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by

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B.S. Rhodes College, 2011

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

Abstract

The spectral signatures of vehicles in hyperspectral imagery exhibit temporal variations due to the preponderance of surfaces with material properties that display non-Lambertian bidirectional reflectance distribution functions (BRDFs). These temporal variations are caused by changing illumination conditions, changing sun-target-sensor geometry, changing road surface properties, and changing vehicle orientations. To quantify these variations and determine their relative importance in a sub-pixel vehicle reacquisition and tracking scenario, a hyperspectral vehicle BRDF sampling experiment was conducted in which four vehicles were rotated at different orientations and imaged over a six-hour period. The hyperspectral imagery was calibrated using novel in-scene methods and converted to reflectance imagery. The resulting BRDF sampled time-series imagery showed a strong vehicle level BRDF dependence on vehicle shape in off-nadir imaging scenarios and a strong dependence on vehicle color in simulated nadir imaging scenarios. The imagery also exhibited spectral features characteristic of sampling the BRDF of non-Lambertian targets, which were subsequently verified with simulations. In addition, the imagery demonstrated that the illumination contribution from vehicle adjacent horizontal surfaces significantly altered the shape and magnitude of the vehicle reflectance spectrum. The results of the BRDF sampling experiment illustrate the need for a target vehicle BRDF model and detection scheme that incorporates non-Lambertian BRDFs. A new detection algorithm called Eigenvector Loading Regression (ELR) is proposed that learns a hyperspectral vehicle BRDF from a series of BRDF measurements using regression in a lower dimensional space and then applies the learned BRDF to make test spectrum predictions. In cases of non-Lambertian vehicle BRDF, this detection methodology performs favorably when compared to subspace detections algorithms and graph-based detection algorithms that do not account for the target BRDF. The algorithms are compared using a test environment in which observed spectral reflectance signatures from the BRDF sampling experiment are implanted into aerial hyperspectral imagery that contain large quantities of vehicles.
To my wife, Anna Laymon, without whose love and support this body of work would not have been possible.
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Chapter 1

Introduction

Hyperspectral images contain hundreds of narrow contiguous bands of spectral information for each pixel proportional to the composition of materials in each pixel’s instantaneous field of view (IFOV). The use of hyperspectral imagery to discriminate targets of interest from scene background using a target signature is an established methodology in the field of remote sensing. Hyperspectral target detection leverages the spectral signature constancy of any given material and the spectral diversity of a hyperspectral image to locate pixels in the imagery that match the spectral signature of the known target. This spatial target localization, based on the remotely imaged spectrum, is a proven technique used to aid vehicle reacquisition and tracking algorithms.

General purpose tracking algorithms incorporate both a feature space measure of similarity in addition to spatiotemporal information such as previous target track positions as a function of time and road network maps using techniques such as Kalman filters, particle filters, and probabilistic data association [1–4]. In a hyperspectral vehicle tracking algorithm, this feature space is populated by the observed vehicle and background spectra, and measures of similarity take the form of spectral operators such as the Adaptive Cosine Estimator (ACE) and the Spectral Matched Filter (SMF) [5]. Vehicle reacquisition using this spectral similarity information is a subset of the vehicle tracking problem in which the goal is to reacquire the location of a vehicle in an image based on previously observed spectra with little or no spatial information considered. More formally stated, given a set of previously observed spectra associated with a specific vehicle $S = \{s_1, s_2, ..., s_n\}$, with known time stamps $T = \{t_1, t_2, ..., t_n\}$, and known sensor-sun geometry $G = \{g_1, g_2, ..., g_n\}$, find the pixels in a new image $\{S', t_{n+1}, g_{n+1}\}$ that most likely represent the location of the same vehicle. While the vehicle reacquisition problem is used in target tracking applications, in situations with large temporal gaps between images, such as space based imagery, the problem domain stands on its own, without a tracking context. The scope of this study is to examine the spectral target reacquisition component of the hyperspectral vehicle tracking problem, focusing solely on vehicle localization using spectral similarity.

In remote sensing there exists a trade space between spatial resolution and spectral resolution. In order to maintain the same signal to noise ratio (SNR), an increase in spectral channels must be accompanied by larger pixel IFOVs. When the aperture reaching photons are segmented into a greater number of spectral bins, the SNR of each bin decreases proportional to the degree of segmentation. In order to make up for the lost signal, larger IFOVs are typically used when integration time and aperture size cannot be increased. For this reason, hyperspectral sensors
typically have ground sample distances (GSDs) much larger than their broadband panchromatic counterparts. This study, therefore, narrows its purview to investigating only spatial resolutions that result in entire vehicles falling within a single pixel IFOV. This sub-pixel/single-pixel hyperspectral imaging domain results in all the target leaving light being lineally integrated on the sensor focal plane, resulting in a single vehicle spectrum.

A Lambertian surface outside on a sunny day distributes reflected light evenly across the hemisphere in such a way that a camera observes the same spectral radiance regardless of the view angle. This surface type is commonly referred to as matte or diffuse. In contrast, a non-Lambertian surface concentrates the reflected light into a specular lobe centered on the reflectance vector, opposite the sun. The observed intensity of these surfaces, called shiny or specular surfaces, depends on the geometry of the sun and observer relative to the surface normal vector. A mirror is the extreme case of a non-Lambertian surface. The function that dictates how a non-Lambertian surface distributes reflected light across a hemisphere, given a specified illumination source and wavelength, is called the bidirectional reflectance distribution function (BRDF) [6].

The majority of a vehicle’s exterior materials, such as the paint, trim, and windows, exhibit non-Lambertian surface properties. In the sub-pixel/single-pixel domain, the individual BRDF spectral returns resulting from the various material and surface normal vector combinations are integrated into a single spectrum. In addition, different vehicles have different distributions of surface materials and surface normal vectors that dictate where in space the specular lobes are centered. Furthermore, when a vehicle rotates, the distribution of surface normal vectors and visible materials changes, altering the integrated BRDF of the vehicle. This integrated BRDF effect of the entire vehicle is referred to as “vehicle level” or “object level” BRDF. The observed radiance spectrum of a vehicle therefore varies based on the positions of the sun and sensor relative to the vehicle, the direction the vehicle is facing, the shape of the vehicle, and the material surface properties of the vehicle.

The elevation angle of the observer plays an important role in the reflected radiance spectrum of a vehicle. Steeper (nadir) view angles result in vehicle signatures dominated by upper horizontal surfaces such as the roof, hood, and trunk, while oblique (off-nadir) view angles result in a spatially integrated spectrum dominated by the vertical side surfaces, such as the doors. This distinction becomes important when considering self-shadowing effects and background adjacency effects on the observed vehicle spectrum. The self-shadowing effects lower the spectral magnitude and alter the spectral shape (color) due to the fact that direct solar and downwelled irradiance have spectrally unique characteristics. Background adjacency effects occur when the road surface and other nearby surfaces and vegetation reflect light onto the vehicle sides. This background illumination again alters the magnitude and color of the vehicle. For example, when a white vehicle is parked on grass, it looks green. These effects—self-shadowing and background adjacency—are most prominent in oblique vantage points where the vehicle sides constitute a greater portion of the visible surfaces.

Inherent in the vehicle reacquisition/tracking problem is the uncertainty of a vehicle’s position and direction. Furthermore, the sensor position and the sun position may change between images, in addition to weather and cloud cover changes. The degree to which these changes occur is dependent on the sensor frame rate or revisit rate. These temporal changes in sun-target-sensor geometry and orientation alter the effective BRDF measurement of the vehicle while changes in
vehicle position within the scene and weather changes alter the vehicles incident illumination. All of these sources of temporal variation manifest as variations in the observed vehicle reflectance spectrum. The goal of this research is to better understand the relative importance of these temporal BRDF effects and quantify the magnitude of their influence on the vehicle reflectance spectrum. By better understanding the phenomenology of these temporal variations in observed vehicle reflectance, vehicle reacquisition and tracking algorithms could potentially refine their models in order to account for these variations in an effort to increase overall hyperspectral tracking accuracies.

In order to study the described factors of variation that affect vehicle BRDF, a hyperspectral BRDF sampling experiment was executed at the Rochester Institute of Technology (RIT) in which four vehicles were rotated and imaged consistently through a six hour span of time in illumination conditions dominated by direct solar radiation. The vehicles were strategically chosen in order to isolate BRDF effects due to vehicle shape and vehicle color. In addition to the BRDF sampling conducted throughout the day, a specific experiment was also executed to isolate and measure the background adjacency effects caused by the illumination of vehicles by the road and nearby background. These experiments provide a time series of reflectance spectra for each vehicle that aid in the understanding of the described underlying temporal BRDF effects.
Chapter 2

Background

2.1 Hyperspectral Vehicle Tracking

Wide area motion imagery (WAMI) sensors are typically mounted on manned and unmanned fixed wing aircraft, helicopters, and dirigibles with city-sized fields of view, frame rates on the order of 1-2 frames per sec, and spatial resolutions on the order of 0.5 meters per pixel [7]. These persistent surveillance geospatial-temporal data products are used by militaries and law enforcement agencies to form context-based statistical models of normal and abnormal behavior in order to identify suspicious individuals and events [7–9]. These behavioral models are formed primarily using the routes of vehicles and individuals making accurate tracking a limiting factor in the success of a WAMI system [7]. Accurate object tracking is also used in post crime forensics in determining who was involved in the event, where they came from, and where they went afterward [9].

The ability to better discriminate and detect in-scene targets using hyperspectral rather than broadband or multispectral imagery has been rigorously shown and canonically accepted by the remote sensing community. Many algorithms leverage this added spectral information to increase object tracking accuracies using sequences of hyperspectral images. Stellman et. al. at the Naval Research Laboratory demonstrated the target detection capabilities of a Predator remotely piloted vehicle equipped with a hyperspectral imaging sensor designed for WAMI applications [10]. Hyperspectral object tracking research at the Army Research Laboratory produced an algorithm that compares two spectral signatures indirectly using randomly selected background pixels to track a taxiing airplane in AVIRIS VNIR-SWIR imagery [11]. Varsano et. al. established a target tracking algorithm that incorporates two steps: a hyperspectral target detection algorithm to transform a series of hypercubes to a series of 2D images (spatial detection) followed by a track-before-detect approach (temporal detection) [12]. The algorithm is demonstrated on synthetic aerial hyperspectral imagery based on a real infrared (IR) imagery of unresolved flying targets under cloud obscuration conditions. Additional hyperspectral tracking research utilizes a ground based VNIR camera for robust pedestrian and vehicle tracking by detecting shadows and using both spectral and motion prediction cues [13, 14]. Similarly, Herweg et. al. explored the required levels of signal-to-noise ratio (SNR) necessary to distinguish between measured pedestrian sub regions such as hair, skin, shirt, and pants for pedestrian tracking applications [15].
The use of hyperspectral imagery to detect and track commercial vehicles was shown by Kerekes et al. using imagery with 70 spectral channels from 0.4 to 1\,\mu m and a ground sample distance (GSD) of 2.5\,m captured by the Rochester Institute of Technology’s (RIT) Modular Imaging Spectrometer Instrument (MISI) [16]. The research proved the feasibility of hyperspectral vehicle tracking by demonstrating the ability to uniquely match a vehicle in one image with the same vehicle in a subsequent image. The research also showed the theoretical feasibility of hyperspectral vehicle tracking in the sub-pixel GSD domain. The four images utilized in the research were captured within 19 minutes of each other at similar nadir view angles and therefore don’t reflect the inherent spectral vehicle variability present in oblique or longer revisit rate collection scenarios. Ientilucci et al. also showed the viability of tracking commercial vehicles between subsequent hyperspectral images in both the radiance and reflectance regimes [17]. In this study, 126 channel VNIR-SWIR HyMap hyperspectral images were captured 22 minutes apart with a GSD of 3\, meters resulting in single pixel vehicle representations. The lowest false alarm rates coincided with subspace detection algorithms with no domain preference reported.

