrations in Ientilucci (2005) that show target detection schemes using ELM outperform processes using RT-based compensation techniques. Adler-Golden et al., (2007), however present their findings on using FLAASH to compensate off-nadir hyperspectral imagery.

2.6 Atmospherically Compensating Oblique HSI

As discussed, for the oblique case \( L_{\text{path}}(\lambda) \) and \( \tau_2(\lambda) \) vary as a function of sensor viewing angle. Specifically, as sensor view angle becomes increasingly oblique (slant range increases), \( L_{\text{path}}(\lambda) \) increases and \( \tau_2(\lambda) \) decreases monotonically (Schott, 2007). Suffice to say, \( L_{\text{path}}(\lambda) \) and \( \tau_2(\lambda) \) can not be assumed to remain constant across an oblique FOV. A linear relationship, however, can be approximated between pixel image position and \( L_s(\lambda) \), giving rise to the prospect of compensating oblique HSI using ELM without requiring calibration points on each line of the image.

2.6.1 Image Location and Sensor-Reaching Radiance- MODTRAN Example

The approximated linear relationship between \( L_s(\lambda) \) and image position can be observed empirically. This relationship is demonstrated here using MODTRAN simulations. An example MODTRAN simulation is presented in Figure 2.6-1. For the example shown here, standard atmospheric parameters were set in MODTRAN and are summarized in Table 2.2-1, the sensor height was set to 1.36 km above the target. Five increments of sensor view angle were used. The five depression angles used simulated varying view angles across an oblique FOV ranging from about 8 degrees below the
horizontal to about 12.5 degrees below the horizontal. The resulting five radiance curves are labeled in Figure 2.6-1. Presented in this familiar radiance versus wavelength format, Figure 2.6-1 illustrates another example, further to those in Section 2.4, of how sensor-reaching radiance changes across an oblique FOV.

Figure 2.6.1: Varying sensor-reaching radiance for different sensor view angles for the same target. Sensor view angle is given in degrees below the horizontal (depression angle).

This example however is expanded to demonstrate the linear relationship between sensor reaching-radiance and image location. Figure 2.6-2 contains the same radiance curves plotted in three dimensions. The additional third dimension is image location measured in line number. The three-dimensional nature of the plot is illustrated in Figure 2.6-2(a). Figure 2.6-2(b) is the same plot rotated such that radiance is plotted as a function of image location for a few example wavelengths. Figure 2.6-2(b) illustrates the linear relationship between image location and sensor reaching radiance at seven example wavelengths, 0.41, 0.67, 0.75, 0.78, 0.86, 1.00 and 1.24 microns. This example demonstrates that as the viewing angle becomes less nadir and the target sensor path
length increases, measured radiance at 0.41 um increases whereas radiance at the longer wavelengths decreases linearly as a function of image position. This is because path radiance increases with path length at these wavelengths more than transmission decreases with path length. This is due to larger Rayleigh scattering effects causing increased path radiance at the shorter “blue” wavelengths.

Figure 2.6.2: (a) Same data as Figure 2.6.1 plotted in 3d, the third dimension is the corresponding location of the target in a radiance image. (b) Same data as (a) rotated such that it demonstrates the qualitative linear relationship between sensor-reaching radiance and image location.

It should be noted that in the empirical observations made using MODTRAN simulations, the linear relationship in question seems most valid in somewhat clear atmospheres with visibilities near 23 km. As will be shown in future studies, as the visibility of the atmosphere is decreased the linear relationship between image location and $L_s(\lambda)$ becomes less valid. Its validity also depends on other factors including the depression angle (Leathers et al., 2007) of the sensor and reflectance curve of the target. However, due to the monotonically varying nature of the relationship between sensor-reaching radiance and image location, the relationship can always be accurately described using a piece-wise linear relationship.
2.6.2 Image Location and Sensor-Reaching Radiance- DIRSIG Example

The linear relationship demonstrated in Figure 2.6-2 can also be demonstrated using DIRSIG. An example is presented here. For this example a simple scene was created in DIRSIG. Three reflectance panels were placed in the scene that ran the length of the scene. These three panels in the scene were simulated Lambertian reflectors with spectrally “flat” reflectance curves. That is to say they have reflectances of 5%, 30% and 50%. The parameters in Table 2.6-1 were used in order to simulate the atmosphere in the scene. It should be noted that for this simple scene a background reflectance was not set.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerosol Model</td>
<td>Rural</td>
</tr>
<tr>
<td>Multiple Scattering</td>
<td>DISORT</td>
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<td>Sensor Altitude</td>
<td>11,811 ft = 3.6 km</td>
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<td>Latt / Long</td>
<td>Latt=38.5, Long=-77.0</td>
</tr>
<tr>
<td>Elevation</td>
<td>262 ft = 0.08 km</td>
</tr>
<tr>
<td>Date</td>
<td>July 1, 2007</td>
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<tr>
<td>DOY</td>
<td>182</td>
</tr>
<tr>
<td>TOD</td>
<td>10am EST = 1500 GMT</td>
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<tr>
<td>Sun Location</td>
<td>ALT=57.9, AZ=109.7 deg</td>
</tr>
<tr>
<td>Wavelength Region</td>
<td>0.380 to 2.510 um</td>
</tr>
<tr>
<td>FWHM</td>
<td>0.010 um</td>
</tr>
</tbody>
</table>

Table 2.6-1: Atmospheric parameters.

An image of the scene was rendered from an oblique look angle with the approximate geometrical setup as seen in Figure 2.6-3. The resulting “true color image” of the simple scene as displayed using ENVI can be viewed in Figure 2.6-4.
Note that the field of view (FOV) in this case works out to be 0.69 degrees which corresponds to just over 1km on the ground. Note that the photons traveling from the far edge of the scene travel about 987m farther than the photons from the close edge of the scene.

Section 2.2.2 has established that as the look angle down from the horizontal increases the path distance will become shorter. The shorter the path length, the higher the transmission and the lower the path radiance associated with that path. In other words, the more oblique the look angle the longer the path length which will mean a lower transmission and higher path radiance. This example provides insight into how transmission and path radiance change with image position. Figure 2.6-5 shows how
average $\tau_2$ and average $L_{path}$ vary as a function of image position for the image presented in Figure 2.6-4. These examples give the first indication that a linear relationship between image position and sensor-reaching radiance can be approximated.

![Graph of Transmission and Image Location](image1)

**Figure 2.6-5:** Transmission and upwelled radiance associated with simple scene. Note that for this example line 0 is the line at the bottom of the image in Figure 2.6-4.

The next step was to observe how $L_s$ varied along each of the panels in the image. An example observation is presented in Figure 2.6-6 for 0.41 um.

![Graph of Image Location and Radiance](image2)

**Figure 2.6-6:** Changing radiance values across 30% reflector panel as a function of image position. Note that for this example line 0 is the line at the bottom of the image in Figure 2.6-4.

Similar observations were made for each wavelength and each reflector panel strip. Linear relationships were fit to the data and in almost every case the associated observed $R^2$ value was above 0.9996. More details about these observations are provided in Appendix A.
In summary, the example simulations performed using MODTRAN and DIRSIG indicate that a linear relationship between $L_s$ and image position relative to the sensor ground-track can be approximated.

### 2.6.3 Compensation Technique

This approximated linear relationship allows for the following method of compensation. At least four ground truth points are required for this approach. Two Lambertian panels of relatively high reflectance and two Lambertian panels of relatively low reflectance are required within the scene under study, as per Figure 2.6-7(b). For illustrative purposes, assume that the highly reflective panels ($r_{HF}$ and $r_{HN}$) have the same reflectance curves. Also assume for this scenario that the low reflective panels ($r_{LF}$ and $r_{LN}$) have identical reflective curves. Note that the subscripts $H/L$ stand for “high”/“low”, and $F/N$ stand for “far”/“near”. The resulting corresponding sensor radiance values, $L_{HF}$, $L_{HN}$, $L_{LF}$ and $L_{LN}$ are then observed for each band. Now the sensor reaching radiance of the fictional interpolated calibration panels, $L_{H-Int}$ and $L_{L-Int}$, can be estimated for each line in the image based on the linear interpolation between the two measured points as shown in the Figure 2.6-8(a). This essentially allows for ELM to be performed line by line in the image (see Figure 2.6-9(b)) as if there were calibration points present on each line in the image. This process is repeated for each spectral band.
Figure 2.6-7: (a) Collection of oblique HSI with calibration points. (b) Resulting HSI contains 4 calibration points \( r_{HF}, r_{HN}, r_{LF} \) and \( r_{LN} \).

Figure 2.6-8: (a) Calibration points for each line are interpolated. (b) Using the interpolated calibration points, ELM can be performed line-by-line.

It should be noted that in practice, the two low reflective panels \( (r_{LF} \) and \( r_{LN} \)) need not have the same reflectance values, nor do the highly reflective panels \( (r_{HF} \) and \( r_{HN} \)). In such a scenario, it is easy to imagine how traditional ELM could be used on the far or near calibration line in order to rectify the situation. Once ELM has been performed on the far or near calibration line, the oblique ELM (OELM) method could be performed as described in the previous paragraphs.
2.6.4 Oblique Compensation Summary

In this section, examples that demonstrate the approximately linear relationship between image location and sensor-reaching radiance were presented. A compensation method based on ELM that exploits this relationship was also presented. Once the imagery is compensated it can be exposed to traditional detection algorithms that are outlined in the following section.

2.7 Target Detection

In this section three standard target detection algorithms are presented. They are applicable in both the radiance and reflectance domains.

2.7.1 Orthogonal Subspace Projection

Orthogonal subspace projection (OSP) (Harsanyi and Chang, 1994) is a target detection algorithm that uses a geometrical perspective. It can be used to detect targets at the subpixel level. It uses a linear mixing model to describe the spectral vector associated with each pixel in the scene. A given pixel is modeled as

\[ x = ta + Ba + \varepsilon, \]  

(2.7.1)

where \( x \) is the spectral vector characterizing the pixel, \( t \) is the spectral vector associated with the target, \( a \) is the unknown fractional abundance of the target within the pixel, \( B \) is a matrix made up of basis vectors which characterize the scene end members, \( a \) is the unknown fractional abundance of each basis vector, and \( \varepsilon \) is the residual error associated with this model (Schott, 2007). It follows that an appropriate hypothesis test for target detection using this model is (Pan & Healy, 2001)

\[ H_0 : x = B\alpha + \varepsilon \]

(2.7.2)
OSP seeks to suppress the contribution of the end members, and after background suppression a matched filter is applied to determine if anything resembling the target’s spectral characteristic is present in the pixel. The final normalized OSP relation is

$$T_{osp}(x) = \frac{t^T P_{\bar{B}} x}{t^T P_{\bar{B}} t}$$

(2.7.3)

where

$$P_{\bar{B}} = I - B(B^T B)^{-1} B^T$$

(2.7.4)

is the orthogonal background projection operator, and I is the identity matrix (Schott, 2007). Essentially the OSP operator projects each pixel into a space orthogonal to the background of the scene (Grimm, 2005). Note that Manolakis et al., (2001) show that the OSP operator in its normalized form is equal to a in equation (2.7.1), the fractional abundance of the target within the pixel. Therefore a high output from equation (2.7.3) corresponds to a high abundance for that pixel, pointing to the alternative $H_1$ in equation (2.7.2) (Schott., 2007).

### 2.7.2 Spectral Angle Mapper

Another widely used target detection algorithm is known as *Spectral Angle Mapper* (SAM). Like OSP, SAM is an algorithm that views hyperspectral data in a geometric or structured sense. The hyperspectral data is contained in an n-dimensional space, where n is the number of bands used to measure the data. Therefore, each pixel is represented as an n-dimensional vector in the space. Consider a pixel represented by a vector $x$ and a known target represented by a vector $t$, the spectral angle, $\theta$, between the two vectors
can be determined. By definition the dot product of \( \mathbf{x} \) and the unit vector in the \( \mathbf{t} \) direction is

\[
\mathbf{x} \cdot \mathbf{t}_u = \mathbf{x}^T \mathbf{t}_u = \mathbf{x}^T \left[ \frac{\mathbf{t}}{\| \mathbf{t} \|} \right] = \| \mathbf{x} \| \cos \theta
\]  \hspace{1cm} (2.7.9)

rearranging equation (2.5.9), the spectral angle can be calculated as:

\[
\theta = \cos^{-1} \left[ \frac{\mathbf{x}^T}{\| \mathbf{x} \|} \left[ \frac{\mathbf{t}}{\| \mathbf{t} \|} \right] \right] = \cos^{-1} \left[ \mathbf{x}_u \cdot \mathbf{t}_u \right].
\]  \hspace{1cm} (2.7.10)

The SAM algorithm, therefore, only considers the directions of the vectors \( \mathbf{x} \) and \( \mathbf{t} \) and not the magnitude. That is to say, the SAM algorithm only takes into account the difference in spectral “color” of the pixel and the target and not the brightness. This allows for SAM to be somewhat independent of illumination effects. In some situations it is appropriate to designate a threshold in terms of spectral angles. Pixels with spectral angles below the threshold can be classified as target pixels (Schott, 2007).