The above examples demonstrate the effectiveness of using hyperspectral imagery to discriminate and track various targets. Despite these advantages, however, hyperspectral sensors suffer from low coverage rates due to the increased dwell time and the high bandwidth requirements associated with the large number of recorded wavelengths and the profusion of data per pixel. These disadvantages preclude the use of wide field of view hyperspectral sensors in persistent surveillance applications. For this reason, research is being conducted into adaptive sensing modalities that can capture normal panchromatic WAMI imagery while dynamically interrogating the spectral content of specified regions of interest (ROI). One such design uses a digital micromirror device (DMD) to simultaneously capture a wide band image and interrogate the spectra of a collection of specified pixels [18, 19]. The micromirrors sit in the focal plane of the main optical path and redirect incident light into either a spectroscopy path or an imaging path. While both paths terminate with a spatial imaging array, the spectroscopy path uses a diffraction grating to transform one spatial dimension of the array into a spectral dimension. The RIT instrument [18] was designed for an astronomical imaging application while the Naval Research Laboratory system [19] was designed for remote sensing WAMI applications such as vehicle and personnel tracking. Other hyperspectral augmentation sensor designs adhere to biology inspired foveal based architectures [20, 21].

In order to take advantage of hyperspectral augmentation technology, Blackburn et al. demonstrate a feature aided tracking algorithm that enhances a panchromatic Kalman filter based kinematic tracker with a slower frame rate hyperspectral feature space based classifier. The algorithm is tested on synthetic imagery constructed using measured vehicle and background spectra [22]. Rice et al. utilize a similar feature aided tracking algorithm to improve kinematic tracking with hyperspectral augmentation. The algorithm utilizes an adaptive background modeling technique to more accurately distinguish vehicles from scene background and was tested in a Digital Imaging and Remote Sensing Image Generation (DIRSIG)[23] generated WAMI tracking scenario. The authors assume a DMD based sensor architecture and use a sensor resource model to minimize a time varying spatial segment entropy function in order to optimally interrogate the scene with the hyperspectral pixels [24–26]. Presnar et al. extend this simulation based research by replacing the panchromatic imagery with degree of linear polarization (DoLP) imagery using simulated micro polarizers in order to better discriminate
vehicles from the background in the DIRSIG generated Megascene \cite{27,28}. Uzkent et. al. similarly developed a simulated adaptive sensor model and tested a vehicle tracking algorithm in the DIRSIG generated Megascene \cite{29}. A kinematic Gaussian sum Kalman filter was combined with the spectral feature vector and road network maps for robust vehicle tracking.

Research in the field of hyperspectral vehicle tracking has demonstrated the viability of utilizing hyperspectral data to better discriminate and track commercial vehicles. While a majority of the high frame rate tracking scenarios utilize both kinematic filters and spectral features to improve tracking performance, this research focuses only on the use of spectral features for reacquisition and tracking applications. An improvement in the spectral reacquisition task will benefit vehicle tracking scenarios of all frame-rates and revisit rates and can always be paired with a kinematic filter or road network map and incorporated into a high frame rate tracking algorithm. This research also aims to measure the variability of vehicle hyperspectral signatures not accounted for by some of the previously discussed vehicle tracking research: both real-world and simulated. The real-world vehicle tracking research efforts incorporate image acquisitions separated by small time intervals, 19 and 22 minutes respectively, and are limited to nadir viewing geometries \cite{16,17}. In addition, the ray tracing engines in the DIRSIG simulated imagery can be simplified for increased computation efficiency and lower rendering times. Users may be tempted to select Lambertian vehicle surface models and turn off adjacency effects that would otherwise make a white car appear more green when driving near trees or foliage in order to render large scenes in a reasonable amount of time. This research will show the importance of modeling these vehicle adjacency effects correctly and measure the spectral variability of vehicles across markedly different sun-vehicle-sensor geometries in both oblique and simulated nadir scenarios.

2.2 Measuring BRDF

Reflectance is a material property defined as the ratio of the magnitude of reflected energy over the magnitude of incident energy. Reflectance is a useful metric in remote sensing because it is an illuminant invariant quantity that remains constant regardless of observer position, scene illumination, time of image acquisition, or imaging system. The most descriptive mathematical tool used to characterize this invariant material property is a function called the bidirectional reflectance distribution function (BRDF) \cite{6}. This function, defined as

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

is the ratio of the reflected radiance $L$ at a specific observer azimuth $\phi_r$ and zenith $\theta_r$ normalized by the incident irradiance $E$ from a specific azimuth $\phi_i$ and zenith $\theta_i$ (see Figure 2.1). The scalar valued BRDF can be a spectrally varying quantity and is expressed in units of inverse steradians. The function is called a distribution function because for any given incident ray vector, the BRDF function describes how that light is reflected across the hemisphere.

Another useful tool in describing the reflectance of a material is the directional-hemispheric reflectance ($\rho_{DHR}(\lambda, \theta_i, \phi_i)$ \cite{6}. This function describes the total amount of reflected radiance into the hemisphere for a given incident direction of irradiance. A diagram of the geometry
and independent variables of the BRDF is shown in Figure 2.1. This function is calculated by integrating the BRDF over the hemisphere of all reflected radiance according to

\[
\rho_{DHR}(\lambda, \theta_i, \phi_i) = \int_{\Omega_r} \rho_{BRDF}(\lambda, \theta_i, \phi_i, \theta_r, \phi_r) d\Omega_r \\
= \int_{\phi_r=0}^{2\pi} \int_{\theta_r=0}^{\pi/2} \rho_{BRDF}(\lambda, \theta_i, \phi_i, \theta_r, \phi_r) \cos\theta_r \sin\theta_r d\theta_r d\phi_r ,
\]

(2.2)

where \(d\Omega = \sin\theta_r d\theta_r d\phi_r\) and \(\cos\theta_r\) accounts for the projected area of the small flat patch of material, \(dA\) inside the radiance term \(L(\lambda, \theta_r, \phi_r)\). Often times in remote sensing a Lambertian reflectance assumption is used to simplify radiative transfer models. This Lambertian assumption states that the reflected radiance of a material is constant across the hemisphere, regardless of observer vantage point or incident illumination vector. The BRDF of a Lambertian surface is therefore constant such that \(\rho_{BRDF}(\lambda, \theta_i, \phi_i, \theta_r, \phi_r) = \rho_{BRDF}(\lambda)\). The \(\rho_{BRDF}\) can therefore be taken outside of the \(\rho_{DHR}\) integral and the DHR of a Lambertian surface loses its dependence on the orientation of the incident irradiance. This gives rise to a simple relationship between the DHR and BRDF of a Lambertian surface expressed as

\[
\rho_{DHR}(\lambda) = \rho_{BRDF}(\lambda) \int_{\phi_r=0}^{2\pi} \int_{\theta_r=0}^{\pi/2} \cos\theta_r \sin\theta_r d\theta_r d\phi_r \\
= \rho_{BRDF}(\lambda) \pi = \frac{L_r(\lambda)}{E_i(\lambda)} \pi ,
\]

(2.3)

where the \(\rho_{BRDF}(\lambda)\) is in units of inverse steradians and the \(\pi\) value is in units of steradians resulting in a unitless \(\rho_{DHR}(\lambda)\). Similar derivations can be found in a paper by Ientilucci et. al. [30] and Schott [31].

This relationship is fundamental to remote sensing because many natural materials exhibit Lambertian-like behavior. In addition, the Lambertian BRDF assumption dramatically simplifies radiative transfer models in outdoor remote sensing scenarios where incident illumination
comes from a spatially varied distribution of sources, allowing tractable solutions to material reflectance and or temperature. For this reason, most forward models such as the diffuse facet model and most physics based atmospheric compensation routines such as ELM [31], FLASH [32], and ATREM [33] incorporate Lambertian reflectance models. As a result, a “reflectance image” in remote sensing is a measure of Lambertian $\rho_{DHR}$, the material leaving radiance normalized by the total ground normal irradiance from all illumination sources.

Materials with specular, non-Lambertian BRDFs represented in reflectance imagery are still useful measurements; however, the value constancy across different illumination and viewing geometries is lost. This constancy characteristic only holds for truly Lambertian surfaces. The reported reflectance values of specular materials in VNIR-SWIR reflectance imagery taken outdoors are closer to a linear combination of solar BRDF ($\rho_{BRDF}$) and downwelled hemispherical-direction reflectance ($\rho_{HDR}$) assuming a hemispherically constant skylight. Hemispherical-direction reflectance (HDR) is the opposite of DHR in that instead of integrating the BRDF equation across the hemisphere of reflected radiance, the BRDF is spatially integrating across the incident irradiance [6]. The representation of a specular object in reflectance imagery is demonstrated by assuming the total target leaving radiance can be expressed as

$$L(\lambda, \theta_{sun}, \phi_{sun}, \theta_r, \phi_r) = \rho_{HDR}(\lambda, \theta_r, \phi_r)E_{sky\perp}(\lambda) + \rho_{BRDF}(\lambda, \theta_{sun}, \phi_{sun}, \theta_r, \phi_r)E_{sun\perp}(\lambda, \theta_{sun}, \phi_{sun})$$.

(2.4)

where $(\theta_{sun}, \phi_{sun})$ is the orientation of the sun with respect to the surface normal, $(\theta_r, \phi_r)$ is the orientation of the sensor with respect to the surface normal during image acquisition, $E_{sky\perp}$ is the ground normal irradiance from the sky (assumed to be spatially constant), and $E_{sun\perp}$ is the ground normal irradiance from the sun. Likewise the total ground normal irradiance is defined as

$$E_{tot\perp}(\lambda, \theta_{sun}, \phi_{sun}) = E_{sun\perp}(\lambda, \theta_{sun}, \phi_{sun}) + E_{sky\perp}(\lambda)$$.

(2.5)

Therefore the quantity of a non-Lambertian material in a reflectance image can be written as

$$\rho_{img}(\lambda) = \frac{L(\lambda, \theta_r, \phi_r)}{E_{tot\perp}(\lambda, \theta_{sun}, \phi_{sun})\pi}$$

(2.6)

$$= C_{sky}\rho_{HDR,sky}(\lambda, \theta_r, \phi_r)\pi + C_{sun}\rho_{BRDF,sun}(\lambda, \theta_{sun}, \phi_{sun}, \theta_r, \phi_r)\pi$$,

where the coefficients $C_{sky}$ and $C_{sun}$ are defined as

$$C_{sky}(\lambda, \theta_{sun}, \phi_{sun}) = \frac{E_{sky\perp}(\lambda)}{E_{sky\perp}(\lambda) + E_{sun\perp}(\lambda, \theta_{sun}, \phi_{sun})}$$

(2.7)

$$C_{sun}(\lambda, \theta_{sun}, \phi_{sun}) = \frac{E_{sun\perp}(\lambda, \theta_{sun}, \phi_{sun})}{E_{sky\perp}(\lambda) + E_{sun\perp}(\lambda, \theta_{sun}, \phi_{sun})}$$.

These coefficients act as weights, sum to one, and range from zero to one, meaning that the representation of a non-Lambertian reflector in a reflectance image is a linear combination of the material’s DHR and BRDF scaled by $\pi$.

In literature, this reflectance value scaled by $\pi$, $L_r(\lambda, \theta_r, \phi_r)/E_{tot\perp}(\lambda)$, is often referred to as BRDF. While the values are not exactly representative of the National Institute of Standard and Technology (NIST) defined material BRDF (Equation 2.1), the difference is small given
that $C_{sky} \ll C_{sun}$ at most VNIR-SWIR wavelengths for most atmospheric profiles, as seen in Figure 2.2. Furthermore, the non-constant spatial and intensity distribution of irradiance across the hemisphere is only dependent on the position of the sun $(\theta_{sun}, \phi_{sun})$ for a given atmospheric profile. This dependence on sun position means that for any given $(\theta_{sun}, \phi_{sun})$, there will always be a corresponding HDR and the resulting target leaving radiance will be the same assuming again that the atmosphere is cloud free and constant. Therefore, despite the fact that the material BRDF and HDR are linearly combining to generate an at sensor radiance, there is still constancy in this combined reflectance value (only dependant on sun position) in addition to the value closely representing the actual BRDF ($C_{sky} \ll C_{sun}$). For the remainder of this research, the term BRDF refers to this outdoor measured, effective BRDF that involves both sun and sky illumination sources. This effective BRDF is related to the previously defined quantities using the equation

$$\rho_{BRDF}^\prime(\lambda, \theta_{sun}, \phi_{sun}, \theta_r, \phi_r) = \frac{L(\lambda, \theta_r, \phi_r)}{E_{tot,\perp}(\lambda, \theta_{sun}, \phi_{sun})} = \rho_{img}(\lambda)\pi,$$

where $\rho_{BRDF}^\prime$ is the effective BRDF and $\rho_{img}$ is the reflectance image pixel. If the material is truly Lambertian, or approximately so, then $\rho_{img} = \rho_{DHR} = \rho_{BRDF}^\prime/\pi$, and the pixel values of a reflectance image are truly invariant to sun-target-sensor geometry. These distinctions between the various reflectance values are small but important. When the canonical reflectance measurements cannot be made due to the inability to characterize all illumination spatially and spectrally for each location in the imaged scene, it is necessary to make both practical and useable assumptions while understanding the departure from theoretical definitions.

Current in-scene BRDF collection efforts focus on analyzing the BRDF of ground surface materials and consist of either large scale aerial and space based data collections or small scale goniometer data collections. Little documented research is devoted to the measurement and exploitation of in-scene object level BRDF. Diner et. al. point to the growing trend of providing multiangle capabilities to space based earth observing imaging systems in order to retrieve physical scene characteristics such as aerosol type, cloud morphology, land cover structure, and surface BRDF [34]. For these reasons, several different spaced based sensors have been designed for multiangle observations where the term multiangle is defined as several observations
of the same scene taken at different times along the flight path. One such instrument, the Moderate Resolution Imaging Spectrometer (MODIS), possesses multangle capabilities facilitating the generation of Earth surface BRDF and albedo products [35]. These products require 16 days of sequential angular observations of the specified surface coordinate to fully characterize the surface BRDF. Even then, the algorithms used are sensitive to clouds and extreme weather conditions, such as snow and rain. The MODIS BRDF calculations use a semiemperical BRDF model that decomposes the BRDF into a linear sum of parametrically defined kernels that represent various scattering modes [36]. The BRDF kernels are linear with respect to their parameters, allowing least-squares analytical solutions in which the error between what is observed and what is modeled is minimized. Surface albedo measurements are then made by hemispherically integrating the modeled BRDF.

On the other end of the spectrum of BRDF collections is the smaller goniometer scale collections. A goniometer is an instrument capable of measuring the amount of reflected light of an object or material at precise angles [37]. Field goniometers are portable instruments placed in a scene in order to capture the BRDF of a surface material in-situ, utilizing real-world, outdoor illumination conditions. These instruments will typically require multiple fore optics in order to measure both the reflected light and the amount of incident illumination in order to compensate for dynamically changing illumination conditions characteristic of outdoor imaging scenarios. Examples of these instruments include: 1) the dual-view field goniometer system (FIGOS) [38] that incorporates a dual view hyperspectral spectrometer to simultaneously sample the spatial distribution of the downwelled and target leaving radiance across the hemisphere and 2) the Goniometer at RIT (GRIT) [39], which also uses a dual-view hyperspectral spectrometer methodology to measure the target leaving radiance and the total downwelled irradiance. While both instruments take accurate hyperspectral measurements of the amount of radiance reflected by the observed surface while simultaneously measuring the incident illumination, both dual-view spectrometer designs capture an incomplete degree of information in order to calculate the true BRDF. A FIGOS type design assumes that the illumination conditions are temporally static throughout the sampling process while the GRIT design measures scene specific, effective BRDF due to the fact that it does not spatially sample the downwelled illumination. To bridge this technology gap, a new goniometer design called GRIT-Two (GRIT-T) integrates the best of both designs by using three spectrometers to simultaneously measure the total downwelled irradiance and the hemispherically varying spatial distributions of the target leaving radiance and downwelled irradiance [37].

2.3 Vehicle BRDF

For remote sensing scenarios, Ientilucci et. al. demonstrate the importance of building target detection schemes that consider the BRDF of non-Lambertian targets by contrasting the ACE detection results of similarly painted non-Lambertian panels at different orientations relative to the sensor in a DIRSIG generate scene with a 10km platform altitude [30]. The authors used measured BRDF spectra from the Nonconventional Exploitation Factors Data System (NEFDS) [40] to simulate the paint properties and showed the departure between $\rho_{DHR}$ and $\rho_{BRDF}$ for these materials in both color and magnitude as a function of view angle. The study found that non-Lambertian targets look most similar in the specular lobe (view orientation of maximum
reflectance) converging towards the illumination source spectrum. The study also shows that using physics based modeling (PBM) [41] to generate physically derived signature spaces (PDSS) [42] with the panel DHR reports better detection scores for all panel orientations than a PDSS based on the tilted panel BRDF spectrum.

The studied importance of considering target BRDF and using subspaces for the detection of non-Lambertian targets is applicable to vehicles given the preponderance of glossy outer surfaces. The reflectance properties of vehicle surfaces are heavily researched in the computer graphics community due to industry demand for fast photo-realistic vehicle rendering engines. Rump et al. give a structural breakdown of the many layers that constitute a standard painted car surface (see Figure 2.3). At the bottom of this diagram is the rough metal body which is covered by an electroplated layer of tin. This tin substrate layer acts as a corrosion prevention mechanism and also helps the primer paint coat adhere to the metal body. The next layer is the primer layer whose purpose is to provide a smooth, diffusely scattering foundation for the bottom of the base paint. This layer is typically polished to compensate for the uneven surface of the tin electroplated layer caused by the rough metal of the car body. The next paint layer, the base paint layer, contains a binder with color pigments that determine the paint color based on their spectral absorption features. In addition to the color pigment, the layer contains metal flakes that are typically larger than the width of the base paint, causing them to lie in horizontal formations. Finally, a clear coat composed of a transparent resin is applied to the top of the base paint for protection and to create a gloss finish appearance.

![Figure 2.3: Diagram depicting the standard layers of car paint. Figure is based on a similar image found in [43].](image)

Understanding the multi-layer configuration and micro-scale composition of vehicle paint is important in determining optimal vehicle surface BRDF models. As part of a study performed by Matusik, the isotropic BRDF of a wide range of materials were measured, including metals, plastics, and painted surfaces [46]. Ngan et. al. used this densely sampled data set of more than 100 materials to test the error of seven analytical BRDF models [47]: Ward, Blinn-Phong
CHAPTER 2. BACKGROUND

[49], Cook-Torrance [50], Lafortune [51], Ashikhmin-Shirley [52], He [53], and the Ward-Dur model [54]. The authors found that the two-lobe model variants of the Cook-Torrance and Lafortune models fit the data better than the single lobe variants for materials that have multiple layers of finishing, such as car paint, but the authors advise against the addition of a third lobe citing instability and marginal improvements [47]. In addition, Ngan et al. emphasise the importance of physics based BRDF models that incorporate a Fresnel effect term for modeling material BRDF at grazing angles and show that without this term, physics based models, such as Cook-Torrance, suffer a 20% increase in error [47]. Using this Cook-Torrance recommendation, both Gunther et al. [55] and Rump et al. [43] image car paint samples and use a 3 lobe and 1-3 lobe Cook-Torrance model respectively. The principal plane of 3-lobe Cook-Torrance BRDFs derived by Gunther et al. [55] for a black and white vehicle paint sample are shown in Figure 2.4.

![Figure 2.4](image)

**Figure 2.4:** The principal plane of the BRDF of a white and black paint sample based on a 3-lobe Cook-Torrance BRDF model (left) (see Equation 2.9). The model parameters were derived by Gunther et al. from imaged spheres painted with automotive paint by a professional shop [55]. The BRDF is normalized by the DHR/π and shown on a logarithmic scale to compare the relative BRDF shapes. The notations highlight the BRDF regions of the various scattering mechanisms [45]. Also shown are rendered images of the two BRDFs made by Gunther et al. [55] (right).

The established prevalence of the two and three lobe BRDF models to replicate the reflectance behavior of vehicle paint is not by accident. Ershov et al. describe that there are three main scattering mechanisms taking place in metallic vehicle paints, gloss, glitter, and shade, caused by light interaction with the finish, flakes, and primer/pigments, respectively [44,45,56]. The interaction with the glossy finish can be largely described using Fresnel reflectance equations, which is why removing this term creates so much error [47]. The horizontal structuring of the metal flakes adds directionality to the diffuse primer layer called “glitter”, aptly named because at close range (a few meters), individual flakes are distinguishable [44]. These flakes can be varied in size, shape, orientation, and density to create different “glitter” reflectance distributions [44]. Finally, the shade is simply the diffuse reflectance result of multiple scattering and pigment absorption within the layered media. These distinct vehicle paint scattering
mechanisms help to explain why multiple researchers find that two and three lobe BRDF models are optimal. In fact, the terms “glitter lobe” and “gloss lobe” are used by multiple authors in the computer graphics field that fit multi-lobe BRDF models to car paints, suggesting community consensus in the correlation of scattering mechanisms to specular lobe characteristics [43, 45, 55, 56]. These scattering mechanisms are labeled in Figure 2.4 and account for different sized specular lobes in the multi-lobe Cook-Torrance BRDF models displayed [45].

An additional BRDF model commonly used in synthetic imagery generation and the NEFDS is the modified Beard-Maxwell model [57]. This model was originally developed and tested on painted surfaces at a wavelength of 1.06 $\mu$m and incorporates three scattering terms: diffuse (surface), volumetric (sub-surface), and a specular lobe [57, 58]. The diffuse scattering term models the reflectance distribution caused by rough surfaces while the volumetric scattering term models the subsurface scattering mechanisms common in painted surfaces [57, 58]. In contrast, the multi-lobe Cook-Torrance model only incorporates combinations of diffuse and specular lobe terms. The modified Beard-Maxwell model was not tested by Ngan et. al. [47] and has not been adopted in current photo-realistic vehicle paint research efforts but remains a time-proven BRDF model in the field of remote sensing.