### 2.7.3 Spectral Matched Filter

One of the most popular statistical-based detection algorithms is the spectral matched filter (SMF). The metric relies on statistical parameters that describe the data set’s background

\[
SMF(\mathbf{x}) = (\mathbf{t} - \mathbf{m})^T \mathbf{S}^{-1} (\mathbf{x} - \mathbf{m}) \geq \eta \Rightarrow \text{target} \\
< \eta \Rightarrow \text{no target}
\]  \hspace{1cm} (2.5.11)

where \( \mathbf{t} \) is the target vector, \( \mathbf{x} \) is the spectral vector of the pixel in question, and \( \mathbf{m} \) and \( \mathbf{S} \) are the mean and covariance matrix of the background (Schott, 2007).
2.8 Background Summary

Chapter two reviewed some basic concepts such as the governing equation and target detection algorithms. It also outlined considerations for the oblique case and methods for dealing with the unique challenges presented by the oblique case. The ideas presented here provide a background for the methods employed and observed results that are presented in later chapters.
3. SYNTHETIC HYPERSPECTRAL DATASET

3.1 Dataset Description

Imagery generated using DIRSIG is used in this project. DIRSIG is a synthetic image generation tool that is used to accurately model the physical properties of 3-D surfaces and atmospheric properties that dictate the behavior of electro-magnetic energy in the visible through thermal infrared regions (Schott et al., 1999). Studies, such as those presented by Ientilucci and Brown (2003) and Barcomb et al. (2004), have shown that DIRSIG can be used to appropriately simulate nadir and oblique captured HSI. The dataset used in this study is a rendering of a portion of a pre-fabricated scene known as MegaScene (Ientilucci and Brown, 2003). MegaScene, is a simulation of the physical layout of a section of Rochester, NY. Each facet of the scene is assigned accurate physical properties such as reflectance values. Essentially, DIRSIG allows for a simulated atmosphere to be defined by MODTRAN. DIRSIG adds the simulated atmosphere to the simulated physical scene and a simulated sensor is used to capture HSI (Schott et al., 1999).

For the HSI used in this study, a 0.12 km x 3.47 km portion of MegaScene was imaged by a simulated 211 band hyperspectral sensor. The sensor had bands centered at 0.01 micron intervals from 0.40 to 2.50 microns. Bad bands were removed and a stable band set was chosen based on a previous study (Aten et al., 2004). The sensor was looking north with a depression angle of 10.30 degrees below the horizon. The FOV assigned to the sensor was 4.34 degrees. The viewing geometry of the simulated sensor is illustrated in Figure 3.1-1.
The atmosphere assigned via MODTRAN was a standard mid-latitude summer, rural atmosphere. The simulation was set for noon on July 1. The atmospheric parameters assigned are summarized in Table 3.1-1.

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<thead>
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<th>Value</th>
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<tr>
<td>FWHM</td>
<td>0.010 um</td>
</tr>
</tbody>
</table>

Table 3.1-1: Atmospheric parameters used to simulate atmosphere over MegaScene.

Two sets of imagery were used in this thesis. The first dataset used had a visibility of 23 km whereas the second dataset had a visibility of 12 km. All other parameters, as well as the physical scene remained constant. The water vapor parameter was held at the default level for this atmosphere type. By using two datasets, observations would not be limited to a specific situation or scenario.

Five groupings of targets and calibration cubes were placed in the scene such that they were roughly equally spaced in the north-south direction. Each grouping consisted of 50% and 5% reflector calibration cubes, a red car, and a dark green truck whose cargo
area was covered with a canvas cover. The car and the two materials comprising the truck were used as targets in this study. RGB versions of both the high visibility and low visibility datasets are presented in Figure 3.1-2

Figure 3.1-2: RGB versions of imagery used in this thesis.
The reflectance spectra of each of the three targets used in this study are presented in Figure 3.1-3.

![Spectral Reflectance - DGP](image1.png)

![Spectral Reflectance - Canvas](image2.png)

![Spectral Reflectance - Red Metal](image3.png)

**Figure 3.1-3: Target reflectance spectra for (a) dark green paint, (b) canvas, and (c) red metal.**

DIRSIG allows for the modeling of non-Lambertian material by assigning a “specularity” value to a material (Sanders et al., 2007). This feature could arguably add an additional element of realism to simulated HSI rendered using DIRSIG. As such the two datasets used in this thesis are rendered twice each, once with Lambertian characteristics assigned to all the targets in the scene and once with the red metal target assigned a specularity value such that the effects of the simulated non-lambertian behavior could be observed.

### 3.2 Dataset Observations

Observations of the two datasets used in this thesis give further evidence that an expanded target space is required in the oblique case in order to account for the varying target-sensor path distances across an FOV. Note that the five instances of each of the three targets have the exact same reflectance properties and are orientated in the same manner, also they are all equally exposed and essentially illuminated in the same fashion. Despite these similarities the difference in measured radiance for each target instance is obvious. Figure 3.2-1 shows the average measured radiance from each instance of the red metal target in the high visibility dataset.
Figure 3.2-1: Average measured radiance for each instance of the red metal target.

Figures 3.2-2 and 3.2-3 demonstrate the difference in measured radiance for the similar physical points on each instance of each target.

This range in values is in keeping with the examples provided in Figures 2.4-2 to 2.4-4 and 2.6-1, and provides further evidence that when performing PBFM on oblique imagery, the target space used should account for the varying ground-sensor path distance across the FOV.

50
As explained in Chapter 2, the changing radiance curves presented in Figures 3.2-1, 3.2-2 and 3.2-3 can be attributed to the changing ground-sensor path length across the oblique FOV illustrated in Figure 3.1-1. The resulting change in $\tau_2(\lambda)$ and $L_{path}(\lambda)$ as a function image position for each dataset are presented in Figure 3.2-4. Note that when a linear fit is applied to each of the curves in Figure 3.2-4, the associated R-squared values are 0.9928 for the high visibility transmission data, 0.9949 for the low visibility transmission data, 0.9864 for the high visibility path radiance data, and 0.9874 for the low visibility path radiance data. These linear trends are the first indication that a linear relationship between sensor-measured/sensor-reaching radiance and image location can be approximated for these data sets.

![Average Path Radiance](image1)

![Average Transmission](image2)

**Figure 3.2-4**: Average path radiance and average transmission as a function of image location for the high and low visibility dataset.

The linear trends in transmission and path radiance lead us to another important observation, an approximately linear relationship between sensor reaching radiance and image position that is present in both the high and low visibility datasets. Figures 3.2-5 to 3.2-8 are plots of sensor reaching radiance from the same point of the calibration cubes from each grouping. This relationship is demonstrated for a few example wavelengths, 0.41, 0.67, 0.75, 0.78, 0.86, 1.00 and 1.24 um.
Figure 3.2-5: Radiance measurements observed for each instance of the 5% reflector in the low visibility dataset.

Figure 3.2-6: Radiance measurements observed for each instance of the 50% reflector cubes in the low visibility dataset.

Figure 3.2-7: Radiance measurements observed for each instance of the 5% reflector cubes in the high visibility dataset.
These plots show that in these realistic simulated datasets, a linear relationship can be approximated with some error. This is in keeping with the examples presented in section 2.6.1 and 2.6.2.

3.3 Dataset Summary

In summary, this chapter presented the datasets used in this thesis. The origin of the datasets is discussed. Observations made in this chapter support the theory and examples discussed in Chapter 2. The datasets presented in this chapter are used to test the theory and processes presented in Chapter 2 and are necessary in completing the goals of this thesis presented in Chapter 1.
4. METHODOLOGY

This chapter explains how the theory and processes in Chapter 2 are applied to the datasets introduced in Chapter 3 in order to accomplish the goals outlined in Chapter 1. The processes applied in each domain are explained in the following sections.

4.1 Reflectance Domain

The simulated HSI under study was compensated using both traditional ELM as well as the oblique ELM (OELM) method outlined in Section 2.6. Traditional ELM was performed using the calibration points in grouping 1 which is labeled in Figure 3.1-2. For OELM, the calibration cubes in groupings 1 & 5 were used as calibration points. Calibration cubes were placed in the scene instead of panels so that the side panels of the cube could also be used to calibrate the scene. When the side surfaces are used as calibration points, this will be referred to as “side OELM” (SOELM). As alluded to previously, in this way we can account for the fact that targets have 3-dimensional profiles when viewed from an oblique angle. That is to say, both the “top” surface and “side” surfaces of a target may be visible at an oblique viewing angle. In summary, both the high and low visibility datasets were compensated using ELM, OELM and SOELM. In an effort to combine the results from OELM and SOELM a simple logical operator was used. This is referred to as hybrid OELM (HOELM). This simple procedure is explained later.

Example compensation results for ELM as well as OELM and SOELM are presented here. Example estimated reflectance curves are presented to demonstrate the outputs from each compensation routine employed. First, compensation results from OELM and ELM are compared, then OELM and SOELM compensation results are compared. First we
compare example estimated reflectance values from the 50% and 5% reflector cubes in Figure 4.1-1 and 4.1-2.

**Figure 4.1-1:** Estimated reflectance for the five instances of the 50% and 5% reflector cubes for the high visibility dataset.

**Figure 4.1-2:** Estimated reflectance for the five instances of the 50% and 5% reflector cubes for the low visibility case

The OELM estimated reflectance is closer to the actual flat reflectance values for each instance of the 50% and 5% reflector cubes. The maximum deviation in the estimated reflectance from the actual reflectance for the OELM compensated data occurs at target instances near the center of the image in grouping 3. Since actual ground truth points used for compensation were taken from groupings 1 and 5, compensation error is lowest for pixels near these locations. The ELM data was compensated using actual ground truth from grouping 1. Not surprisingly, the deviation of estimated reflectance from actual
reflectance is minimal for the target instances closest to grouping 1. The deviation in estimated reflectance from actual reflectance increases as the instance of the target is moved away from the near edge of the scene, the maximum deviation is associated with grouping 5. Note how the error in estimated reflectance increases for both reflectance cubes increases in the low visibility dataset. This is especially apparent in the blue region of the spectrum for ELM. Direct comparisons for estimated reflectance derived from OELM are presented for each reflector cube in Figure 4.1-3 showing that compensation error is greater in the low visibility case.

Figure 4.1-3: Estimated reflectance for 50% and 5% reflector cubes in grouping 3 using OELM. Estimated reflectance from each dataset is presented for easy comparison.

It should also be noted that the accuracy in the estimated reflectance in each case could be improved by removing additional bands, however a stable band set was desired for all experiments in this thesis and was selected based on passed studies (Aten et al., 2005).

The difference in estimated reflectance using SOELM and OELM is illustrated by an example presented in Figure 4.1-4. The Figure shows how SOELM correctly estimates the reflectance of the side surface of the 50% reflectance cube while OELM correctly estimates the reflectance of the top surface of the 50% reflectance cube. The example presented is for the 50% reflector cube in grouping 3 from high visibility dataset.
Grouping 3 is where maximum error in estimated reflectance occurs for OELM and SOELM. A rudimentary attempt at addressing this discrepancy is discussed later.

Figure 4.1-4: Example estimated reflectances for side and top surface of 50% calibration cube in high visibility dataset.

Figure 4.1-4 indicates that the surface used to perform compensation is important. It shows that a surface orientated similarly to the surfaces used to calibrate the image is assigned an accurate estimated reflectance, whereas a surface orientated differently than the surface used to calibrate the image can be assigned an estimated reflectance that is quite different than the actual reflectance of the object. In other words, when OELM is used, the top surface is assigned an appropriate estimated reflectance whereas the side surface of the object is assigned an estimated reflectance below that of the actual reflectance. The opposite is true when SOELM is used. The side surface is assigned a reflectance value relatively close to a spectrally flat 50% reflector curve whereas the estimated reflectance of the top surface is assigned a curve which is above the actual reflectance of the surface.

Once the radiance image was compensated using ELM, OELM and SOELM using the top and side surfaces of the calibration cubes, the resulting reflectance cubes were subjected to SAM, SMF, and OSP. With regards to OSP, MaxD was used to determine
the endmembers of the scene (Lee, 2003). As the goal of this study was to compare results from each domain, in all cases the number of endmembers used was held constant at 15. No attempt was made to investigate the ideal number of endmembers to use with OSP for the datasets used in this study.

After the data was subjected to the SAM, SMF and OSP detectors, a simple logical operator was applied to attempt to rectify the discrepancies between OELM and SOELM. For each detection output and for each pixel the higher of the two outputs from the SOELM and OELM derived reflectance cubes was used. In this way true positive target pixels would be assigned the higher of the two output values. This also has the negative effect of assigning the higher of the two values to background pixels as well. The thinking behind this method was that the top surface target pixels would likely be assigned an accurate estimated reflectance by OELM, and side surface target pixels would likely be assigned accurate estimated reflectance values by SOELM, in a non-random fashion. This in fact was observed in examples such as the one presented in Figure 4.1-2. One could assume that pixels that were candidates to be false alarms would “randomly” be assigned estimated reflectance values that were similar to the target thus triggering a false alarm. Let us continue this thought experiment with a fictional example. Let us say that an imaged target has a top surface pixel, TT, and a side surface TS. Now let us say there is a background pixel, B, that is a candidate to be a false alarm due to its similarity in assigned estimated reflectance to the actual reflectance curve of the target under study. For the sake of explanation let us consider a fictional measure of reflectance similarity, RS, that has a scale between 0 and 1 where 0 is not similar and 1 is a perfect
match. Let us assume that after OELM is applied to the imagery the following RS values in Table 4.1-1 are observed.

<table>
<thead>
<tr>
<th>Pixel</th>
<th>RS score</th>
</tr>
</thead>
<tbody>
<tr>
<td>TT</td>
<td>0.9</td>
</tr>
<tr>
<td>TS</td>
<td>0.5</td>
</tr>
<tr>
<td>B1</td>
<td>0.6</td>
</tr>
<tr>
<td>B2</td>
<td>0.6</td>
</tr>
</tbody>
</table>

Table 4.1-1: Observed fictional RS values when OELM is observed.