The polarimetric diffuse and spectral components of a vehicle panel were extracted using outdoor polarimetric VNIR hyperspectral imagery by Bartlett et. al. [59]. The authors make the assumption that the polarimetric BRDF (p-BRDF) is composed of a only two values: a polarized specular and unpolarized diffuse Lambertian term. In this experiment diffuse and specular calibration panels positioned at strategic angles were used to characterize the direct and downwelled irradiance. The authors then use the derived values and MODTRAN-P generated measurements of the atmosphere to solve for the polarimetric parameters using constrained non-linear least squares. In order to maintain an over-determined system of equations, the authors assume that the specular component of the p-BRDF for the car panel is spectrally flat. This assumption was confirmed with lab measurements using an instrument that measures DHR with or without the specular component. The spectral flatness of the specular component was also shown in imagery in which the specular component was isolated using a linear polarization filter.

In order to investigate the hyperspectral object level BRDF of vehicles in outdoor imagery for this research, a BRDF sampling field experiment was performed at RIT [60]. As mentioned in Chapter 1, four vehicles were rotated and imaged with a VNIR-SWIR imaging spectrometer over a six hour span of time. The explanation of this experiment constitutes a small portion of this thesis (see Chapter 3). Perkins et. al. use the portable spectrometer DHR measurements of this experiment (see Section 3.4.5) and modify the BRDF according to a NEFDS car paint of similar color [61]. This fully characterized BRDF paint model is then used in a synthetic image generation utility called quick image display (QUID) to generate a collection of reflectance spectra that capture the full variability of the vehicle resulting from various poses. The authors then implant the whole-vehicle reflectance spectra into hyperspectral images and test a sub pixel detection scheme using a subspace adaptive cosine/coherence estimator (ACE) algorithm. The authors model the target subspace using a positivity constraint on the spectral basis vectors such that the basis vectors act as end-members. This work is an extension of the experiments conducted by Sundberg et. al. [62]. In both papers, the authors report that the synthetic data variability is best modeled using a subspace composed of three end-members.
2.4 Multi-Lobe Cook-Torrance BRDF Model

The BRDF model developed by Cook et. al. [50] is a theoretical physics based micro-facet BRDF model that incorporates both specular and diffuse scattering terms. The diffuse scattering terms assume a Lambertian BRDF while the specular lobes are a function of the micro-facet slope distribution function \(D\), the Fresnel reflectance \(F\), the geometrical attenuation factor \(G\), and the source-sample-sensor geometry \((\hat{l}, \hat{n}, \hat{v}, \hat{h})\) (see Figure 2.5). The originally proposed multi-lobe model incorporated multiple surface roughness by allowing the facet slope distribution function \(D\) to be a linear of sum of several distribution functions [50]. Other multi-lobe variants, such as the model used by Gunther et. al. [55], allow all the specular lobe parameters to vary between lobes. This more generalized BRDF function is written as

\[
\rho_{BRDF}(\hat{l}, \hat{v}) = \frac{\rho_d}{\pi} \sum_{i=1}^{N} \frac{\rho_{s,i} F(r_{\perp,i}, \hat{v} \cdot \hat{h}) D(m_i, \hat{l} \cdot \hat{h}) G(\hat{n}, \hat{h}, \hat{v}, \hat{l})}{(\hat{n} \cdot \hat{l})(\hat{n} \cdot \hat{v})},
\]

(2.9)

where \(\rho_d\) is the diffuse reflectance, \(\rho_s\) is the specular reflectance, \(r_{\perp}\) is the incident irradiance surface normal Fresnel reflectance, \(m\) is the root-mean-square slope of the facet distribution function, and \(i\) is the specular lobe index.

![Figure 2.5: The unit vectors used in the Cook-Torrance BRDF model describing the surface normal (\(\hat{n}\)), the source (\(\hat{l}\)), the sensor (\(\hat{v}\)), and the bisection vector between the source and sensor (\(\hat{h}\)).](image)

A micro-facet model assumes the surface is composed of a distribution of smooth planar micro-facets that reflect light into a single specular direction. Therefore, only the micro-facets with surface normal vectors equal to the bisection vector will contribute to the specular lobe [50]. The ratio of micro-facets that meet this criteria is governed by the micro-facet distribution function expressed as

\[
D(m, k) = \frac{1}{m^2 k^4} \text{exp} \left( \frac{k^2 - 1}{m^2 k^2} \right),
\]

(2.10)

where \(k\) is the cosine of the angle between the normal vector and the bisection vector \((k = \hat{n} \cdot \hat{h})\) [63]. In addition to this directional distribution of the modeled micro-facets, the geometric attenuation due to inter-facet shadowing and masking effects must be considered. To find an analytical solution for these effects the micro-facets are modeled as symmetric “V” shape grooves or cavities with equal angles relative to the surface normal [64, 65]. Shadowing is caused when incident light is blocked from entering the cavity and masking is caused when reflected light is
blocked from leaving the cavity [64]. The geometric attenuation solution is found by taking the worst case scenario (minimum) for the two possibilities and expressed as

\[
G(\hat{n}, \hat{h}, \hat{v}, \hat{l}) = \min \left\{ 1, \frac{2(\hat{n} \cdot \hat{h})(\hat{n} \cdot \hat{v})}{(\hat{v} \cdot \hat{h})}, \frac{2(\hat{n} \cdot \hat{h})(\hat{n} \cdot \hat{l})}{(\hat{v} \cdot \hat{h})} \right\},
\]

(2.11)

where the second term is the attenuation due to masking and the third term is the attenuation due to shadowing [65].

The complex index of refraction \((i, k)\) is used to calculate the unpolarized Fresnel reflectance for a given source-sample-sensor geometry. These values, however, are often not available, so Cook et. al. devised a method for solving for the Fresnel reflectance at all angles based on the more common material property of measured reflectance [50]. If this reflectance measurement was made with surface normal parallel incident irradiance, the measurement can be used as an estimate for the Fresnel reflectance for non-conductive materials \((k=0)\) according to the equations

\[
F(r_{\perp}, c) = \frac{1}{2} \left( \frac{g^2}{g^2 + c^2 - 1} \right) \left( 1 + \frac{[c - 1(g + c)]^2}{[c(g - c) + 1]^2} \right) \frac{g^2 - n^2 + c^2 - 1}{1 + \sqrt{r_{\perp}}},
\]

(2.12)

where \(c\) is the cosine of the angle between the view vector and the bisection vector \((c = \hat{v} \cdot \hat{h})\) and \(r_{\perp}\) is the measured reflectance [50]. Using a rational fraction approximation, Schlück found a shorter, computationally cheaper approximation for Equation 2.12 written as

\[
F(r_{\perp}, c) = r_{\perp} + (1 - r_{\perp})(1 - c)^5,
\]

(2.13)

where again \(c\) is the cosine of the angle between the view vector \((\hat{v})\) and the bisection vector \((\hat{h})\) [66].

### 2.5 Diffuse Facet Model

The diffuse facet model addresses the various sources of illumination and paths of light propagation that contribute to the aperture reaching radiance of a target starring sensor. These sources and propagation paths can be divided into two regimes according to illumination source: a solar reflective regime and a thermal emissive regime. The propagation paths of the solar reflective regime are the direct target path (sun-target-sensor), the downwelled path (sun-atmosphere-target-sensor), the background path (sun-background-target-sensor), and the upwelled path (sun-atmosphere-sensor). The propagation paths in the thermal emissive regime are the target self emission (target-sensor), the atmospheric downwelled self emission (atmosphere-target-sensor), the background self emission (background-target-sensor), and finally the atmospheric upwelled self emission (atmosphere-sensor). This research focuses primarily on the solar reflective regime (VNIR/SWIR) where the solar reflective radiance dominates the thermal emission radiance. Therefore, the self-emission terms are not considered in further radiance calculations [31].
The direct target path references light emanating from the sun, propagating through the atmosphere, reflecting off the target, and propagating back through a different portion of atmosphere before finally reaching the sensor. Mathematically this path can be expressed as

$$ L_{tgt}(\lambda, \theta_r, \phi_r) = E_s(\lambda)\tau_1(\lambda)\cos(\theta_{sun})\rho_{BRDF}(\lambda, \theta_{sun}, \phi_{sun}, \theta_r, \phi_r)\tau_2(\lambda), $$

where $L_{tgt}$ is the sensor reaching radiance from this path, $E_s$ is the top of atmosphere solar irradiance, $\theta_{sun}$ is the solar zenith angle, $\rho_{BRDF}$ is the target reflectance, and $\tau_1$ and $\tau_2$ are the transmission loss for the optical path to the target and from the target to the sensor, respectively [31].

The downwelled path, also called skylight, is calculated in a similar manor but now the incident irradiance direction must be spatially integrated across the hemisphere. The same spatial integration is also accomplished for the background path as well. In this specific instance, the term background refers to vertical objects with a line-of-sight to the target surface, i.e. background objects that fall within the observed hemisphere of the target. Horizontal background objects are also important since radiance scattered off these objects can also be scattered onto the target, even if these objects do not have a line-of-sight to the target [67]. This effect, called the adjacency effect, is assumed to be buried in the downwelled radiance term. The spatial integration of the downwelled and background sensor reaching radiance is expressed as

$$ L_{dr}(\lambda, \theta_r, \phi_r) = \tau_2(\lambda) \int_{\Omega_F} L_d(\lambda, \theta_i, \phi_i)\rho_{BRDF}(\lambda, \theta_i, \phi_i, \theta_r, \phi_r)\cos(\theta_i)\sin(\theta_i)d\theta_id\phi_i $$

$$ L_{bgr}(\lambda, \theta_r, \phi_r) = \tau_2(\lambda) \int_{2\pi-\Omega_F} L_{bg}(\lambda, \theta_i, \phi_i)\rho_{BRDF}(\lambda, \theta_i, \phi_i, \theta_r, \phi_r)\cos(\theta_i)\sin(\theta_i)d\theta_id\phi_i, $$

where $L_d$ is the downwelled radiance, $L_{bg}$ is the background radiance, and the solid angle values $\Omega_F$ and $2\pi - \Omega_F$ represent the solid angle spatial distribution of the skylight and background respectively [31]. The notation $2\pi - \Omega_F$ is used because the total solid angle integrated by both components should yield $2\pi$.

Lastly, the upwelled path radiance $L_u(\lambda)$ is the result of back scattered solar illumination into the sensor aperture [31]. In addition to this back scattered light, the upwelled path also incorporates light scattered from surfaces other than the target, such as light originating from adjacent background objects. This effect is also referred to as an adjacency effect or an atmospheric point spread function due to its spatial, linear, shift invariant nature across both dimensions of an image. The upwelled path radiance is a function of both sensor position and orientation relative the sun.

The total aperture reaching radiance can now be calculated as

$$ L_{total}(\lambda) = L_{tgt}(\lambda) + L_{dr}(\lambda) + L_{bgr}(\lambda) + L_u(\lambda), $$

where the functional dependence on orientation and geometry has been omitted for brevity. While this function is more physically accurate, several assumptions result in a more usable form of Equation 2.16. Assuming the downwelled radiance ($L_d$) and background radiance ($L_{bg}$) are spatially constant and that the target has a Lambertian BRDF ($\rho_{BRDF}$), all three terms
can be taken outside of the integrals of Equation 2.15. These assumptions give rise to a new simplified form of the sensor reaching radiance,

\[ L_{\text{total}} = \left[ E_s \tau_1 \cos(\theta_{\text{sun}}) + FL_d \pi + (1 - F)L_{\text{bg}} \pi \right] \frac{\rho_{\text{DHR}}}{\pi} \tau_2 + L_u, \]  

(2.17)

where the solid angle integration limits \( \Omega_F \) are now expressed as a normalized shape factor \( F \) that ranges from zero to one depending on the amount of skylight viewable from the target. This simplified representation of the solar reflective part of the sensor reaching radiance model is called the Diffuse Facet Model.[31]

### 2.6 MODTRAN

MODTRAN version five is a moderate spectral resolution radiative transport model used to predict how light propagates through the Earth’s atmosphere. MODTRAN was created in the 1980’s by Spectral Science Inc as part of an effort sponsored by the Air Force Research Laboratory (AFRL) to update its lower spectral resolution predecessor LOWTRAN [68]. MODTRAN is a narrow band model that simulates a multilayered, horizontally homogeneous atmosphere and integrates two multiple scattering models to optimize both speed and accuracy: a discrete-ordinate radiative transfer (DISORT) model and ISAACS 2-stream model [69–71].

For a given simulation, MODTRAN incorporates user defined illumination source-target-sensor geometry, atmospheric composition (molecular and particulate), top of atmosphere solar irradiance, temperature, pressure, target reflectance, background reflectance, and sensor spectral response functions. The model incorporates multiple-scattering effects and background adjacency effects into both the target reaching radiance and sensor reaching radiance. In addition to the reported of path transmission, perceived temperature, and top of atmosphere solar irradiance, the program reports the total sensor reaching radiance and its constituent contributions: direct solar, downwelled, upwelled, solar scattering, total thermal, and thermal scattering. MODTRAN reports all these values spectrally in accordance with user input and possesses the capability of modeling the atmosphere from the UV to the far infrared 0.2\( \mu m \) to 10,000\( \mu m \) with a 0.1\( cm^{-1} \) spectral resolution. [71]

MODTRAN comes with several default atmospheric profiles, each with predefined altitude look up tables that determine molecular composition and ambient temperature. These profiles were built to capture the diversity of global environments and include tropical, sub-arctic summer, sub-arctic winter, mid-latitude summer, and mid-latitude winter models. The mid-latitude summer model is frequently used as the default for the continental US and is based on a 45 degree latitude location. This model is used as the starting point for all MODTRAN simulations executed as part of this research.

### 2.7 Principal Components Analysis

Principal components analysis (PCA) is a technique used in exploratory data analysis and a dimensionality reduction tool that decomposes a high dimensional data feature space into a lower dimensional space. This is achieved by first solving for the orthonormal vectors that describe the data variability. These orthonormal vectors form a new unitary basis set for the
data space and are calculated by diagonalizing the data covariance matrix using eigenvalue decomposition. The technique first calculates the eigenvalue ($\sigma^2_j$) eigenvector ($v_j$) pairs of the data covariance matrix ($C$) such that

$$Cv_j = \sigma^2_j v_j,$$

(2.18)

where the eigenvalue ($\sigma^2_j$) represents the variance in the direction of the associated eigenvector. The covariance matrix can now be written in terms of its eigenvectors and eigenvalues,

$$C = V D V^T,$$

(2.19)

where $V$ is a column matrix of the eigenvectors ordered by eigenvalue and $D$ is a diagonal matrix formed with the ordered eigenvalues. This identity demonstrates that the diagonalized eigenvalues represent a covariance matrix with zero covariance that is a linear transformation of the original covariance matrix. The eigenvectors, or principal components of data variability, can be used as a new basis for the high dimensional data where the eigenvector matrix constitutes a linear transformation of the data space expressed as

$$Z = V^T X,$$

(2.20)

where $X$ is a column vector matrix composed of the data point in the original feature space and $Z$ is the same data in the new feature space. If all eigenvectors are used, this linear transformation is lossless and the reverse transformation will yield the original data in their entirety. The eigenvalues, however, carry information about the magnitude of variance expressed by the data across each dimension, allowing an ordering of the eigenvectors based on relative importance. To perform dimensionality reduction, the ordered eigenvectors are truncated and only the subset with the highest eigenvalues are used in the data transformation defined in Equation 2.20. Therefore $Z$ becomes a lower dimensional representation of the original data set $X$, and uses the leading eigenvectors as the new basis. This technique is useful in real-world acquired data sets since the additive noise is typically expressed in all dimensions, even when the data occupies a lower dimensional space. PCA can therefore be thought of as a noise reduction technique in addition to a dimensionality reduction technique. [67]

Finally, PCA facilitates the approximation of the inherent dimensionality of the high dimensional data by observing the relationship between the number of ordered eigenvectors used and the cumulative summation of their respective normalized eigenvalues. The eigenvalues are normalized by the total sum of all eigenvalues in order to compare the dimensionality of different data sets. The more eigenvectors needed to achieve a certain threshold of cumulative variance, the higher the underlying dimensionality of the data set, assuming information is proportional to variance. Furthermore, this cumulative normalized eigenvalue metric can be used to help drive the decision of how many leading eigenvectors to use in a dimensionality reduction. And finally, the shape of the leading eigenvectors can also convey useful information about the contributing factors to the variance of a distribution of data points. [67]

### 2.8 Laplacian and Schrodinger Eigenmaps

Hyperspectral dimensionality reduction is an important aspect in processing hyperspectral data sets because the data generally reside in lower dimensional manifolds. These manifolds are typically nonlinear and governed by the variations in in-scene materials, material orientation/BRDF,
illumination conditions, and linear and non-linear material combinations. Linear dimensionality reduction techniques such as Principal Components Analysis (described in Section 2.7) fail to preserve the non-linear local structure of hyperspectral data [72]. For this reason a class of dimensionality reduction algorithms called manifold learning seek to preserve local geometry by mapping the embedded manifolds to a new global coordinate system with a lower dimensional representation than the original data space. Examples of these algorithms are Kernel Principal Components Analysis (KPCA) [73, 74], Local Linear Embedding [75, 76] (LLE), Isometric Feature Mapping (ISOMAP) [77, 78], and Laplacian Eigenmaps [79,80] (LE). All algorithms utilize eigendecomposition on some variation of a local similarity matrix to solve for the manifold embedding using the leading or trailing eigenvectors. The calculated coordinates constitute a lower dimensional manifold mapping that preserves the local geometry of the high dimensional hyperspectral data.

For the LE algorithm, this lower dimensional data space is determined by the smallest leading eigenvectors of the normalized graph Laplacian [81]. This LE algorithm was first introduced by Belkin and Niyogi in 2003 and has three steps [79]:

1. Construct an undirected graph \( G = \{X, E\} \) where the nodes \( X \) are the hyperspectral data points and the edges \( E \) are based on euclidean proximity. The proximity can be calculated using a constant epsilon neighborhood or using k-nearest neighbors. During this step its important to check to make sure the graph is fully connected. This can be enforced using a minimum spanning tree.

2. Construct the weights graph \( W \) such that \( w_{i,j} \) is the weight of the edge between nodes \( x_i \) and \( x_j \). This is calculated using the Gaussian based heat kernel where \( w_{i,j} = \exp(-\|x_i - x_j\|^2/\sigma) \) if there is an edge between \( x_i \) and \( x_j \) and 0 otherwise.

3. Construct the diagonal weight matrix \( D \) such that \( d_{i,i} = \sum_j w_{i,j} \). Next, calculate the Laplacian matrix \( L = D - W \). Finally, to calculate a \( p \) dimensional embedding map of the data, calculate the \( p+1 \) smallest eigenvectors \( f_k \) of the generalized eigenvector problem \( Lf = \lambda Df \) and discard the smallest eigenvector \( f_0 \) (this is the trivial eigenvector). The \( p \) dimensional representation of data point \( x_i \) is now \( x_i = (f_1(i), f_2(i), \ldots, f_p(i)) \).

The LE algorithm can be extended with the Schrodinger Eigenmap (SE) algorithm in order to incorporate prior class label knowledge into the dimensionality reduction process [82, 83]. The SE algorithm adds a potential matrix \( (M) \) to the Graph Laplacian \( (L) \) in order to bias the dimensionality reduction process towards keeping data points of the same class close together in the lower dimensional manifold embedding. These class label constraints are encoded as soft must-link constraints using the cluster potential matrix \( V \) defined as

\[
V_{k,l}^{(i,j)} = \begin{cases} 
1, & (k,l) \in \{(i,i),(j,j)\} \\
-1, & (k,l) \in \{(i,j),(j,i)\} \\
0, & (k,l) \in \text{otherwise} 
\end{cases}
\]  

(2.21)

where \((i,j)\) are the indexes of the two nodes which belong in the same class and \((k,l)\) are the row and column of the matrix \( V \) [80]. The cluster potentials for each node pair are combined
into a single potential matrix $M$ according to

$$M = \sum_{(x_{ik}, x_{jk}) \in M} \eta V^{(ik,jk)},$$

(2.22)

where $M = \{(x_{im}, x_{jm})\}$ is the set of $m$ node pairs and $\eta$ is an importance weight for each must-link constraint which is here set as a constant in order to weight all link constraints equally [80]. Cahill et. al. recommend a constant weighting value of $\eta = tr(L)/(2m)$ [80]. Finally the potential matrix $M$ is combined with the Graph Laplacian $L$ according to the SE algorithm by now solving the generalized eigenvector problem $(L + \beta M)f = \lambda Df$.

2.9 Support Vector Machines

A support vector machine (SVM) is a trained binary classifier that seeks to maximize the margin between two classes using a bisecting hyperplane decision boundary. At its core, an SVM is a two-class linear model classifier of the form

$$y(x) = w^T \phi(x) + b,$$

(2.23)

where $\phi(x)$ is the feature space mapping function from data point to feature vector and $w^T$ and $b$ are the learned weights and offset for mapping the features to either a positive or negative binary decision value, such that $y(x) \leq 0$. The hyperplane margin is maximized using Lagrange multipliers to solve a constrained optimization problem via quadratic programming. This linear hyperplane SVM definition can be extended to a non-Linear formulation by incorporating the use of dual representation kernel based functions into the Lagrangian used for the optimization. The final kernel based classifier,

$$y(x) = \sum_{n=1}^{N} a_n t_n k(x, x_n) + b,$$

(2.24)

uses the learned Lagrange multipliers ($a_n$), the training labels ($t_n \in \{-1,1\}$), and learned offset ($b$) to make a binary prediction of the input data ($x$) based on the selected kernel function ($k(x, x_n)$) and training data points ($x_n$). This mathematical tool (SVM) is aptly named because many of the Lagrange coefficients are zero, resulting in a finite set of training data or “support vectors” used for prediction. Gaussian radial basis functions are selected as the kernel functions utilized in the SVMs as a part of this research. [84]

2.10 Hyperspectral Target Detection Algorithms

The goal of hyperspectral target detection algorithms are to produce metrics of spectral similarity between a known target signature and a collection of unknown pixels that may or may not contain the target spectrum. Two of the simplest metrics of similarity, are the spectral angle mapper (SAM) and the euclidean distance detector (ED). The SAM detector reports the angle between the signature spectrum and the test spectrum while the ED detector reports the euclidean
distance between the two spectra. While both of these detectors utilize a single spectrum as the target signature, other algorithms incorporate a collection of target spectra in order to model the target variability or target subspace.