We see that B1 and B2 would induce a false alarms assuming the fictional RS metric is directly related to target detection output. Now let us assume that after SOELM is applied to the imagery the following RS values in Table 4.1-2 are observed.

<table>
<thead>
<tr>
<th>Pixel</th>
<th>RS score</th>
</tr>
</thead>
<tbody>
<tr>
<td>TT</td>
<td>0.5</td>
</tr>
<tr>
<td>TS</td>
<td>0.9</td>
</tr>
<tr>
<td>B1</td>
<td>0.7</td>
</tr>
<tr>
<td>B2</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Table 4.1-2: Observed fictional RS values when SOELM is performed.

Here we see that the TS pixel RS value increases and the TT pixel decreases in a predictable manner. B1 and B2’s RS value have changed as well, but theoretically in a “random” manner. Their similarity to the actual target reflectance curve is “random” no matter which calibration points are used to compensate the image. It is apparent that when either reflectance cube is used by itself pixel B1 will trigger a false alarm and B2
will also trigger an alarm in the OELM compensated data. However if each pixel is assigned the highest RS value we would have the situation present in Table 4.1-3.

<table>
<thead>
<tr>
<th>Pixel</th>
<th>RS score</th>
</tr>
</thead>
<tbody>
<tr>
<td>TT</td>
<td>0.9</td>
</tr>
<tr>
<td>TS</td>
<td>0.9</td>
</tr>
<tr>
<td>B1</td>
<td>0.7</td>
</tr>
<tr>
<td>B2</td>
<td>0.6</td>
</tr>
</tbody>
</table>

Table 4.1-3: Observed fictional RS values when HOELM is performed.

Though this example is removed from reality for a number of reasons, if one can assume that OELM will very accurately assign estimated reflectance values to the top surfaces of the target, and SOELM will assign very accurate values to the side surfaces of a target and background pixels will be assigned reflectance values that are “randomly” like or unlike the target it may have some value. Of course an additional problem is that the detection outputs in each case must be normalized in a way such that the outputs from each reflectance cube can be compared in a meaningful way. Though OSP and SMF can be normalized as explained in Section 2.7, the normalization is highly dependant on the dataset used, making direct comparisons in output values from different datasets minimally useful. Therefore this HOELM technique was only expected to potentially have a small impact on the SAM detection outputs where direct comparisons between datasets can be made in terms of radians. Though the HOELM metric was not expected to make an impact on results do to the unrealistic assumptions made it does offer a way to combine the outputs of OELM and SOELM in a single output.
Reflectance domain processing was also applied to the datasets that contained non-Lambertian red-metal targets. Specifically, only OELM was applied in these cases to determine how detection results for this particular simulated non-Lambertian target would change compared to the Lambertian version of the target.

Detection results observed from ELM, OELM, SOELM and HOELM were observed in the form of ROC curves for the targets under study. AFAR was used to summarize each ROC curve to facilitate comparisons.

4.2 Radiance Domain

Three studies were done in the radiance domain. First, ideal target spaces for each target were created. These ideal target spaces are presented in Figure 4.2-1 and Figure 4.2-2. The target spaces were collapsed into a single mean target space vector. This vector was used as the target vector and SAM, SMF and OSP were applied to the radiance domain images. Results were observed in the form of ROC curves and summarized in terms of AFAR.

![Ideal Target Space](image)

Figure 4.2-1: Ideal target spaces associated with the high visibility dataset for each of the three targets used in this thesis. The average vector for each target space is highlighted in red in each plot.
Figure 4.2-2: Ideal target spaces associated with the low visibility dataset for each of the three targets used in this thesis. The average vector for each target space is highlighted in red in each plot.

The next step was to investigate how results would change as ideal target spaces were replaced with “operational” target spaces. These target spaces were created in MODTRAN by varying the parameters discussed in Section 2.2 and 2.3. An operational target space was created for each scenario. Each target space was represented by a single mean target vector. The operational target spaces populated for each scenario are presented Figures 4.2-3 and 4.2-4.

Figure 4.2-3: Operational target spaces associated with the high visibility dataset for each of the three targets used in this thesis. The average vector for each target space is highlighted in red in each plot.

Figure 4.2-4: Operational target spaces associated with the low visibility dataset for each of the three targets used in this thesis. The average vector for each target space is highlighted in red in each plot.
The average operational target space vectors were used as inputs to the SAM, SMF and OSP detection algorithms and results were captured in the form of ROC curves and AFAR values just as with the ideal target spaces.

An attempt was made to vary parameters in a similar way as would likely have been done in a real operational scenario. However, the selection of the input parameters used to populate the operational target spaces was inherently arbitrary. As a result a method was sought out to create other operational target spaces. The desire was to obtain target space representation vectors that were “in between” the somewhat arbitrary operational target spaces in Figures 4.2-3 and 4.2-4, and the ideal target spaces in Figures 4.2-1 and 4.2-2. For the red target space associated with the high visibility an additional operational target space was created using MODTRAN in the same way the previous operational target spaces were created. The input parameters were chosen such that the output average representative vector would more closely resemble the average ideal target space vector. This target space that had a mean vector more similar to that of the ideal target space is referred to as the “improved operational target space”. The drawback to the PBFM as it is presented in this thesis is that the process used to create target spaces is computationally intensive and time consuming (Ientilucci and Bajorski, 2006). In order to avoid this for the other five scenarios a linear mixing model was used to simulate different target space mean vectors. This simple model can be expressed as

\[
\tilde{t}_{mix}(\lambda) = \beta \tilde{t}_{ideal}(\lambda) + (1 - \beta) \tilde{t}_{operational}(\lambda),
\]

where \(\tilde{t}_{mix}(\lambda)\) is the simulated average target space vector, \(\tilde{t}_{ideal}(\lambda)\) is the mean vector of the ideal target space, \(\tilde{t}_{operational}(\lambda)\) is the mean vector of the associated operational target space, and \(\beta\) is the mixing percentage. The mixing percentage was set at various
percentages in order to simulate different operational target spaces. The percentages used were 90, 75, 50 and 25%. The resulting target vectors associated with the high visibility dataset are presented in Figure 4.2-5.

Figure 4.2-5: Target space mean vectors associated with the high visibility dataset for each target.

The operational target spaces that were associated with the low visibility dataset were considerably “closer” to the corresponding ideal target spaces. The difference between each target space representative vector and ideal target space mean vector in terms of spectral angle can be viewed in Table 4.2-1.

<table>
<thead>
<tr>
<th>Color</th>
<th>OP</th>
<th>OPI</th>
<th>25% Ideal</th>
<th>50% Ideal</th>
<th>75% Ideal</th>
<th>90% Ideal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canvas</td>
<td>vis=23km</td>
<td>0.011463</td>
<td>0.008646</td>
<td>0.005796</td>
<td>0.002915</td>
<td>0.001170</td>
</tr>
<tr>
<td></td>
<td>vis=12km</td>
<td>0.006283</td>
<td>0.004779</td>
<td>0.003232</td>
<td>0.001640</td>
<td>0.000662</td>
</tr>
<tr>
<td>Green</td>
<td>vis=23km</td>
<td>0.150638</td>
<td>0.119392</td>
<td>0.084319</td>
<td>0.044776</td>
<td>0.018593</td>
</tr>
<tr>
<td></td>
<td>vis=12km</td>
<td>0.065387</td>
<td>0.049764</td>
<td>0.033668</td>
<td>0.017084</td>
<td>0.006894</td>
</tr>
<tr>
<td>Red</td>
<td>vis=23km</td>
<td>0.083399</td>
<td>0.028855</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>vis=12km</td>
<td>0.021931</td>
<td>0.016566</td>
<td>0.011123</td>
<td>0.005602</td>
<td>0.00225</td>
</tr>
</tbody>
</table>

Table 4.2-1: Difference in spectral angle between mean operational target space vectors and mean ideal target space vectors.

Results for each target space were observed and compared in terms of ROC curves and AFAR.

The effect of performing target detection on a localized area was also investigated. As discussed, the varying target-sensor path distance requires an expansion of the traditional target space as an additional parameter is varied. This varying path distance also affects
the background in a radiance domain image. The varying path length should ensure that the background endmembers and statistical parameters differ throughout the image. By sub-sectioning the image the effects of the varying path distance are diminished. In this case the radiance image was sub sectioned into five equal parts. Local target spaces and background descriptions were created and then subjected to SAM, SMF and OSP. Results were compared in terms of ROC curves and AFAR metrics. This study is presented in Appendix B.

4.3 Methodology Summary

In summary, four compensation routines are applied in this thesis, ELM, OELM, SOLEM and HOELM. Target detection is then performed on the resulting reflectance cube using standard detection algorithms for each target in both datasets. In addition OELM is used to compensate high and low visibility datasets containing non-Lambertian targets. In the radiance domain, different ideal and operational target spaces were used. The mean vector associated with each target space was used as the input target vector to SAM, SMF and OSP. Results from these processes are presented in the following chapters. Also, local target detection was performed in the radiance domain using similarly derived target spaces, local detection results are presented in Appendix B. In addition, the effects of non-Lambertian targets are also investigated and are presented in Appendix C.
5. RESULTS AND ANALYSIS- REFLECTANCE DOMAIN

In this section we display results from each target detection process employed in the reflectance domain. The goal is to determine if the improved compensation methods used in this thesis produce better target detection results compared to standard ELM. Comparison is made in terms of target detection performance by analyzing observed ROC and AFAR results.

Section 4.1 demonstrates the compensation ability of ELM, OELM and SOELM. The main goal of this chapter is to demonstrate if there is a connection between compensation accuracy and detection results. That is to say, the results presented in this chapter seek to demonstrate if the added compensation accuracy of OELM and SOELM over traditional ELM translates into better detection results. Detection results from the reflectance domain are presented in the form of ROC curves. The results are quantified using the AFAR summary metric. Results are presented for each algorithm used and for each target type. This chapter considers the targets described in Chapter 3 with Lambertian properties assigned. Example cases where non-Lambertian target properties are assigned to the targets will be discussed later.

5.1 SAM

The first results presented are for the SAM detector. Figure 5.1-1 shows the detection results for the red metal target in the form of ROC curves. The results are quantified using the AFAR metric in Figure 5.1-1.
The results observed for the SAM detector and red target are somewhat intuitive. For both visibilities the modified ELM compensation techniques (OELM, SOELM, and HOELM) outperform traditional ELM. This indicates that it was beneficial to account for the varying target-sensor path distance when compensating the imagery. It so happens that when the side-surface of the calibration cubes were used as the calibrating surfaces (SOELM) the best performance was observed. These trends were observed in both datasets. As expected the clearer visibility resulted in better target detection results.

The next scenario to be considered is the performance of SAM detecting the dark green paint target. Figure 5.1-2 shows the resulting ROC curves and Figure 5.1-2 contains the corresponding observed AFAR values.
As might be expected, due to the “camouflaged” nature of the green target it turns out to be more difficult for SAM to detect than the red target. The other observations made for SAM on the red target are valid for the green target as well. SOELM performs the best, and detection results from the clearer visibility are better than those from the dataset with lower visibility.

SAM was also used to detect the canvas target. These results are presented in Figure 5.1-3 and quantified in Figure 5.1-3.
Figure 5.1-3: Results for SAM on canvas target.

For the canvas target the same trends are observed, the modified ELM techniques outperform traditional ELM. In this case the HOELM achieves the highest results for both visibilities. The decrease in visibility also has a large effect on detection results in this scenario.

To summarize, the SAM detection results in the reflectance domain highlight the importance of considering the changing target-sensor path distance throughout an oblique FOV. In both the low and high visibility cases traditional ELM achieves inferior detection results compared to the methods that account for the varying path length. The second observation is that decreasing visibility has a negative effect on detection results. Since SAM is a simple detector that considers only the target vector, and not the relationship between the target and background, the better results in the high visibility
case can be explained by the results observed in section 4.1. That is to say, the larger compensation error for the low visibility case results in decreased detection performance.

5.2 SMF

SMF detection results are presented in this section. Results for the red target are presented in Figure 5.2-1 and Figure 5.2-1 for each dataset.

![Figure 5.2-1: Results for SMF on red metal target.](image)

<table>
<thead>
<tr>
<th>SMF- Red Metal Reflectance Domain</th>
<th>VIS= 23km AFAR</th>
<th>1-AFAR</th>
<th>VIS = 12km AFAR</th>
<th>1-AFAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>REF- ELM</td>
<td>0.000008</td>
<td>0.999992</td>
<td>0.000002</td>
<td>0.999998</td>
</tr>
<tr>
<td>REF- OELM</td>
<td>0.000005</td>
<td>0.999995</td>
<td>0.000001</td>
<td>0.999999</td>
</tr>
<tr>
<td>REF- SOELM</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
<td>1.000000</td>
</tr>
<tr>
<td>REF- HOELM</td>
<td><strong>0.000000</strong></td>
<td><strong>1.000000</strong></td>
<td><strong>0.000000</strong></td>
<td><strong>1.000000</strong></td>
</tr>
</tbody>
</table>

![Figure 5.2-1: AFAR results for SMF on red metal target](image)

Note that with this scenario perfect detection results were observed when the SOELM and HOELM compensation techniques were used and therefore the associated ROC curve plots are not included in Figure 5.2-1. Also note that the OELM, SOELM and HOELM marginally outperformed ELM in both cases.

ROC results for the dark green paint target are presented in Figure 5.2-2. The associated AFAR values are presented in Figure 5.2-2.
Figure 5.2-2: SMF on dark green paint target.

<table>
<thead>
<tr>
<th>Reflectance Domain</th>
<th>VIS= 23km</th>
<th>VIS= 12km</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AFAR</td>
<td>1-AFAR</td>
</tr>
<tr>
<td>REF- ELM</td>
<td>0.00157</td>
<td>0.99843</td>
</tr>
<tr>
<td>REF- OELM</td>
<td>0.00061</td>
<td>0.99939</td>
</tr>
<tr>
<td>REF- SOELM</td>
<td>0.00031</td>
<td>0.99969</td>
</tr>
<tr>
<td>REF- HOELM</td>
<td>0.00031</td>
<td>0.99969</td>
</tr>
</tbody>
</table>

For this scenario OELM, SOELM and HOELM outperform ELM for the higher visibility case. Note that for the low visibility case an anomaly occurs in that ELM slightly outperforms OELM, however, Figure 5.2-2 indicates that all of the OELM target pixels are found before all the ELM target pixels are found.

Detection results for the canvas target using SMF are presented in Figure 5.2-3. The corresponding AFAR values are presented in Figure 5.2-3. Results from both the low and high visibility datasets are presented.
The observed canvas detection results trends for SMF are similar to those seen for the other two targets. AFAR results from the ELM compensated reflectance cube are inferior to results achieved using the other compensation techniques.

In summary, the fact that results are slightly better for the lower visibility case is somewhat counter intuitive. It seems that even though the compensation errors presented can be larger for the lower visibility case, the SMF detector is not necessarily adversely affected. The purpose of having two different datasets was to observe trends in detection results under different conditions, for example in this section, it has been demonstrated that modifications to ELM that account for the changing ground-sensor distance (i.e., OELM, SOELM, and HOELM) are generally beneficial in both the low and high visibility cases. An investigation into how detection results change as a function of visibility is beyond the scope of this thesis.
5.3 OSP

Detection results using OSP are presented in this section. As with the other detectors results are presented for each target type. Figure 5.3-1 and Figure 5.3-1 contain the results observed for the red metal target. MaxD was used to identify endmembers. Endmembers were selected from the HSI presented in Chapter 3.

![Figure 5.3-1: OSP on red metal target.](image)

<table>
<thead>
<tr>
<th>OSP - Red Metal</th>
<th>VIS= 23km</th>
<th>VIS = 12km</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reflectance Domain</td>
<td>AFAR 1-AFAR</td>
<td>AFAR 1-AFAR</td>
</tr>
<tr>
<td>REF- ELM</td>
<td>0.000000</td>
<td>1.000000</td>
</tr>
<tr>
<td>REF- OELM</td>
<td>0.000007</td>
<td>0.999993</td>
</tr>
<tr>
<td>REF- SOELM</td>
<td>0.000009</td>
<td>0.999991</td>
</tr>
<tr>
<td>REF- HOELM</td>
<td>0.000009</td>
<td>0.999991</td>
</tr>
</tbody>
</table>

Figure 5.3-1: AFAR values for red metal target.

The results for this scenario were all very similar. The OSP detector was able to find the red target relatively easily.

The results for the green target are given in terms of ROC curves and AFAR metrics in Figure 5.3-2 and Figure 5.3-2 respectively.
The OSP detection results for the dark green paint target indicate that the modified ELM compensation techniques offer an advantage over traditional ELM. In both datasets SOELM performs the best.

The OSP detection results for the canvas target are presented in Figure 5.3-3 and Figure 5.3-3.
Results for this scenario indicate that OELM compensated data achieves the best detection results for both the low and high visibility case.

In summary, OSP detection results seem to benefit from taking into account the varying target-sensor path distance. Observed ELM results are not as good as the results achieved using the modified ELM compensation routines. When considering results obtained using OSP three things must be considered. The first is how the endmembers were selected. As discussed, MAXD was used here to select background endmembers. Studies have shown that the method of endmember selection is not as important as other steps in the target detection process (Grimm, 2005), however, there is no way of knowing what are the “real” endmembers of a dataset. Indeed this may be a philosophical question, in that the “real” endmembers of a dataset may change depending on the use of the data, and could be defined as the data points that give you the best results. The second consideration is that the number of endmembers chosen drastically changes results. Though this number can be loosely associated with dimensionality of the data, often the “ideal” number of endmembers, the number which achieves superior performance, is different from the estimated dimensionality of the dataset (Bajorski et al., 2004). The third strike against OSP is that target pixels must not be selected as endmembers. Unless the target locations are known *a priori* this is a difficult task especially with the common

<table>
<thead>
<tr>
<th>OSP-Canvas</th>
<th>Reflectance Domain</th>
<th>VIS= 23km</th>
<th>VIS= 12km</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1-AFAR</td>
<td>1-AFAR</td>
</tr>
<tr>
<td>REF- ELM</td>
<td>0.24160</td>
<td>0.75840</td>
<td>0.28842</td>
</tr>
<tr>
<td>REF- OELM</td>
<td>0.19079</td>
<td>0.80921</td>
<td>0.17908</td>
</tr>
<tr>
<td>REF- SOELM</td>
<td>0.24502</td>
<td>0.75498</td>
<td>0.22594</td>
</tr>
<tr>
<td>REF- HOELM</td>
<td>0.24616</td>
<td>0.75384</td>
<td>0.22818</td>
</tr>
</tbody>
</table>

Figure 5.3-3: AFAR values for OSP for canvas target.
semi-autonomous methods of endmember selection that are available. Often when OSP is used in research situations the targets pixels are first removed and then the background endmembers are selected as was done in this thesis.

5.4 Reflectance Domain Results Summary

The goal of this chapter was to present results that provided evidence that the modified ELM techniques introduced in earlier chapters offered advantages over traditional ELM. As discussed, these modified techniques account for the varying path lengths associated with oblique viewing angles. Indeed, Section 4.1 provides evidence that they in fact do achieve better compensation results in terms of estimated reflectance. Sections 5.1 to 5.3 provide evidence that this improvement in compensation translates in most cases to marginally better detection results. This is most apparent when SAM is used as the detection algorithm. When OSP and SMF are used, results tend to be more similar, though in almost all cases the modified ELM techniques still out perform traditional ELM. These results are important in moving forward as they confirm the notion presented in this thesis about the varying path lengths in the oblique case. Also, the “best-case scenario” results from each situation are identified here and can be used to compare against the “best-case scenario” in the radiance domain.

One unexpected auxiliary observation was that decreasing visibility did not necessarily result in inferior detection results. This could be due to reduced “complexity” in the lower visibility dataset due to its lower contrast. This trade study did not add noise to the datasets. In real datasets noise would have a greater impact on the lower contrast low visibility scene. However, as discussed the usage of two datasets was not necessarily to study the difference in results from each dataset as much as it was to have two data sets
in order to confirm trends. That is to say, the effects of visibility on target detection is not the goal of this thesis and do to time constraints will be considered in future work.

The results presented in this chapter will be compared and contrasted with radiance domain results that are presented in the next chapter.
6. RESULTS AND ANALYSIS- RADIANCE DOMAIN

In this chapter radiance domain results are presented. The main goal of this chapter is to demonstrate how detection results change when different target spaces are used. The target spaces used in this chapter are presented in Chapter 4 in Figures 4.2-1-4.2-5. Radiance domain results are organized in terms of detector and target type. Results are presented for both the high and low visibility datasets. This chapter considers the datasets presented in Chapter 3 in a global sense. That is to say target spaces as well as background descriptors such as statistical parameters and geometrical endmembers are taken from the datasets as a whole. Appendix B considers how results would change if local target spaces and their associated background descriptors were used.

6.1 SAM

The results for SAM detecting the red metal target are presented in the form of ROC curves in Figure 6.1-1, these results are quantified in terms of AFAR values in Table 6.1-1.

Figure 6.1-1: ROC results for SAM on the red metal target.
Table 6.1-1: AFAR results for SAM on the red metal target.

For the high visibility case the improved operational target space achieved the best results in terms of AFAR. For the low visibility case the operational target space achieved the best AFAR results. Though it may be expected that the ideal target space should achieve the maximum results it is shown here that this is not necessarily the case. Consider Table 4.2-1 that shows how close target spaces are to the ideal target space in terms of spectral angle. Table 4.2-1 shows that for the high visibility dataset the original operational target space is the most unlike the ideal target space. All of the other operational target spaces are relatively close to the ideal target spaces for both the high and low visibility cases (less than 0.03 radians in terms of spectral angle). This indicates that though the best results may not be achieved using an ideal target space, the target spaces that do achieve the best results are similar to the ideal target space. The fact that an ideal target space does not achieve the best results may be in part due to the target space representation, which, as discussed earlier, is the mean target space vector in this study. This mean vector representation may not be the best way to represent a target space as will be discussed in future sections.

The results for SAM detecting the dark green paint target are presented in Figure 6.1-2 and Table 6.1-2.
Figure 6.1-2: ROC results for SAM on the dark green paint target.

Table 6.1-2: AFAR results for SAM on the dark green paint target.

For this target the ideal target spaces achieve the best results as was generally expected. This is the case for both the high and low visibility datasets. The dark green target spaces used differed more than the target spaces used for the other two targets as demonstrated in Table 4.2-1. As the target space average vector becomes less similar to that of the ideal target space target detection results degrade.

Detection results in terms of ROC curves and AFAR values for SAM on the canvas target are presented in Figure 6.1-3 and Table 6.1-3 respectively for both the high and low visibility datasets.
Table 6.1-3: AFAR Results for SAM on the canvas target.

<table>
<thead>
<tr>
<th>SAM</th>
<th>VIS= 23km</th>
<th>VIS= 12km</th>
</tr>
</thead>
<tbody>
<tr>
<td>Radiance Domain Global</td>
<td>AFAR</td>
<td>1-AFAR</td>
</tr>
<tr>
<td>RAD- Operational TS1</td>
<td>0.06451</td>
<td>0.93549</td>
</tr>
<tr>
<td>RAD- Operational TS2</td>
<td>0.06407</td>
<td>0.93593</td>
</tr>
<tr>
<td>RAD- Operational TS3</td>
<td>0.06365</td>
<td>0.93635</td>
</tr>
<tr>
<td>RAD- Operational TS4</td>
<td>0.06323</td>
<td>0.93677</td>
</tr>
<tr>
<td>RAD- Operational TS5</td>
<td>0.06297</td>
<td>0.93703</td>
</tr>
<tr>
<td>RAD- Ideal TS</td>
<td><strong>0.06279</strong></td>
<td><strong>0.93721</strong></td>
</tr>
</tbody>
</table>

For this target the ideal and operational target spaces are very close for both the high and low visibility cases as can be seen in Table 4.2-1. Not surprisingly, detection results observed for each target space are quite similar. For the high visibility case the best results were achieved when the ideal target space was used. For the low visibility dataset slightly improved AFAR results were observed when the operational target space was used due to the similarity in mean target vectors for each target space.

In summary, this section shows how SAM detection results vary when different target spaces are used. Results indicate that the best results occur when a target space similar to that of the ideal target space is used, though the best results are not necessarily associated with ideal target spaces.
6.2 SMF

In this section results are presented for the SMF detector in the radiance domain. First results are presented for the red metal target in Figure 6.2-1 and Table 6.2-1. Results are presented for both datasets.

![ROC results for SMF on the red metal target.](image)

Figure 6.2-1: ROC results for SMF on the red metal target. Note that scenarios where perfect detection occurs are not plotted.

<table>
<thead>
<tr>
<th>SMF</th>
<th>VIS= 23km</th>
<th>VIS = 12km</th>
</tr>
</thead>
<tbody>
<tr>
<td>Radiance Domain Global</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RAD- Operational TS1</td>
<td>OP</td>
<td>AFAR</td>
</tr>
<tr>
<td>RAD- Operational TSI</td>
<td>OP Improved</td>
<td>1-AFAR</td>
</tr>
<tr>
<td>RAD- Operational TS2</td>
<td>25% Ideal</td>
<td>AFAR</td>
</tr>
<tr>
<td>RAD- Operational TS3</td>
<td>50% Ideal</td>
<td>1-AFAR</td>
</tr>
<tr>
<td>RAD- Operational TS4</td>
<td>75% Ideal</td>
<td>AFAR</td>
</tr>
<tr>
<td>RAD- Operational TS5</td>
<td>90% Ideal</td>
<td>1-AFAR</td>
</tr>
<tr>
<td>RAD- Ideal TS</td>
<td>Ideal</td>
<td>AFAR</td>
</tr>
</tbody>
</table>

Table 6.2-1: AFAR results for SMF on the red metal target.

For this detector and target, perfect detection occurs when the ideal target space is used as the target space becomes less ideal false alarms begin to occur.

Results for SMF on the dark green paint target are presented in terms of ROC curves in Figure 6.2-2 and in terms of AFAR in Table 6.2-2. Results for both datasets are presented.
Table 6.2-2: SMF AFAR results for dark green paint target.

<table>
<thead>
<tr>
<th>SMF</th>
<th>VIS= 23km</th>
<th>VIS= 12km</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AFAR</td>
<td>1-AFAR</td>
</tr>
<tr>
<td>Radiance Domain Global</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RAD- Operational TS1 OP</td>
<td>0.00335</td>
<td>0.99665</td>
</tr>
<tr>
<td>RAD- Operational TS2 25% Ideal</td>
<td>0.00256</td>
<td>0.99744</td>
</tr>
<tr>
<td>RAD- Operational TS3 50% Ideal</td>
<td>0.00157</td>
<td>0.99843</td>
</tr>
<tr>
<td>RAD- Operational TS4 75% Ideal</td>
<td>0.00041</td>
<td>0.99959</td>
</tr>
<tr>
<td>RAD- Operational TS5 90% Ideal</td>
<td>0.00006</td>
<td>0.99994</td>
</tr>
<tr>
<td>RAD- Ideal TS Ideal</td>
<td>0.00000</td>
<td>1.00000</td>
</tr>
</tbody>
</table>

For this detector and target type the best results were observed when an ideal target space was used. As the target space became less ideal detection results degraded. This was the case for both datasets.