Most target detection algorithms are formulated using a binary hypothesis test; either the pixel contains the target or it does not. These hypotheses are incorporated into a likelihood ratio test according to the Neyman-Pearson lemma, which states that the optimal binary classification decision is made by setting a threshold ($\xi$) on the likelihood ratio, given as [67]

$$\xi \leq l(x) = \frac{p(x|H_1)}{p(x|H_0)}.$$  \hspace{1cm} (2.25)

This treatment of the two hypothesis is called the likelihood ratio test (LRT). The threshold value changes the probability of false alarms while maximizing the probability of detection. A single detection statistic therefore has many different probability of detection and probability of false alarm value pairs based on where the threshold of detection ($\xi$) is set. This range of possible probabilities can be captured in a Receiver Operating Characteristic (ROC) curve. These curves are produced by varying the threshold over all possible values and plotting the probabilities of detection and false alarm on a 2D line plot. Test statistics that produce ROC curves that have a larger area under curve represent better metrics of discrimination [85].

Often there are free parameters that describe the modeled probability distribution functions of the two hypotheses. When these parameters are not known a priori, maximum-likelihood estimates (MLEs) are used to estimate the value of these parameters based on the observed data. This process, called the Generalized Likelihood Ratio Test (GLRT), maximizes the probabilities of the hypotheses and is expressed as [67]

$$l(x) = \frac{\max_{\theta_1} p(x|H_1)}{\max_{\theta_0} p(x|H_0)},$$  \hspace{1cm} (2.26)

where $\theta_0$ and $\theta_1$ are the free parameters for the target present and null hypotheses, respectively. Both the LRT and GLRT functions can be manipulated by any operators as long as the resulting function is also monotonic [67]. For example, the log-likelihood ratio is commonly used when the probability distributions are modeled as multivariate Gaussian functions.

### 2.10.1 Spectral Matched Filter (SMF)

The spectral matched filter (SMF) uses an additive mixture model for the “target present” hypothesis given as

$$H_0 : x = b$$  
$$H_1 : x = \alpha s + b,$$  \hspace{1cm} (2.27)

where $b$ is the background contribution and $\alpha$ is the abundance coefficient [67]. The SMF utilizes a multivariate Gaussian distribution to model the background with a mean ($\hat{\mu}$) and covariance matrix ($\Sigma$) estimated from the available data. The conditional probability functions of the two
hypotheses is therefore

\[ p(x|H_0) = \frac{1}{(2\pi)^{k/2}} \frac{1}{|\Sigma|^{1/2}} \exp \left\{ -\frac{1}{2} (x - \hat{\mu})^T \hat{\Sigma}^{-1} (x - \hat{\mu}) \right\} \]

\[ p(x|H_1) = \frac{1}{(2\pi)^{k/2}} \frac{1}{|\Sigma|^{1/2}} \exp \left\{ -\frac{1}{2} (x - \hat{\alpha}s - \hat{\mu})^T \hat{\Sigma}^{-1} (x - \hat{\alpha}s - \hat{\mu}) \right\}, \tag{2.28} \]

where \( k \) is the dimensionality. The likelihood ratio is therefore expressed as

\[ l(x) = \exp \left\{ -\frac{1}{2} (x - \hat{\alpha}s - \hat{\mu})^T \hat{\Sigma}^{-1} (x - \hat{\alpha}s - \hat{\mu}) + \frac{1}{2} (x - \hat{\mu})^T \hat{\Sigma}^{-1} (x - \hat{\mu}) \right\} \tag{2.29} \]

where the bottom equation has been simplified [67]. The log likelihood ratio can then be expressed as

\[ r(x) = \hat{\alpha}s^T \hat{\Sigma}^{-1} x - \frac{1}{2} \hat{\alpha}^2 s^T \hat{\Sigma}^{-1} s - \hat{\alpha} s^T \hat{\Sigma}^{-1} \hat{\mu}, \tag{2.30} \]

where \( r(x) = \log(l(x)) \). The abundance coefficient \( \alpha \) is unknown and therefore the MLE is used by calculating the value \( \alpha \) that maximizes the “target present” hypothesis probability. In order to find this value, the exponential argument of the PDF is minimized by setting the partial derivative with respect to the abundance coefficient equal to zero, this yields the MLE of [67]

\[ \hat{\alpha} = \frac{s^T \hat{\Sigma}^{-1} (x - \hat{\mu})}{s^T \hat{\Sigma}^{-1} s}. \tag{2.31} \]

The GLRT test statistic is found by inserting the MLE for \( \alpha \) from Equation 2.31 into the LRT of Equation 2.30, resulting in

\[ r(x) = -\frac{1}{2} \left[ \frac{s^T \hat{\Sigma}^{-1} (x - \hat{\mu})}{s^T \hat{\Sigma}^{-1} s} \right]^2. \tag{2.32} \]

This function is multiplied by negative one half to yield the classical matched filter (multiplication is a monotonic transformation). As pointed out by Eismann, this statistic has two problems: 1) the function allows non-physical negative values of the abundance coefficient and 2) a unity abundance value still incorporates an additive background signal which is again, not physically possible [67]. The first issue is corrected by taking the square root of the function and the second issue is corrected by substituting \( s - \mu \) for \( s \) [67]. This substitution changes the “target present” hypothesis to a variation of a sub-pixel replacement model, \( H_1: x = \alpha s + (1 - \alpha)b \), assuming \( b = \mu \). The final SMF detector is therefore given as

\[ r_{SMF}(x) = \frac{(s - \hat{\mu})^T \hat{\Sigma}^{-1} (x - \hat{\mu})}{\sqrt{(s - \hat{\mu})^T \hat{\Sigma}^{-1} (s - \hat{\mu})}}. \tag{2.33} \]

where the denominator can be omitted if using a global estimate for the background covariance matrix.
2.10.2 Adaptive Coherence/Cosine Estimator (ACE)

The derivation of the SMF detector used the GLRT of two probability distributions representing the “target present” and null hypotheses. The covariance matrices for both probability distributions was assumed to be equal to the sample covariance of the background. This assumption was shown to be invalid by Kelly, who derived MLE estimates for the background covariance matrices of both hypothesis ($\hat{\Sigma}_0$ & $\hat{\Sigma}_1$) to produce a more theoretically valid GLRT detection statistic [67, 86]. This detector, called the Kelly Detector, was extended by Kraut and Scharf by adding another MLE parameter that scales the size of the background contribution. This adaptive GLRT detector, called the Adaptive Coherence/Cosine Estimator (ACE), assumes a mean subtracted background and target signature, and uses the hypotheses

$$H_0 : x = \beta b$$
$$H_1 : x = \alpha s + \beta b,$$

(2.34)

where $\beta$ is the background scaling coefficient. Both the Kelly and ACE detectors originated from radar research [67, 87, 88].

Kraut and Scharf found that the MLEs for two hypotheses are written as

$$\hat{\Sigma}_0 = \left( \frac{1}{n+1} \right) \left( \frac{1}{\hat{\beta}_0^2} \hat{x}x^T + n\hat{\Sigma} \right)$$
$$\hat{\Sigma}_1 = \left( \frac{1}{n+1} \right) \left( \frac{1}{\hat{\beta}_1^2} (x - \hat{\alpha}s)(x - \hat{\alpha}x)^T + n\hat{\Sigma} \right),$$

(2.35)

and the corresponding background scaling coefficient MLEs are defined as

$$\hat{\beta}_0^2 = \left( \frac{n - k + 1}{nk} \right) (x^T \hat{\Sigma}^{-1} x)$$
$$\hat{\beta}_1^2 = \left( \frac{n - k + 1}{nk} \right) ((x - \hat{\alpha}s)^T \hat{\Sigma}^{-1} (x - \hat{\alpha}x)),$$

(2.36)

where $n$ is the number of samples, $k$ is the dimensionality, the subscript zero refers to the null hypothesis, and the subscript one refers to the “target present” hypothesis [87]. Similar to the SMF detector, the MLE for the target abundance coefficient $\hat{\alpha}$ is defined in Equation 2.31, where the dependence on $u$ is removed because the data in this case is mean subtracted. The MLE estimate therefore is expressed as

$$\hat{\alpha} = \frac{s^T \hat{\Sigma}^{-1} x}{s^T \hat{\Sigma}^{-1} s}.$$

(2.37)

The GLRT detection statistic that utilizes these MLE values to model the background distribution and target signature abundance, according to the hypotheses defined in Equation 2.34, is the ACE detector, written as

$$r_{ACE}(x) = \frac{(s^T \hat{\Sigma}^{-1} x)^2}{(s^T \hat{\Sigma}^{-1} s)(x^T \hat{\Sigma}^{-1} x)}.$$

(2.38)
2.10.3 Adaptive Generalized Likelihood Ratio Test (A-GLRT)

A class of hyperspectral target detection algorithms called Matched Subspace Detectors use a subspace representation to model the background data. As explained in Section 2.8, hyperspectral data typically reside in lower dimensional manifolds, with dimensionality less than the total number of wavelengths. These algorithms leverage this phenomena by modeling the background pixels as a linear combination of basis vectors. These vectors can be either leading eigenvectors of the background covariance matrix (orthogonal, no loading positivity constraints) or background end-members (non-perpendicular, strictly positive loadings). This subspace background model gives rise to the following “target present” and null hypotheses:

\[
H_0 : \mathbf{x} = \mathbf{B}\beta + \mathbf{n} \\
H_1 : \mathbf{x} = \alpha \mathbf{s} + \mathbf{B}\beta + \mathbf{n},
\]

where \(\mathbf{B}\) is the background subspace composed of columns of basis vectors, \(\beta\) contains the background subspace loadings, and \(\mathbf{n}\) is zero-mean Gaussian normal white noise with constant standard deviation \(\sigma_n\) [67].

Under these hypotheses, Scharf and Friedlander formulate two GLRT detectors based on known noise and unknown noise variance assumptions [89]. Both detectors use the MLE for the target abundance coefficient written as

\[
\hat{\alpha} = \frac{s^T P_B^\perp \mathbf{x}}{s^T P_B^\perp s},
\]

where \(P_B\) is the projection operator into the background subspace and \(P_B^\perp\) is the complement background projection operator into the subspace orthogonal to the background subspace [67,89]. These projection operators are defined as

\[
P_B = \mathbf{B} (\mathbf{B}^T \mathbf{B})^{-1} \mathbf{B}^T \\
P_B^\perp = I - P_B,
\]

where \(I\) is the identify matrix [67]. Another important operator to define is the joint projection operator, \(P_{sB}\), which defines the projection into the subspace formed by both the target and background basis vectors concatenated together. For both detectors, Scharf and Friedlander use MLEs of the noise and background loading coefficients (\(\beta\)) to derive GLRT detection statistics.