Results for SMF on the canvas target are presented in Figure 6.2-3 and Table 6.2-3.
For this target, SMF achieves the best results when an ideal or close to ideal target space is used. As mentioned the difference between the canvas target space representative vectors is quite small as demonstrated in Table 4.2-1.

In summary, as with SAM, the best results for SMF are observed when an ideal target space or close to ideal target space is used.

### 6.3 OSP

OSP detector results are presented in this section. Table 6.3-1 shows the results for the OSP detector on the red metal target. The OSP detector works perfectly for every target space used and for each dataset.

#### Table 6.3-1: AFAR results for OSP on the red metal target.

The OSP results for the dark green paint target are presented in Figure 6.3-1 and Table 6.3-2.
Figure 6.3-1: ROC results for OSP on the dark green paint target.

![Figure 6.3-1](image)

<table>
<thead>
<tr>
<th>OSP</th>
<th>VIS = 23km</th>
<th>VIS = 12km</th>
</tr>
</thead>
<tbody>
<tr>
<td>Radiance Domain Global</td>
<td>AFAR</td>
<td>1-AFAR</td>
</tr>
<tr>
<td>RAD- Operational TS1 OP</td>
<td>0.15442</td>
<td>0.84558</td>
</tr>
<tr>
<td>RAD- Operational TS2 25% Ideal</td>
<td>0.15161</td>
<td>0.84839</td>
</tr>
<tr>
<td>RAD- Operational TS3 50% Ideal</td>
<td>0.14704</td>
<td>0.85296</td>
</tr>
<tr>
<td>RAD- Operational TS4 75% Ideal</td>
<td>0.13899</td>
<td>0.86101</td>
</tr>
<tr>
<td>RAD- Operational TS5 90% Ideal</td>
<td>0.12956</td>
<td>0.87044</td>
</tr>
<tr>
<td>RAD- Ideal TS Ideal</td>
<td><strong>0.11816</strong></td>
<td><strong>0.88184</strong></td>
</tr>
</tbody>
</table>

Table 6.3-2: AFAR results for OSP on dark green paint.

These results show that as the target space becomes less ideal target detection results degrade. The best results occur for the ideal target space in both the high and low visibility data sets.

Finally, results for OSP detecting the canvas target are presented in Figure 6.3-2 and Table 6.3-3.

Figure 6.3-2: ROC curve results for OSP on the canvas target.

![Figure 6.3-2](image)
Table 6.3-3: AFAR results for OSP on the canvas target.

Results, regardless of the target space, are very similar in this case. As noted earlier the canvas target space average vectors are quite similar thus the results are comparable. Since each average target space vector is quite comparable to the ideal target space average vector, it is not surprising to see that the best results are not necessarily observed for the ideal target space in both cases.

In summary, the same conclusions can be made for the OSP detector as the other two detectors. When target spaces unlike the ideal target space are used results are not as good as they are for the ideal target space. However, the ideal target space is not necessarily associated with the best results. Apparent anomalies such as results from the low visibility dataset being better than those from the high visibility dataset are likely the results of the finicky nature of OSP. That is to say, the endmembers that were selected and used in each case had a big impact on the detection results.

6.4 Radiance Domain Results Summary

As was expected results using ideal target spaces were among the best observed. However, in many situations if a target space was similar enough to the ideal target space the associated results ranged from nearly as good to better than results associated with the ideal target space. This indicates that one does not need to populate an ideal target space, merely a target space that can be represented by a vector that is similar to that of the ideal target space representation. Also, as alluded to earlier, these results are from when the
target space is represented by a mean target space vector. Other methods of representing a target space are not proposed in this thesis and are the subject of other projects.

Appendix B shows that these trends are similar when local detection processes are employed. The results show that radiance domain detection results can be marginally improved by considering individual local sections of an image. They also show that in the local case, target space representation is important as detection results degrade as target spaces become less ideal.
7. RESULTS AND ANALYSIS- DOMAIN COMPARISON

In this chapter direct comparisons between reflectance and radiance domain results are made. These results speak to the main goal of this thesis. Results that were presented in the previous two chapters are presented together here to facilitate direct comparison. As in the previous two chapters, results are grouped by detector and target type. The best results observed for each scenario from each domain are highlighted. Though the detection results presented in this chapter are for Lambertian targets, similar example results are presented in Appendix C for specular targets.

7.1 SAM

The results achieved using SAM to detect the red metal target are presented first. The results in terms of ROC curves are presented in Figure 7.1-1 and are quantified in terms of AFAR in table 7.1-1. Note that results from each reflectance domain process and each radiance domain process are presented together to facilitate comparisons.

Figure 7.1-1: All radiance and reflectance domain results using SAM to detect the red metal target.
It is apparent for this detector and target type, that for both the high and low visibility datasets, the reflectance domain achieved the best results. Specifically, for both visibilities SOELM achieved the best results, HOELM achieved nearly as good results followed by OELM. All radiance domain results, however, were better than traditional ELM in terms of AFAR. For this scenario, therefore, a slight advantage can be given to the reflectance domain. However, due to the easy detectability of the red target, these results may not necessarily represent a results from a more realistic situation.

The results using SAM to detect the dark green paint target are presented in Figure 7.1-2 and table 7.1-2. As with the red target, all results are presented here from both domains in order to facilitate comparisons.
For this scenario the radiance domain results are superior. This is apparent in the ROC curve plots in Figure 7.1-2 where a clear separation between radiance domain and reflectance domain results is present. In terms of AFAR, only SOELM and HOELM have higher “1-AFAR” values than the lowest radiance domain AFAR value for the high visibility dataset. The highest results for both datasets were achieved in the radiance domain using an ideal target space. Interestingly, the radiance domain results were seemingly less affected by the thicker atmosphere compared to reflectance domain results. For this scenario the radiance domain seems to be advantageous in both detection
results and reliability. That is to say, results indicate that forward modeling is more advantageous than compensation.

The following results in Figure 7.1-3 and table 7.1.3 contain results that were observed when SAM was used to detect the canvas target.

![Figure 7.1-3: ROC results achieved using SAM to detect the canvas target.](image)

<table>
<thead>
<tr>
<th>SAM</th>
<th>Reflectance Domain</th>
<th>VIS= 23km</th>
<th>VIS= 12km</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>AFAR</td>
<td>1-AFAR</td>
</tr>
<tr>
<td>REF- ELM</td>
<td>0.40998</td>
<td>0.59002</td>
<td>0.59638</td>
</tr>
<tr>
<td>REF- OELM</td>
<td>0.11519</td>
<td>0.88481</td>
<td>0.41347</td>
</tr>
<tr>
<td>REF- SOELM</td>
<td>0.12649</td>
<td>0.87351</td>
<td>0.34788</td>
</tr>
<tr>
<td>REF- HOELM</td>
<td>0.09074</td>
<td>0.90926</td>
<td>0.33766</td>
</tr>
<tr>
<td>Radiance Domain Global</td>
<td>AFAR</td>
<td>1-AFAR</td>
<td>AFAR</td>
</tr>
<tr>
<td>RAD- Operational TS1</td>
<td>OP</td>
<td>0.06451</td>
<td>0.93549</td>
</tr>
<tr>
<td>RAD- Operational TS2</td>
<td>25% Ideal</td>
<td>0.06407</td>
<td>0.93593</td>
</tr>
<tr>
<td>RAD- Operational TS3</td>
<td>50% Ideal</td>
<td>0.06365</td>
<td>0.93635</td>
</tr>
<tr>
<td>RAD- Operational TS4</td>
<td>75% Ideal</td>
<td>0.06323</td>
<td>0.93677</td>
</tr>
<tr>
<td>RAD- Operational TS5</td>
<td>90% Ideal</td>
<td>0.06297</td>
<td>0.93703</td>
</tr>
<tr>
<td>RAD- Ideal TS</td>
<td>Ideal</td>
<td><strong>0.06279</strong></td>
<td><strong>0.93721</strong></td>
</tr>
</tbody>
</table>

Table 7.1-3: AFAR results achieved using SAM to detect the canvas target.

For this scenario the radiance domain results achieved were superior to the reflectance domain results in every instance. Also, the results did not degrade as much for the low visibility dataset in the radiance domain compared to the reflectance domain.

In summary for the SAM detector the radiance domain results observed were generally as good as or better than the reflectance domain results. The SAM detector
performed better in the radiance domain for almost every case for the canvas and dark green paint targets when detection was done in the radiance domain. Also, for these targets, results in the radiance domain did not degrade as much for the low visibility dataset as they did in the reflectance domain when visibility was degraded. For the red target the best results came in the reflectance domain, however the radiance domain results were an improvement over traditional ELM. Considering all of the observed results as a whole for the SAM detector, as a general conclusion, the radiance domain outperformed the reflectance domain. The best radiance domain “1-AFAR” values from each target and dataset are highlighted in bold in tables 7.1-1 to 7.1-3. When these values are averaged the value is 0.9161. Similarly, the best reflectance domain “1-AFAR” values are highlighted in bold for each target and each dataset in the tables 7.1-1 to 7.1-3. When these values are averaged the value is 0.8168. This indicates that the average “1-AFAR” value for the best case scenario radiance results is greater than the average “1-AFAR” value for the best case scenario reflectance results.

7.2 SMF

SMF is considered in this section. Figure 7.2-1 and table 7.2-1 contain the results for SMF detecting the red metal target. Note that due to the nature of the red metal target many processes resulted in perfect detection and therefore ROC curves for these situations are not presented.
Figure 7.2-1: ROC results for SMF on the red metal target. Scenarios where perfect detection occurred are not plotted.

Table 7.2-1: AFAR values for SMF detecting the red metal target.

<table>
<thead>
<tr>
<th>SMF</th>
<th>Reflectance Domain</th>
<th>VIS= 23km</th>
<th>VIS= 12km</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>AFAR</td>
<td>1-AFAR</td>
</tr>
<tr>
<td>REF- ELM</td>
<td>0.000008</td>
<td>0.999992</td>
<td>0.000002</td>
</tr>
<tr>
<td>REF- OELM</td>
<td>0.000005</td>
<td>0.999995</td>
<td>0.000001</td>
</tr>
<tr>
<td>REF- SOELM</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
</tr>
<tr>
<td>REF- HOELM</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Radiance Domain</th>
<th>AFAR</th>
<th>1-AFAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>RAD- Operational TS1 OP</td>
<td>0.027919</td>
<td>0.972081</td>
<td>0.000003</td>
</tr>
<tr>
<td>RAD- Operational TSI OP Improved</td>
<td>0.012026</td>
<td>0.987974</td>
<td>0.000001</td>
</tr>
<tr>
<td>RAD- Operational TS2 25% Ideal</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
</tr>
<tr>
<td>RAD- Operational TS3 50% Ideal</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
</tr>
<tr>
<td>RAD- Operational TS4 75% Ideal</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
</tr>
<tr>
<td>RAD- Operational TS5 90% Ideal</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
</tr>
<tr>
<td>RAD- Ideal TS Ideal</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
</tr>
</tbody>
</table>

For this detector and target all results are quite good, as false alarms are minimal in all cases. In both domains the “best-case” scenarios achieve perfect detection. For the less than ideal cases, operational target spaces and traditional ELM, perfect detection is not achieved but few false alarms occur. These results are due to the fact that the red target is spectrally different from the background and that SMF accounts for this difference. Due to the ease of detection for this target no real conclusions can be based on which domain achieved better results.
Figure 7.2-2 and table 7.2-2 contain results from using SMF to detect the dark green paint target.

![Figure 7.2-2: ROC results for SMF detecting dark green paint target.](image)

<table>
<thead>
<tr>
<th>SMF</th>
<th>Reflectance Domain</th>
<th>VIS= 23km</th>
<th>AFAR</th>
<th>1-AFAR</th>
<th>VIS= 12km</th>
<th>AFAR</th>
<th>1-AFAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>REF- ELM</td>
<td></td>
<td></td>
<td>0.00157</td>
<td>0.99843</td>
<td>0.00051</td>
<td>0.99949</td>
<td></td>
</tr>
<tr>
<td>REF- OELM</td>
<td></td>
<td></td>
<td>0.00061</td>
<td>0.99939</td>
<td>0.00052</td>
<td>0.99948</td>
<td></td>
</tr>
<tr>
<td>REF- SOELM</td>
<td></td>
<td></td>
<td>0.00031</td>
<td>0.99969</td>
<td>0.00017</td>
<td>0.99983</td>
<td></td>
</tr>
<tr>
<td>REF- HOELM</td>
<td></td>
<td></td>
<td><strong>0.00031</strong></td>
<td><strong>0.99969</strong></td>
<td><strong>0.00017</strong></td>
<td><strong>0.99983</strong></td>
<td></td>
</tr>
<tr>
<td>Radiance Domain Global</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RAD- Operational TS1</td>
<td>OP</td>
<td></td>
<td>0.00335</td>
<td>0.99665</td>
<td>0.00988</td>
<td>0.99012</td>
<td></td>
</tr>
<tr>
<td>RAD- Operational TS2</td>
<td>25% Ideal</td>
<td></td>
<td>0.00256</td>
<td>0.99744</td>
<td>0.00433</td>
<td>0.99567</td>
<td></td>
</tr>
<tr>
<td>RAD- Operational TS3</td>
<td>50% Ideal</td>
<td></td>
<td>0.00157</td>
<td>0.99843</td>
<td>0.00129</td>
<td>0.99871</td>
<td></td>
</tr>
<tr>
<td>RAD- Operational TS4</td>
<td>75% Ideal</td>
<td></td>
<td>0.00041</td>
<td>0.99959</td>
<td>0.00011</td>
<td>0.99989</td>
<td></td>
</tr>
<tr>
<td>RAD- Operational TS5</td>
<td>90% Ideal</td>
<td></td>
<td>0.00006</td>
<td>0.99994</td>
<td>0.00002</td>
<td>0.99998</td>
<td></td>
</tr>
<tr>
<td>RAD- Ideal TS</td>
<td>Ideal</td>
<td></td>
<td><strong>0.00000</strong></td>
<td><strong>1.00000</strong></td>
<td><strong>0.00000</strong></td>
<td><strong>1.00000</strong></td>
<td></td>
</tr>
</tbody>
</table>

Table 7.2-2: AFAR results for SMF detecting dark green paint target.