For the known noise variance case, the GLRT detector is defined as

\[
t_{SP-GLRT}(\mathbf{x}) = \begin{cases} 
0 & \hat{\alpha} \leq 0 \\
\frac{1}{\sigma_n} \mathbf{x}^T (P_B^\perp - P_{sB}) \mathbf{x} & \hat{\alpha} > 0
\end{cases},
\]

where “SP-GLRT” stands for the Sub-Pixel GLRT detector. Positivity of the abundance coefficient is not enforced in MLE estimation of Equation 2.40, therefore a positive detection score is conditional on a positive, physically possible, target spectrum abundance coefficient. For the unknown noise variance case, the GLRT detector is expressed as

\[
t_{A-GLRT}(\mathbf{x}) = \begin{cases} 
0 & \hat{\alpha} \leq 0 \\
\mathbf{x}^T (P_B^\perp - P_{sB}) \mathbf{x} & \hat{\alpha} > 0
\end{cases},
\]

where

\[
l (\mathbf{x}) = \frac{1}{\sigma_n} \mathbf{x}^T (P_B^\perp - P_{sB}) \mathbf{x}.
\]
where “A-GLRT” stands for the Adaptive GLRT detector.

### 2.10.4 Target Subspace Detectors

The four hyperspectral target detection algorithms introduced thus far use a GLRT to compare a “target present” hypothesis to a null hypothesis to produce a detection statistic that assesses the similarity between a test spectrum and a target spectrum. While these signature-matched detectors model the distribution of the background, they only incorporate a point estimate for the target signature. The class of hyperspectral target detection algorithms that model both the background and target distributions are called Target Subspace Detectors [67]. These detection algorithms incorporate the distribution of target signatures by modeling the target subspace as a linear combination of basis vectors similar to the background subspace model used in Section 2.10.3. Each of the introduced algorithms can be converted into its corresponding subspace detection algorithm.

The original hypotheses used in the SMF GLRT (see Equation 2.27) are rewritten to describe the target with a subspace model as

$$ H_0 : x = b $$

$$ H_1 : x = S\hat{\eta} + b, $$

where \( \hat{\eta} \) is now a row vector that contains the target subspace loadings and \( S \) is a matrix of concatenated column vectors that span the target subspace. Essentially to convert this detector into a subspace detector \( \hat{\alpha}s \) was substituted for \( S\hat{\eta} \) according to the relationship

$$ S\hat{\eta} = \hat{\alpha}s. $$

Some authors use the same coefficient symbol for both \( \hat{\alpha} \) and \( \hat{\eta} \) but there is an important distinction between them; \( \hat{\alpha} \) only describes the target signature abundance while \( \hat{\eta} \) characterizes both the target abundance (\( \hat{\alpha} \)) and the basis vector loadings (\( \gamma \)). Therefore, \( \hat{\eta} \) is a product of both the target abundance, or pixel fill, and the basis vector loadings according to

$$ \hat{\eta} = \hat{\alpha}\gamma. $$

This distinction is important in a learning framework in which knowledge of either \( \gamma \) or \( \alpha \) may exist but not both.

Assuming mean background subtracted data, mean subtracted signature, and a global covariance matrix, the SMF detector defined in Equation 2.33 can be re-written as

$$ r_{SMF}(x) = s^T\hat{\Sigma}^{-1}x. $$

Because the covariance matrix is symmetric, and assuming it is non-singular, the inverse covariance matrix is also symmetric, allowing the SMF to be further rewritten as

$$ r_{SMF}(x) = x^T\hat{\Sigma}^{-1}s. $$

In addition, by substituting Equation 2.45 into the MLE estimate for the abundance coefficient, originally presented in Equation 2.31 and rewritten in Equation 2.37 to account for the mean centering, the MLE estimate for \( \hat{\eta} \) can be shown to be

$$ \hat{\eta} = (S^T\hat{\Sigma}^{-1}S)^{-1}S^T\hat{\Sigma}^{-1}x. $$
Now the signature-matched SMF is converted into a subspace SMF by substituting Equations 2.45 and 2.49 into equation 2.48, yielding the subspace SMF detector (SS-SMF) \[90],

\[
r_{SS-SMF}(x) = x^T \hat{\Sigma}^{-1} S (S^T \hat{\Sigma}^{-1} S)^{-1} S^T \hat{\Sigma}^{-1} x.
\] (2.50)

The residual \(\alpha\) coefficient is removed in this process; doing so is a legal monotonic transformation that does not change the relative ordering of the pixels scores.

A similar process is repeated for the ACE detector resulting in the new hypotheses of

\[
H_0 : x = \beta b \\
H_1 : x = S \eta + \beta b.
\] (2.51)

And again using Equation 2.45 to substitute \(S\) for \(s\), the ACE detector is redefined according to the subspace target model. The definition of the subspace ACE detector (SS-ACE) is given as

\[
r_{SS-ACE}(x) = \frac{x^T \hat{\Sigma}^{-1} S (S^T \hat{\Sigma}^{-1} S)^{-1} S^T \hat{\Sigma}^{-1} x}{x^T \hat{\Sigma}^{-1} x}.
\] (2.52)

Lastly, the SP-GLRT and A-GLRT (see Equations 2.42 and 2.43) are converted into their target subspace variants by observing that these Matched Subspace Detectors were already utilizing the single target spectrum as a target subspace. Therefore, the target subspace extension simply swaps the original target subspace \(s\) for the new subspace \(S\). The new GLRT hypotheses are redefined as

\[
H_0 : x = B \beta + n \\
H_1 : x = S \eta + B \beta + n,
\] (2.53)

and the sub-space variants of these detectors are

\[
r_{SS-SPGLRT}(x) = \frac{1}{\sigma_n} x^T (P_B^\perp - P_{SB}^\perp) x
\] (2.54)

and

\[
r_{SS-AGLRT}(x) = \frac{x^T (P_B^\perp - P_{SB}^\perp) x}{x P_{SB}^\perp x},
\] (2.55)

where the projection operator \(P_{SB}^\perp\) has been replaced with \(P_{SB}^\perp\) and the conditional dependence on the sign of the pixel abundance coefficient has been removed.
Chapter 3

Hyperspectral Data Collection

3.1 Introduction

Hyperspectral target detection of non-Lambertian objects with complex geometries, such as vehicles, is challenging due to the aggregation of specular surfaces whose reflectance spectra are highly sensitive to sun-target-sensor geometry. To address this issue and better understand the problem domain, hyperspectral imagery was taken of four vehicles from a roof at the Rochester Institute of Technology (RIT) during a six hour period in illumination conditions dominated by direct solar radiation. The four vehicles were continuously rotated during the span of the collection, resulting in many combinations of vehicle orientation, sun azimuth, and sun zenith.

The imagery was taken with two line scanning imaging spectrometers, resulting in 482 contiguous bands from 0.4 to 2.5 microns (VNIR-SWIR) and a spatial resolution on the order of 5cm GSD. Figure 3.1 displays an aerial view of the collection topology while Figure 3.2 shows an example of the acquired imagery. To control for and model illumination conditions, several instruments characterized the sun and atmosphere at sub-minute sampling intervals. Additional instruments measured the DHR of the targets and the BRDF of the dominant background surfaces. Furthermore, time lapse photography and the GPS measurements of in-scene fiducials were used to later extract the vehicle positions.

The vehicles were continuously rotated throughout the data collection in order to sample the hyperspectral BRDF of the four vehicles over a diverse set of independent variables. This BRDF sampling facilitates several experiments aimed at understanding the vehicle BRDF dependence on vehicle orientation, shape, and color. In addition, the BRDF sampling provides a useful data set for testing vehicle reacquisition and tracking algorithms. An additional experiment was also performed during the data collection to quantify the vehicle background adjacency effect.

Initial data processing consisted of characterizing the atmosphere and extracting the vehicle positions using the fiducial GPS measurements and time lapse imagery.
Figure 3.1: A birds eye view of the data collection topology. Note that the partial urban canyon creates downwelled illumination differences between the top of the buildings and the area of interest (Image courtesy of Google Maps).

Figure 3.2: Hyperspectral imagery consisting of four vehicles in a scene including grass and a parking lot was acquired from the roof of a building at RIT. Shown are two color realizations of the 482 contiguous VNIR-SWIR bands: RGB based on the human visual system spectral response curves (left) and a SWIR false color RGB image with Gaussian response functions centered at 2.1, 1.65, and 1.25 $\mu m$, respectively (right).

3.2 Experiments

Hyperspectral imagery (HSI) was collected from 10:23am to 4:18pm, during which time the sun traversed 27 degrees of zenith and 98 degrees of azimuth. Preceding each image capture, the
four vehicles were all rotated in one of four orientations in a round robin order such that the
sun position would maximally change between two images of a vehicle at the same orientation.
A total of 23 hyperspectral cubes were taken in order to fulfill the requirements of three exper-
iments designed to better understand phenomenological dependencies of sun position, vehicle
orientation, vehicle material, and vehicle shape on the observed imagery in the hyperspectral
domain.

The first experiment is to utilize the spectral diversity of the imaged vehicle BRDF spectra
to test hyperspectral vehicle reacquisition algorithms (see Section 3.2.1). The second experiment
was designed to probe the effect of vehicle color, shape, and orientation on the observed BRDF
of a vehicle (see Section 3.2.2). Lastly, the third experiment was designed to determine the
contribution of background adjacency effects (i.e. earth shine) onto the surface of a vehicle (see
Section 3.2.3).

3.2.1 Target Vehicle Reacquisition

The spectral signature of an ideal homogeneous Lambertian reflector, laid flat on the ground,
will be independent of orientation and sun position. With such a target the spectral signature
at time $t_1$ and orientation $\theta_1$ could be successfully used in a spectral signature search, such as
spectral matched filter, at a later time $t_2$ and new orientation $\theta_2$ assuming similar atmospheric
conditions. Due to the Lambertian, flat, and homogeneous material properties, the reflected
radiance is scattered evenly, independent of source-target-sensor geometry, resulting in similar
spectra at $t_1$ and $t_2$. Therefore the spectral matched filter score of a Lambertian target is largely
independent of either orientation ($\theta_1, \theta_2$).

In contrast, if the target is specular, has complex geometric structure, or does not exhibit
radial symmetry, the spectra at time $t_1$ and $t_2$ may vary considerably. If using the spectral
signature at $t_1$ to reacquire the same vehicle at $t_2$, knowledge of this spectral perturbation pro-
vides a spectral transformation to facilitate better reacquisition rates. A simple example of this
spectral transformation would be a panel with a characterized gloss but unknown diffuse under-
coat. The first measurement and the gloss BRDF would facilitate the calculation of subsequent
measurement at a new source-object-sensor geometry. Furthermore, if the atmospheric condi-
tions vary considerably between $t_1$ and $t_2$, knowledge of this spectral perturbation again elicits
a spectral transformation allowing the conversion of the signature at $t_1$ into the domain of $t_2$.
A simple example of this spectral transformation involves the same panel but now the second
measurement is made under cloudy conditions whereas the first measurement was made under
sunny conditions. This transformation requires the spectra color and magnitude to be adjusted
based on the material BRDF in order to use the first spectrum in a measure of similarity with
the second.