These results show that the best results achieved were in the radiance domain when an ideal target space was used. Depending how close the target space used was to the ideal target space results in the radiance domain were better than reflectance domain results. This is highlighted by the fact that for both datasets the “90% Ideal” target spaces resulted in results that were better than the reflectance domain. As the target space is degraded radiance domain results become poorer than results observed in the reflectance domain.
Results for when SMF was used to detect the canvas target are presented in Figure 7.2-3 and table 7.2-3.

**Figure 7.2-3: ROC results for SMF detecting canvas target.**

<table>
<thead>
<tr>
<th>SMF</th>
<th>Reflectance Domain</th>
<th>VIS= 23km</th>
<th>VIS= 12km</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AFAR</td>
<td>1-AFAR</td>
<td>AFAR</td>
</tr>
<tr>
<td>REF- ELM</td>
<td>0.00017</td>
<td>0.99983</td>
<td>0.00021</td>
</tr>
<tr>
<td>REF- OELM</td>
<td>0.00012</td>
<td>0.99988</td>
<td>0.00011</td>
</tr>
<tr>
<td>REF- SOELM</td>
<td>0.00005</td>
<td>0.99995</td>
<td>0.00003</td>
</tr>
<tr>
<td>REF- HOELM</td>
<td><strong>0.00005</strong></td>
<td><strong>0.99995</strong></td>
<td>0.00003</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Radiance Domain Global</th>
<th>AFAR</th>
<th>1-AFAR</th>
<th>AFAR</th>
<th>1-AFAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>RAD- Operational TS1</td>
<td>OP</td>
<td>0.19028</td>
<td>0.80972</td>
<td>0.00049</td>
</tr>
<tr>
<td>RAD- Operational TS2</td>
<td>25% Ideal</td>
<td>0.08296</td>
<td>0.91704</td>
<td>0.00035</td>
</tr>
<tr>
<td>RAD- Operational TS3</td>
<td>50% Ideal</td>
<td>0.02502</td>
<td>0.97498</td>
<td>0.00021</td>
</tr>
<tr>
<td>RAD- Operational TS4</td>
<td>75% Ideal</td>
<td>0.00228</td>
<td>0.99772</td>
<td>0.00008</td>
</tr>
<tr>
<td>RAD- Operational TS5</td>
<td>90% Ideal</td>
<td>0.00019</td>
<td>0.99981</td>
<td><strong>0.00006</strong></td>
</tr>
<tr>
<td>RAD- Ideal TS</td>
<td>Ideal</td>
<td><strong>0.00008</strong></td>
<td><strong>0.99992</strong></td>
<td>0.00010</td>
</tr>
</tbody>
</table>

**Table 7.2-3: AFAR results for SMF detecting canvas target.**

In this case results from each domain are comparable. For the high visibility dataset the ideal target space in the radiance domain resulted in an AFAR value lower than but comparable to the SOELM/HOELM results and higher than ELM and OELM results. As the target space is degraded the radiance domain results become worse than the reflectance domain results. The results for the lower visibility dataset are quite comparable. The best results were observed in the reflectance domain for
SOELM/HOELM, radiance domain results were comparable and depending on the target space used were slightly better than results observed using OELM and ELM.

To summarize, results found from using SMF from each domain were quite comparable. The best results in the radiance domain ranged from nearly as good to slightly better than results obtained in the reflectance domain. The best radiance domain “1-AFAR” values from each target and dataset are highlighted in bold in tables 7.2-1 to 7.2-3. When these values are averaged the value is 0.99998. Similarly, the best reflectance domain “1-AFAR” values are highlighted in bold for each target and each dataset in the tables 7.2-1 to 7.2-3. When these values are averaged the value is 0.99991. This indicates that the average “1-AFAR” value for the best case scenario radiance results is similar to the average “1-AFAR” value for the best case scenario reflectance results. This is similar to what was observed for the SAM detector in section 7.1.

### 7.3 OSP

In this section the results using OSP from each domain are compared. The results from OSP used to detect the red target are presented in table 7.3-1. ROC curves for results achieving less than perfect detection can be seen in Figure 5.3-1.

<table>
<thead>
<tr>
<th>OSP Reflectance Domain</th>
<th>VIS= 23km AFAR</th>
<th>VIS= 23km 1-AFAR</th>
<th>VIS= 12km AFAR</th>
<th>VIS= 12km 1-AFAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>REF- ELM</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
<td>1.000000</td>
</tr>
<tr>
<td>REF- OELM</td>
<td>0.000007</td>
<td>0.999993</td>
<td>0.000004</td>
<td>0.999996</td>
</tr>
<tr>
<td>REF- SOELM</td>
<td>0.000009</td>
<td>0.999991</td>
<td>0.000004</td>
<td>0.999996</td>
</tr>
<tr>
<td>REF- HOELM</td>
<td>0.000009</td>
<td>0.999991</td>
<td>0.000004</td>
<td>0.999996</td>
</tr>
<tr>
<td>Radiance Domain Global</td>
<td>AFAR</td>
<td>1-AFAR</td>
<td>AFAR</td>
<td>1-AFAR</td>
</tr>
<tr>
<td>RAD- Operational TS1</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
<td>1.000000</td>
</tr>
<tr>
<td>RAD- Operational TS2</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
<td>1.000000</td>
</tr>
<tr>
<td>RAD- Operational TS3</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
<td>1.000000</td>
</tr>
<tr>
<td>RAD- Operational TS4</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
<td>1.000000</td>
</tr>
<tr>
<td>RAD- Operational TS5</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
<td>1.000000</td>
</tr>
<tr>
<td>RAD- Ideal TS</td>
<td>0.000000</td>
<td>1.000000</td>
<td>0.000000</td>
<td>1.000000</td>
</tr>
</tbody>
</table>

Table 7.3-1: Results for OSP on red metal target.
Detection results are perfect in the radiance domain and very few false alarms were observed in the reflectance domain. Due to the difference between the red target and the background it is easily detected by the OSP detector and results in each domain are similar.

The results that were observed using OSP to find the dark green paint target are presented in Figure 7.3-1 and table 7.3-2.

![Figure 7.3-1: ROC results for OSP on the dark green paint target.](image)

<table>
<thead>
<tr>
<th>OSP Reflectance Domain</th>
<th>VIS= 23km</th>
<th>VIS= 12km</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AFAR</td>
<td>1-AFAR</td>
</tr>
<tr>
<td>REF- ELM</td>
<td>0.33236</td>
<td>0.66764</td>
</tr>
<tr>
<td>REF- OELM</td>
<td>0.28037</td>
<td>0.71963</td>
</tr>
<tr>
<td>REF- SOELM</td>
<td><strong>0.19151</strong></td>
<td><strong>0.80849</strong></td>
</tr>
<tr>
<td>REF- HOELM</td>
<td>0.21242</td>
<td>0.78758</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Radiance Domain Global</th>
<th>VIS= 23km</th>
<th>VIS= 12km</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AFAR</td>
<td>1-AFAR</td>
</tr>
<tr>
<td>RAD- Operational TS1</td>
<td>0.15442</td>
<td>0.84558</td>
</tr>
<tr>
<td>RAD- Operational TS2</td>
<td>0.15161</td>
<td>0.84839</td>
</tr>
<tr>
<td>RAD- Operational TS3</td>
<td>0.14704</td>
<td>0.85296</td>
</tr>
<tr>
<td>RAD- Operational TS4</td>
<td>0.13899</td>
<td>0.86101</td>
</tr>
<tr>
<td>RAD- Operational TS5</td>
<td>0.12956</td>
<td>0.87044</td>
</tr>
<tr>
<td>RAD- Ideal TS</td>
<td><strong>0.11816</strong></td>
<td><strong>0.88184</strong></td>
</tr>
</tbody>
</table>

Table 7.3-2: AFAR results for OSP on dark green target.

For this detector and target, detection performance is better in the radiance domain compared to performance in the reflectance domain. No reflectance domain results are as good as results observed in the radiance domain. This is the case for both the high and low visibility data sets.
Results for the OSP detector on the canvas target are presented in Figure 7.3-2 and table 7.3-3.

For this detector and target the radiance domain results are superior to results observed in the reflectance domain. This is the case for both the high and low visibility data sets.

To summarize, radiance domain results observed for OSP are the same or better than reflectance domain results. The best radiance domain “1-AFAR” values from each target and dataset are highlighted in bold in tables 7.3-1 to 7.3-3. When these values are averaged the value is 0.94891. Similarly, the best reflectance domain “1-AFAR” values are highlighted in bold for each target and each dataset in the tables 7.3-1 to 7.3-3. When
these values are averaged the value is 0.88778. This indicates that the average “1-AFAR” value for the best case scenario radiance results is greater than the average “1-AFAR” value for the best case scenario reflectance results.

7.4 Results Summary

The information that was presented in this chapter can be summarized in various ways. Table 7.4-1 summarizes the domain in which the best detection results were observed in terms of AFAR.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>SAM</th>
<th>SMF</th>
<th>OSP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red Metal- High Vis</td>
<td>REF</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Red Metal- Low Vis</td>
<td>REF</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Dark Green Paint- High Vis</td>
<td>RAD</td>
<td>RAD</td>
<td>RAD</td>
</tr>
<tr>
<td>Dark Green Paint- Low Vis</td>
<td>RAD</td>
<td>RAD</td>
<td>RAD</td>
</tr>
<tr>
<td>Canvas- High Vis</td>
<td>RAD</td>
<td>REF</td>
<td>RAD</td>
</tr>
<tr>
<td>Canvas- Low Vis</td>
<td>RAD</td>
<td>REF</td>
<td>RAD</td>
</tr>
</tbody>
</table>

Table 7.4-1: Domain in which best results were observed for each scenario.

Table 7.4-1 lists which domain had the best results for each of the 18 scenarios considered. Note that in ten scenarios the best results observed were in the radiance domain. In four scenarios the best results observed were in the reflectance domain. In four situations perfect detection was achieved in both domains. It should be noted that for the scenarios when the reflectance domain results were better, that the radiance domain results were comparable. Also, two scenarios where the reflectance domain results were better occurred for the red metal target. Since this target is perhaps unrealistic in that it is highly detectable these results could be dismissed.

Another way to summarize the results in this chapter is to compare the average best “1-AFAR” values for each detector for each domain. The best results from each of the six scenarios for each detector were noted and averaged. These values were listed in the previous sections and are summarized in Table 7.4-2.
<table>
<thead>
<tr>
<th>Detector</th>
<th>RAD 1-AFAR</th>
<th>REF 1-AFAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAM</td>
<td>0.91403</td>
<td>0.81469</td>
</tr>
<tr>
<td>SMF</td>
<td>0.99998</td>
<td>0.99991</td>
</tr>
<tr>
<td>OSP</td>
<td>0.94891</td>
<td>0.88778</td>
</tr>
</tbody>
</table>

Table 7.4-2: Average “1-AFAR” results for each detector, for the best observed results in each domain in each situation.

This summary indicates that the SAM and OSP detectors performed slightly better in the radiance domain as indicated in Figures 7.1-2, 7.1-3, 7.3-1 and 7.3-2. The SMF detector seems to achieve similar detection results in both domains as seen in section 7.2.

This chapter has shown that in general radiance domain results are as good as or better than reflectance domain results. This addresses the main goal of this thesis. Further results for specular targets are presented in Appendix C. These results show that similar results are achieved when a target is specular vice Lambertian but detection can be degraded. It is also shown that this degradation could be theoretically corrected in the radiance domain by accounting for a target’s BRDF in the associated target space.
8. CONCLUSIONS

As with any study of this nature, it is difficult to state hard conclusions based on observations from relatively few datasets. Also, observations made in this thesis were sometimes unique evoking the common phrase of “the results were scene/target/situation dependant.” However, the datasets presented in this study are realistic and not-unlike a typical operational dataset. Furthermore there were general trends observed in this work that point us towards some general conclusions. The observations made in this thesis can be grouped into three main conclusions. The first speaks directly to the main goal of this thesis and is that the radiance domain is the more attractive domain in which to process oblique HSI. The second is that there are additional challenges associated with the oblique case and that some of these challenges can be overcome and accounted for. The third conclusion is that additional processes can be applied in the PBFM in order to improve results; however these benefits can be negated by not populating an appropriate target space. These conclusions are explained further in the following sections, along with additional work that could be done in future studies to address related questions.

8.1 Radiance Domain Benefits

As presented in Chapter 7 detection results in the radiance domain tended to be similar or slightly better than results observed in the reflectance domain. These results are broadly summarized in Tables 7.4-1 and 7.4-2. Note these summary tables consider only the “best-case scenario” in each domain in order to be able to make a meaningful comparison. The results can be attributed to a number of factors. The compensation technique presented and employed makes a few different assumptions. The first is that the relationship between radiance and reflectance is linear. As explained, ELM makes
this assumption and it is widely accepted, however it is an approximation and results in some compensation error. Secondly, it assumes that all surfaces in the scene are illuminated and orientated in the same fashion. This assumption is also widely accepted for the nadir case, however due to the wide range of viewable target surface orientations in the oblique case it is not as valid. This gives rise to notable compensation error as demonstrated in Figure 4.1-4. This compensation error is not an issue in PBFM and radiance domain processing. Surfaces of any orientation and illumination that are present in the scene can be accounted for in the target space generation process. The other compensation related error caused by the employed compensation method is when the change in target-sensor path length accounted for. Traditional ELM does not account for this oblique angle issue, and the associated errors are larger than those associated with OELM as demonstrated in Figures 4.1-1 and 4.1-2. OELM attempts to account for this however compensation error still occurs at a reduced level as seen in the aforementioned figures. PBFM in the radiance domain however, does not need to make any assumptions about the target-sensor path distance as this can be accounted for directly in the target space. Though the compensation errors caused by the techniques employed in this thesis are caused by imperfect assumptions, all compensation techniques require assumptions that result in compensation error and as discussed ELM is generally accepted as one of the most accurate atmospheric correction techniques available. In fact, the ground-truth based compensation methods employed in this body of work are likely more accurate than any other method available. Therefore one could not necessarily say that the reflectance domain results could be improved by a different compensation technique. PBFM in the radiance domain however, does not need to make any assumptions about
the target *per se*. As is discussed later, when PBFM is used, the detection error is mainly attributable to target space generation and characterization. The work in this thesis indicates that when target space generation error is minimized detection results are just as good as when compensation error is minimized. This is in keeping with the results presented by Lentilucci (2005).

The radiance domain processing presented here is applicable in any situation. As discussed the process employed here is an intuitive extension to a proven process used in the nadir case. In contrast, the reflectance domain process presented here was chosen in order to minimize compensation error and is applicable mainly in research situations. Other compensation techniques are available that are applicable in operational settings, however as discussed, previous studies have shown them to be inferior to ELM. This trade-off between applicability and reliability for compensation routines in the reflectance domain is a non-issue for PBFM in the radiance domain. This, combined with the detection results presented in Chapter 7 make the radiance domain the more attractive domain for oblique detection.

In summary, this work shows that the PBFM process allows us to achieve radiance domain detection results that are just as good as reflectance domain detection results. The compensation routines introduced and employed in this thesis represent the “best-case scenario” in terms of compensation ability and provides research grade level reflectance cubes. This ground-truth based technique may not be applicable in many situations. The PBFM process used in this thesis, on the other hand, would be applicable in any situation. Since results from the PBFM radiance domain process were comparable to results achieved in the reflectance domain using an unrealistically accurate compensation
process, it is apparent that the PBFM process should be considered a prime candidate for off-nadir target detection.

8.2 Oblique Case Challenge Mitigation

This body of work has shown that there are additional challenges associated with the oblique case. This thesis has provided ways to mitigate some of the challenges associated with oblique captured HSI. It has also been shown that these methods offer improved detection results. For example, in Chapter 2 the varying path length issue was identified as was the target surface illumination and orientation issue. These issues were addressed in the reflectance domain by using OELM, SOELM and HOELM. As seen in Chapter 5, these techniques offered superior detection results over traditional ELM. Similarly, these issues were addressed in the radiance domain by creating expanded target spaces. This thesis has confirmed that oblique target detection is possible and that the additional challenges, including the varying target-sensor path distance, can be accounted for.

8.3 Radiance Domain Observations

The third group of conclusions that can be drawn from this body of work are related to the radiance domain. As mentioned in section 8.1 this thesis has shown that the work originally presented by Lentilucci is quite applicable to the oblique case. Its versatile nature allows us to account for additional challenges by expansion of a target space. It has been shown that the versatile nature of the process can be extended to potentially account for the BRDF of a target, which is hypothetically a more important issue in the oblique case. It has also been shown that further improvements are possible by processing radiance cubes locally. However, as with PBFM in the nadir case, this study has shown that results using PBFM for the oblique case depend on the quality of the target space created. When the target space used is unlike that of the ideal target space, detection
results are degraded. How well the target space is defined depends directly on the user’s
knowledge of conditions at the time of a data collect and *a priori* knowledge of the target.
A potential area of improvement for the PBFM is the characterization of the target space.
This study collapsed the target space into a single representative mean vector. Past
studies have attempted to describe target spaces using endmembers and have shown that
a mean vector representation achieves superior results. Future research should investigate
statistical and geometrical methods of characterizing the target space that could increase
the utility of the PBFM process even further, both for the oblique and nadir cases.

8.4 Thesis Summary

In summary, the goal of the thesis developed by DIRS and its sponsors and set out in
Chapter 1 was met. This work has shown that results in the reflectance and radiance
domain were similar; however, the applicability of the radiance domain process indicates
it is more appropriate for the oblique case. Contributions to the field of remote-sensing
include a review and investigation into the challenges presented by the oblique case.
Though many of the additional challenges are outlined in the literature, no previous work
explicitly addresses or accounts for the varying target-sensor path length, which has been
a major component of this thesis. That is to say, this work has helped define the varying
target-sensor path distance issue in the oblique case. Furthermore, a compensation
technique, though applicable mainly in research settings, has been presented and results
indicate that it is relevant and applicable for compensating oblique imagery. Similarly, an
extension to Lentilucci’s PBFM has been presented here along with example test results
that indicate it is relevant for use with oblique HSI. Example results that investigate how
PBGM can be used to account for a target’s BRDF are also presented. This work has
demonstrated how the choice of target space vectors is important to detection when using standard detectors and how local processing can affect detection results.

8.5 Future Work

As alluded to earlier, the most interesting work related to this topic would be the development of an improved method of target space characterization. The average vector provides decent results, however it seems that there should be other mathematical ways to describe such a space. A method should be sought that not only accurately characterizes or summarizes a target space, but it should also be able to compensate for a user’s inability to sufficiently or appropriately populate a target space. Ideally, a method should be developed that can maximize the contribution of target vectors in the space that are present in the imagery under study and minimize the contribution of those vectors that are least likely be present in the imagery under study. This work would improve the applicability of PBFM in both the nadir and oblique cases.

Another extension to this project would be to test some of the conclusions found here on real datasets. At this time no such data is readily available. The simulated data used in this thesis was adequate for this initial study and provided the unique ability to study the question at hand with perfect ground truth and with the ability to minimize unwanted factors such as noise. However, more realistic simulated datasets would arguably lend more credibility to any observations made. Real data would allow for observations that would be accepted by the entire community that is not familiar with DIRSIG.

Another topic that would be interesting to pursue would be the development of a more applicable oblique compensation method. As discussed this method has been developed to optimize accuracy. A more in depth study using real data to investigate the
image position/radiance relationship would be interesting to pursue. If this relationship could be confirmed with a more in depth study it could potentially be used to create a more widely useable compensation routine.
APPENDIX A. RADIANCE & IMAGE POSITION

A.1 Background/Purpose

This study seeks to investigate how an image that has been acquired from an oblique look angle may be appropriately atmospherically compensated and thus be made available to various “traditional” target detection schemes. Specifically, this study aims to determine the relationship between sensor reaching radiance and image location.

A.2 Procedure/Setup

For this study a simple scene was created in DIRSIG which can be seen in Figure 1. The scene contains various simple shapes made up of various materials that will be used in future studies. For this study, there were three additional reflectance panels that ran the length of the scene. These three panels that represent Lambertian reflectors had spectrally flat reflectances of 5%, 30% and 50%. The following parameters in Table 1 were used by MODTRAN in order to simulate the atmosphere in the scene:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerosol Model</td>
<td>Rural</td>
</tr>
<tr>
<td>Multiple Scattering</td>
<td>DISORT</td>
</tr>
<tr>
<td>Sensor Altitude</td>
<td>11,811 ft = 3.6 km</td>
</tr>
<tr>
<td>Latt / Long</td>
<td>Washington, DC, Latt = 38.5, Long = -77.0</td>
</tr>
<tr>
<td>Elevation</td>
<td>262 ft = 0.08 km</td>
</tr>
<tr>
<td>Date</td>
<td>July 1, 2007</td>
</tr>
<tr>
<td>DOY</td>
<td>182</td>
</tr>
<tr>
<td>TOD</td>
<td>10am EST = 1500 GMT</td>
</tr>
<tr>
<td>Sun Location</td>
<td>ALT = 57.9, AZ = 109.7 deg</td>
</tr>
<tr>
<td>Wavelength Region</td>
<td>0.380 to 2.510 um</td>
</tr>
<tr>
<td>FWHM</td>
<td>0.010 um</td>
</tr>
</tbody>
</table>

Table 3: Atmospheric parameters.
An image was rendered from an oblique look angle with the approximate geometrical setup as seen in Figure 2. The resulting “true color image” of the simple scene as displayed using ENVI can be viewed in Figure 3. Sensor reaching radiance was measured at every line of the 50% and 5% reflectors.

Figure 5: Viewing geometry of scene

Figure 6: True color radiance image displayed in ENVI.
A more precise geometry of the scene is shown in Figure 4. Note that the field of view (FOV) in this case works out to be 0.69 degrees which corresponds to just over 1km on the ground. Note that the photons traveling from the far edge of the scene travel about 987m farther than the photons from the close edge of the scene. It follows that each of the 600 lines in the image do not represent an equal space on the ground. The pixels on the far edge of the image correspond to larger footprints compared to the pixels on the close edge.

![Figure 7: Detailed viewing geometry.](image)

The geometrical relationship between the look angle down from the horizontal, $\theta$, and path distance, $z$, is as follows:

$$z = \frac{\text{sensor height}}{\sin \theta}$$

(1)

As the look angle down from the horizontal increases the path distance will become smaller. The shorter the path length, the higher the transmission and the lower the path radiance associated with that path. In other words, the more oblique the look angle the longer the path length which will mean a lower transmission and higher path radiance. This concept is illustrated in Figures 5 and 6. These plots are derived from the DIRSIG truth image for the scene in Figure 3 and demonstrate how transmission and path radiance change with image location.
Figure 8: Average transmission as a function of image location

Figure 9: Average path radiance as a function of image location
A.3 Results

Figures 7-25 show the relationship between sensor reaching radiance and image location for various bands. Bad bands were excluded based on observations made by Aten et al., (2004) and empirical data observed for this particular data set. The observed sensor reaching radiance is plotted in blue. Line 0 corresponds to the bottom line in Figure 3 which is the line corresponding to the point in the scene which is closest to the sensor. Linear relationships are fit to the data and are shown in black. The approximated linear relationships are presented in equation form on each graph. The R-squared metric is used to determine how appropriate the approximated relationship is (Johnson & Wichern, 2002).

5% reflector data

![Graph showing linear relationship](image)

Figure 10: Sensor reaching radiance for 5% reflector at .38 um.
Figure 11: Sensor reaching radiance for 5% reflector at .42 um.

Figure 12: Sensor reaching radiance for 5% reflector at .46 um.
Figure 13: Sensor reaching radiance for 5% reflector at .5 um.

Figure 14: Sensor reaching radiance for 5% reflector at .62 um.
Figure 15: Sensor reaching radiance for 5% reflector at .74 um.

Figure 16: Sensor reaching radiance for 5% reflector at .86 um.
Figure 17: Sensor reaching radiance for 5% reflector at .98 um.

Figure 18: Sensor reaching radiance for 5% reflector at 1.06 um.
Figure 19: Sensor reaching radiance for 5% reflector at 1.26 um.

Figure 20: Sensor reaching radiance for 5% reflector at 1.54 um.
50% reflector data

Figure 21: Sensor reaching radiance for 5% reflector at 0.38 um.

Figure 22: Sensor reaching radiance for 5% reflector at 0.50 um.
Figure 23: Sensor reaching radiance for 5% reflector at 0.62 um.

Figure 24: Sensor reaching radiance for 5% reflector at 0.74 um.

\[ y = -8E-08x + 0.0191 \]
\[ R^2 = 0.9999 \]

\[ y = -2E-07x + 0.0141 \]
\[ R^2 = 0.9999 \]
Figure 25: Sensor reaching radiance for 5% reflector at 0.86 um.

Figure 26: Sensor reaching radiance for 5% reflector at 0.98 um.
Figure 27: Sensor reaching radiance for 5% reflector at 1.06 um.

Figure 28: Sensor reaching radiance for 5% reflector at 1.26 um.
A.4 Discussion

As image location increased in terms of line number (hence, view angle), the associated increase in path distance resulted in decreased transmission and increased upwelled radiance. Generally, for the low 5% reflector the increase in upwelled radiance outweighed the effects of decreased transmission and the sensor reaching radiance increased with line number. The opposite was observed for the 50% reflector.

Almost every plot indicates that a linear approximation can be made when considering the relationship between image location and sensor reaching radiance. The exception to this is for the 50% reflector at .38 um. The shape in this plot can be attributed to lens fall off (Schott, 2007). For this reflectance value and wavelength the change in radiance across the scene due to change in path radiance and transmission through the atmosphere is not that much greater than the change across the scene due to the lens fall off of the sensor and hence the spike in the scene in the middle of the image.

A.5 Conclusion

A linear approximation for the relationship between image location and sensor reaching radiance is valid for this sort of viewing geometry and situation. Even greater accuracy could be obtained if piece-wise linear interpolation is used. It should be noted that this study does not consider spatial variation in the atmosphere as the atmosphere is constant in the data set considered here. Real imagery would contain variation in the atmosphere.
APPENDIX B. LOCAL TARGET DETECTION IN THE RADIANCE DOMAIN

In this appendix the effects of performing target detection on local regions of a dataset are investigated. So far in this thesis, when performing target detection in the radiance domain, target spaces have been created that are associated with targets located throughout the image. The target space for an oblique dataset can be considered an expanded version of a traditional nadir target space. In a sense, the target space for an oblique dataset can be considered the sum of several local target spaces, each of which is populated by varying the 5 original parameters presented by Ientilucci (2005). Each local target space is associated with a specific local area within the image where the target-sensor path distance associated with each pixel within the area can be approximated as constant. That is to say, by considering a small section of the sensor FOV, the target-sensor path distance can be considered constant, much like it is in the nadir case. Similarly, the background pixels within this same area could be considered similar, in that background pixels of the same material will have the same measured spectral radiance signature, unlike pixels of the same material not within the local region. Each local region would have a different set of background endmembers and statistical parameters. Since the target spaces and background descriptors for each local section are unique from each other and indeed different from their global counterparts it stands to reason that performing target detection locally may increase detection performance. In this appendix, results from local and global detection are compared for each target using the high visibility dataset. The high visibility dataset was broken up into five equal sections along the longer spatial dimension of the image presented in Figure 3.1-2. Results are organized by detector and target type. As with the global case presented in
chapter 6, different target spaces were created by mixing the mean ideal and mean operational target vectors in various ratios. Though this data is presented to give further weight to the conclusions drawn from chapter 6, direct comparisons between local and global detection results are only made for the instances when the ideal target spaces were used. This is because of the arbitrary nature of populating operational target spaces. An operational target space selected for a given local area may be an excellent or very poor prediction of the actual target vectors within that area compared to the operational target space populated for the global case.

B.1 SAM

The SAM detector is considered first. Figure B.1-1 illustrated the observed results in terms of ROC curves. Results for the ideal global case as well as the ideal local case and operational local scenarios are provided. The results in terms of AFAR are presented in Table B.1-1. The ideal global results are included to facilitate an easy comparison.

Figure B.0-1: ROC Results associated with local processing in the radiance domain for the high visibility dataset.
<table>
<thead>
<tr>
<th>SAM</th>
<th>Canvas</th>
<th>DGP</th>
<th>Red</th>
</tr>
</thead>
<tbody>
<tr>
<td>RAD- Ideal TS</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ideal</td>
<td>0.06279</td>
<td>0.93721</td>
<td>0.03763</td>
</tr>
<tr>
<td>0.07659</td>
<td>0.92341</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Radiance Domain Local</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RAD- Operational TS1 Local OP</td>
<td>0.05534</td>
<td>0.94466</td>
<td>0.24342</td>
</tr>
<tr>
<td>RAD- Operational TS2 Local 25% Ideal</td>
<td>0.04873</td>
<td>0.95127</td>
<td>0.18074</td>
</tr>
<tr>
<td>RAD- Operational TS3 Local 50% Ideal</td>
<td>0.04304</td>
<td>0.95696</td>
<td>0.09891</td>
</tr>
<tr>
<td>RAD- Operational TS4 Local 75% Ideal</td>
<td>0.03813</td>
<td>0.96187</td>
<td>0.05954</td>
</tr>
<tr>
<td>RAD- Operational TS5 Local 90% Ideal</td>
<td>0.03764</td>
<td>0.96236</td>
<td>0.04243</td>
</tr>
<tr>
<td>RAD- Ideal TS, Local Stats Ideal</td>
<td>0.03775</td>
<td>0.96225</td>
<td>0.03286</td>
</tr>
<tr>
<td>0.07673</td>
<td>0.92327</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table B0-1: AFAR results for local radiance domain detection for high visibility dataset.

It is apparent that the local processing results in improved detection for the canvas target, marginally better results for the green target and similar results for the red target. As a whole therefore, local processing seems to provide a marginal advantage over global processing when the SAM detector is used. Also, as with the global scenarios presented in chapter 6, it is shown here that target spaces with mean vectors similar to the mean vector of the ideal target space achieve the best results. That is to say, though detection can be marginally improved in the radiance domain by doing local processing, the benefits of populating an accurate target space are much greater and effort should be expended on these tasks accordingly.

B.2 SMF

The SMF detector is considered next. Results are presented in Figure B.2-1 and Table B.2-1. Results for the ideal global case as well as the ideal local case and operational local scenarios are provided. The ideal global results are included to facilitate an easy comparison.
The SMF detector achieves improved results when the local processing is performed for the canvas and dark green paint targets. Perfect detection occurs for the red target. As with SAM in section B.1 and in chapter 6, the best results are observed for target spaces similar to the ideal target space. As with the SAM detector, results can be improved slightly by processing the HSI locally, however this effort should not be expended at the expense of populating a relevant target space.

**B.3 OSP**

The OSP detector is considered next. Results are presented in Figure B.3-1 and Table B.3-1. Results for the ideal global case as well as the ideal local case and operational local scenarios are provided. The ideal global results are included to facilitate an easy comparison.
Table B0-1: ROC Results associated with local processing in the radiance domain for the high visibility dataset. Results for the red target are not presented as perfect detection occurred for this target.

Table B.3-1: AFAR results for local radiance domain detection for the high visibility dataset.

For OSP, results were improved for the canvas target when local processing was done. In terms of AFAR local processing achieved results that were worse than the global detection results for the dark green paint target. However, all true target pixels were found in the local scenario before they were found in the global scenario as can be seen in Figure B.3-1. Perfect detection results were observed in both situations for the red target.

As with SAM and SMF and as seen in chapter 6, detection results seem to improve the more similar the target space vector used was to the mean ideal target space vector. This improvement seems to be greater than the improvement (or non-improvement as seen for the green target) observed by performing local processing.
B.4 Summary

There are two cases where the global detection process outperformed the local process in terms of AFAR. This occurred when SAM was used to detect the red metal target and when OSP was used to detect the dark green paint target. In five other scenarios the local detection process generated better results and in two cases both processes produced perfect detection results. Therefore in general one could conclude that the local process is advantageous.

The downside to the local process is the amount of time it takes to process the data. Statistical parameters are required for each local area in order to perform SMF. Similarly, background endmembers are required to be found for each local area. This extra processing may not be feasible in all situations.

Overall for this dataset, the improvements in detection performance observed by processing locally versus globally were not as significant as other factors. For example, as is shown in the preceding sections, if the target space is represented by a mean vector that is unlike the ideal target space mean vector, local results can degrade to be worse than observed global results. Therefore emphasis should be placed on ensuring a reasonable global target space is populated over putting effort into local processing. Though the benefits are seemingly minimal, the option of local processing demonstrates the versatility of the PBFM and radiance domain processing. This is another factor when choosing the domain in which to process oblique HSI.
APPENDIX C. NON-LAMBERTIAN TARGETS

The targets modeled in this thesis have all been Lambertian. This appendix provides example detection results for a non-lambertian target in both datasets used in this thesis. The target was modeled using DIRSIG. A specularity value of 0.9 was assigned to the red target in both the high and low visibility datasets presented in chapter 3. The specularity variable set in DIRSIG describes the ratio of the reflected radiance from the specular direction over the total reflected radiance. Therefore a ratio of 1.0 represents a very specular target, and a ratio of 0.0 represents a diffuse Lambertian target (Sanders et al., 2007). By assigning a value of 0.9 the red metal target is modeled as a specular target. Since this is only a first order approximation of a material BRDF only limited trials were conducted with this data to demonstrate the effects on detection results. Specifically, OELM was performed on both data sets and SAM was applied on the resulting reflectance cubes. Comparisons to the corresponding results observed for the Lambertian version of the target were then made.

Radiance domain processing was performed but only ideal target spaces were considered. Ideal target spaces associated with the specular datasets were identified and representative mean target vectors were calculated for each target space. SAM was applied using the representative target space vectors. The Lambertian ideal target spaces used for the Lambertian datasets were also used on the specular dataset. The Lambertian target spaces represent the best-case scenario in terms of target space population when a target’s BRDF is not known. Radiance domain results for the specular targets were compared to results achieved for the corresponding Lambertian targets.
C.1 Radiance Curves and Compensation Results

Example radiance curves resulting from the modeled non-Lambertian target are presented in Figure C.1-1. Note that the assignment of a specularity of 0.9 to the target material results in different radiance curves. Since all of the target pixels in these datasets are in the “non-specular direction” radiance values are lower for the target that is assigned a specularity. If radiance measurements of the target were taken of the spectral lobe of the target material, radiance values would be higher for the specular target. Note that the examples shown in Figure C.1-1 are for a target pixel on the “front” of the red car in grouping 1. The discrepancy between the radiance for the Lambertian and specular targets is different for each target pixel in the image, the examples presented represent one of the more noticeable discrepancies observed for these datasets. That is to say, many target pixels had similar radiance curves for both the Lambertian and specular cases.

![Figure C.1-1: Examples of discrepancies between Lambertian and specular radiance curves for a target pixel in grouping 1.](image)

As one would expect, the resulting reflectance curves for the target as estimated by OELM were slightly different as well. Example OELM derived reflectance curves are presented in Figure C.2-2.
C.2 Reflectance Domain Detection Results

The difference in radiance curves between the specular and Lambertian targets resulted in different estimated reflectance curves in each case. This section presents target detection examples for the reflectance domain. SAM detection results are presented in Figure C.2-1 and Table C.2-1.

<table>
<thead>
<tr>
<th></th>
<th>Lambertian</th>
<th>Non-Lambertian</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vis =23 km</td>
<td>AFAR</td>
<td>1-AFAR</td>
</tr>
<tr>
<td></td>
<td>0.00617</td>
<td>0.99383</td>
</tr>
<tr>
<td>Vis=12 km</td>
<td>0.10823</td>
<td>0.89177</td>
</tr>
</tbody>
</table>

Table C.2-1: AFAR results for Lambertian and specular targets.

AFAR results indicate that results for the specular target are not as good as detection results observed for the Lambertian target. This is backed up in the ROC curve in Figure
C.2-1 for the low visibility case. For the high visibility case the ROC results indicate that the specular dataset achieved better detection results at low FARs. In both datasets detection results for the Lambertian and specular targets are comparable, especially in the high visibility dataset.

This preliminary study indicates that by changing the target properties detection performance in the reflectance domain does change, as one would expect. Overall, detection of Lambertian targets is better but not necessarily at all FARs. This makes intuitive sense, since the specularity of the target directly impacts the targets spectral radiance signal sometimes this will enhance the detectability of the target signal other times it will degrade the target signal. The change that occurs is inherently situation dependant.

C.3 Radiance Domain Detection Results

The mean representative target space vectors for both the Lambertian and specular datasets are presented in Figure C.3-1. Note that there is a discrepancy between the average specular and average Lambertian vectors. This is in keeping with the example presented in Figure C.1-1.
The results for the specular targets are compared against those for the Lambertian target. Also the Lambertian target space is used on the specular datasets. This is to show how PBFM can be used to handle the BRDF of a target. These results are presented in Figure C.3-2 and Table C.3-1.

![Figure C.3-2: Detection results for specular and Lambertian targets in the radiance domain.](image)

<table>
<thead>
<tr>
<th>Vis = 23 km</th>
<th>Lambertian Target- Lambertian TS</th>
<th>Specular Target- Specular TS</th>
<th>Specular Target - Lambertian TS</th>
</tr>
</thead>
<tbody>
<tr>
<td>AFAR</td>
<td>0.07659</td>
<td>0.07200</td>
<td>0.08011</td>
</tr>
<tr>
<td>1-AFAR</td>
<td>0.92341</td>
<td>0.92800</td>
<td>0.91989</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Vis = 12 km</th>
<th>Lambertian Target- Lambertian TS</th>
<th>Specular Target- Specular TS</th>
<th>Specular Target - Lambertian TS</th>
</tr>
</thead>
<tbody>
<tr>
<td>AFAR</td>
<td>0.22851</td>
<td>0.21989</td>
<td>0.27318</td>
</tr>
<tr>
<td>1-AFAR</td>
<td>0.77149</td>
<td>0.78011</td>
<td>0.72682</td>
</tr>
</tbody>
</table>

Table C.3-1: AFAR results comparing Lambertian and specular targets.

The results from each scenario are quite similar for each dataset. For the high visibility dataset 1-AFAR results range from 0.9199 to 0.9280 and the ROC curves are all quite similar. Note that the worst results were observed when the specular dataset was processed using the Lambertian target space. This indicates that if the BRDF of a target is not considered, detection results may degrade. However, the nature of PBFM allows us to take into account the BRDF of a target. This process is simulated by taking the ideal target space of the specular dataset. The resulting ROC curve and associated AFAR value indicate an improved detection rate. This trend occurs in the low visibility dataset as well.
These examples demonstrate the utility and adaptability inherently associated with the PBFM process.

C.3 Summary

This appendix contains examples that show how detection results degrade when a target’s reflective properties become less Lambertian and more specular. Though this trend is very subtle it can be easily mitigated in the radiance domain due to the inherently versatile nature of PBFM. This is another advantage that could be considered when choosing the processing domain for oblique HSI since the non-Lambertian properties of targets are normally more apparent at oblique viewing angles compared to nadir viewing angles.
Bibliography