While characterization of the later transformation, based on atmospherics, is independent
of the vehicle, the prior transformation is heavily dependant on vehicle size, shape, orientation,
and material BRDF. With known illumination and full a priori knowledge of the target vehicle,
a forward model could be used to predict the sensor reaching radiance at any sun-target-sensor
geometry. However, when only partial knowledge is available a reacquisition algorithm may need
to exhibit simultaneous learning and detection behavior and operate based on distributions of
possible vehicle parameters.
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This data set benefits from high spatial and spectral resolutions which will facilitate the down sampling to various detection regimes from high resolution to sub-pixel imaging scenarios. Although in this research only the former, sub-pixel domain is considered, the goal of this HSI data collection is to provide a data set that would facilitate the testing of a wide range of hyperspectral vehicle reacquisition algorithms.

3.2.2 Geometric and Material Contribution to Vehicle BRDF

Similar to the canonical use of BRDF as a material property, the term object BRDF refers to the reflected radiance of an object as a function of source-object-sensor geometry normalized by the incident irradiance. Object BRDF is a summation of all the materials in a pixel’s instantaneous field of view (IFOV) and therefore has many contributing factors such as the number and distribution of visible materials, the distribution of incident illumination and shadowed material elements, the materials’ BRDF, and the materials’ orientations with respect to the sun and sensor. All of these factors are a function of the source-object-sensor geometry, the object geometry, and the vehicle orientation. Object geometry used in this context refers to all the information gained from an ideal facet model of the object, whereas source-object-sensor geometry refers to the polar coordinates of the source and sensor with respect to the target. Note that vehicle orientation can be thought of as a function of source-object-sensor geometry because an orientation about any axis can also be thought of as a rotation of the source and sensor about the target. The aim of this experiment is to better understand how changes in the dominant material of a vehicle, the vehicle paint, affect the vehicle BRDF, how changes in vehicle geometry (shape) affect the vehicle BRDF, and finally how changes in orientation affect the vehicle BRDF.

To attempt to better understand these vehicle BRDF relationships, two vehicles of the same make and model but different colors were rotated together and imaged at various sun-target-sensor geometries throughout the day. In addition, two vehicles of the same make and color but vastly different shapes were also similarly rotated together and imaged throughout the day. Understanding these relationships will aid in the transfer learning of characterized vehicle models to other unknown, previously unseen vehicles. For example, if all sedans have BRDFs that change similarly as a function of orientation, generalization can be made about how the spectra of a new sedan will change as it makes a turn. In addition, understanding these BRDF dependencies will facilitate the use of classifying unknown vehicles based on their observed BRDF.

3.2.3 Background Adjacency Effect

The complete characterization of a vehicle’s BRDF and illumination is not sufficient for determining the sensor reaching spectral radiance. The target background contributes to the observed signal through both directly reflected energy (linear mixing) and secondary reflections in which photons are reflected from the background onto the vehicle and into the sensor aperture (non linear mixing). These secondary photon bounces are referred to as earth shine because the effect is characterized by the amount of light emanating from the ground that is illuminating the vehicle. If a vehicle is parked near grass portions of the vehicle will look “greener” than if it were parked on concrete.
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Figure 3.3: The four images shown were captured by the RGB time lapse camera and show the different vehicle scene configurations for each of the earth shine HSI acquisitions.

The effect of the direct photon bounces can be predicted by observing nearby pixels that contain only the specified background material to obtain the magnitude. The background spectral magnitude is then multiplied by the per pixel background IFOV fill factor to account for mixed target background pixels. This fill factor can be calculated using un-mixing algorithms or maximum likelihood estimation (MLE) abundance estimation techniques. The prediction of secondary photon bounces, however, is more complicated—knowledge of background BRDF, vehicle material BRDF, and vehicle geometry is needed. This experiment aims to quantify this vehicle earth shine effect using a white SUV.

In order to quantify this vehicle background adjacency effect, the SUV was imaged in front of two different backgrounds (grass and asphalt) using control images such that the photons originating from the background and reflecting off the vehicle could be directly measured. This process required four hyperspectral images as seen in Figure 3.3. In the first image the SUV is parked in front of grass. In the second image the SUV is parked in front of grass and a 1m x 1m black Lambertian panel is placed directly in front of the vehicle. In the third image the SUV is parked on a concrete parking lot. In the fourth image the SUV is parked on the concrete and the black panel is placed on the ground in front of it. The black panel acts as a control in that it creates two images in which the only difference between them is a 1m x 1m patch directly in front. The four images therefore establish two instances in which the difference of earth shine is known and the effect can be directly measured as a change in spectral radiance magnitude.
Finally, in order to characterize the entire process of a secondary photon bounce, GRIT (see Section 3.4.4) was used to measure the spectral BRDF of the grass and concrete backgrounds. GRIT output of both measurements is shown in Figure 3.12.

### 3.3 Targets

The principal targets of this data collection are four vehicles strategically chosen such that two are the same color and manufacturer but different shapes and two are the same model and manufacturer but different colors in order to fulfill the experiment requirements outlined in Section 3.2.2. The make and model of the four vehicles is displayed in Table 3.1. The two vehicles that are the same make and model but different colors are the two Chevrolet Sparks. The two vehicles that share a common color and manufacturer are the white Spark and the white traverse. It should be noted that upon visual inspection, although both vehicles are painted white, the shade/hue of white does not match exactly to the naked eye. The fourth vehicle was selected in order to add color and shape diversity. This red sports car is a Chrysler Crossfire. Images of the vehicles are shown in Figure 3.4.

In addition to the four vehicles, vertical and horizontal calibration panels were placed in the scene. These panels were added in order to perform radiometric calibration of the hyperspectral images and obtain reflectance imagery using techniques like irradiance retrieval and the empirical line method (ELM). Four colored horizontal felt panels were placed in the grass to the right of the vehicle (see Figure 3.5). Three grey-scale vertical panels were also placed at the bottom of the FOV (see Figure 3.6). These vertical panels became self-shadowed around 2:40 pm, after which point identical horizontal calibration panels were added to the scene. Both set of panels, vertical and horizontal, contained a black felt panel, a grey felt panel, and a white Tyvek panel. Although these panels were selected for their Lambertian BRDF properties, as seen in the images, both sets of felt panels have a distinct shine or glimmer, indicating that a Lambertian BRDF assumption for these panels may be incorrect.

### Table 3.1: Vehicles used in the data collection

<table>
<thead>
<tr>
<th>Color</th>
<th>Manufacturer</th>
<th>Model</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>Chevrolet</td>
<td>Spark</td>
<td>2014</td>
</tr>
<tr>
<td>Blue</td>
<td>Chevrolet</td>
<td>Spark</td>
<td>2013</td>
</tr>
<tr>
<td>White</td>
<td>Chevrolet</td>
<td>Traverse LTZ</td>
<td>2015</td>
</tr>
<tr>
<td>Red</td>
<td>Chrysler</td>
<td>Crossfire</td>
<td>2005</td>
</tr>
</tbody>
</table>
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Figure 3.4: Photographs of the four vehicles imaged in this data collection: the white Spark (top left), the blue Spark (top right), the red Crossfire (bottom left), and the white Traverse (bottom right).

Figure 3.5: Photographs of the horizontal felt panels used for image calibration. The colors, listed from left to right, are blue, red, green, and brown.

Figure 3.6: Photographs of the vertical calibration panels used for image calibration. The white calibration panel is made of Tyvek (left) while the grey (middle) and black (right) calibration panels are made of felt.
3.4 Sensor Systems

During the data collect, a line-scanning hyperspectral imaging spectrometer acquired imagery of the scene while a time-lapse camera took colored images. In addition to these cameras, various sensors gathered information to aid in the characterization of the atmosphere, target positions and reflectance spectra, and scene background spectral BRDF.

3.4.1 Imaging Spectrometers

Two Headwall Micro-HyperSpec Imaging Spectrometers\cite{91}, one visible near infrared (VNIR) and one short wave infrared (SWIR), were used to capture high resolution hyperspectral images that constitute the main data product of this collection. Both instruments are line scanning pushbroom spectrometers that together produce hyperspectral data cubes composed of 482 contiguous bands spanning wavelengths from 400 nm to 2500 nm. The VNIR camera uses a complementary metaloxidesemiconductor (CMOS) focal plane to operate from 400-1000 nm and the SWIR camera uses a mercury cadmium telluride (MCT) focal plane to operate from 900-2500 nm. The two cameras are co-boresignted, use optics that result in similar fields of view, and are mounted on the same horizontal scanning instrument shown in Figure 3.7. As seen in Table 3.2 however, the SWIR camera has a larger pixel pitch than the VNIR camera, resulting in a disparity in spatial sampling. On average the GSD of the SWIR images are larger than than the VNIR images by a factor of 3.36.

<table>
<thead>
<tr>
<th>Modality</th>
<th>VNIR</th>
<th>SWIR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwidth</td>
<td>400-1000 nm</td>
<td>900-2500 nm</td>
</tr>
<tr>
<td>Bands</td>
<td>370</td>
<td>178</td>
</tr>
<tr>
<td>Spatial Samples</td>
<td>1600</td>
<td>384</td>
</tr>
<tr>
<td>FOV</td>
<td>26.02°</td>
<td>20.8°</td>
</tr>
<tr>
<td>IFOV</td>
<td>0.97'</td>
<td>3.25'</td>
</tr>
<tr>
<td>FPA</td>
<td>CMOS</td>
<td>MCT</td>
</tr>
<tr>
<td>Pixel Pitch</td>
<td>6.5 µm</td>
<td>24 µm</td>
</tr>
<tr>
<td>Bit Depth</td>
<td>16</td>
<td>16</td>
</tr>
</tbody>
</table>

3.4.2 Total Sky Imager

The Yankee Environmental Systems TSI-440\cite{92} total sky imager consists of an RGB camera that stares down onto a hemispherical mirror. The camera takes photos at 15 second intervals in order to characterize the cloud cover throughout the duration of the collection. In order to keep the direct solar light from saturating the camera, the mirror is covered with a strip of black tape. A microcontroller re-positions the orientation of the tape such that the image of the sun is
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Figure 3.7: The hyperspectral imaging spectrometer is composed of two co-boresighted cameras, one VNIR and one SWIR. Both sensors are push-broom line scanning instruments that scan the scene horizontally in order to build the image.

always minimized by the black tape. The images are post processed and provide a pixel map of fractional cloud coverage as a function of time (see Figure 3.8) that can be used to characterize the downwelled scene illumination.

Figure 3.8: The Total Sky Imager (left) images a mirror (middle) that provides an image of the entire sky. The images are post processed to produce a per pixel cloud cover map (right).

3.4.3 Shadow Band Radiometer

The Yankee Environmental Systems MFR-7 Shadow Band Radiometer[93] (SBR) directly measured incident irradiance at six strategic band passes centered at 413, 496, 613, 672, 870, and 937 nm throughout the duration of the collection. The instrument cannot perfectly shadow the sun without shadowing part of the hemisphere so a direct measurement of diffuse/downwelled or direct solar irradiance is impossible. Therefore, the values are measured indirectly with two
adjacent diffuse measurements made on either side of the detector according to

\[ E_{\text{direct solar}} = \frac{1}{2}(E_{\text{diffuse}1} + E_{\text{diffuse}2}) - E_{\text{shadow}}. \]  

(3.1)

The orientation of the shadow band with respect to the detector for each of the measurements can be seen in Figure 3.9. The diffuse/downwelled measurement is then the difference between the total and direct solar irradiance measurements; e.g. \( E_{\text{diffuse}} = E_{\text{total}} - E_{\text{direct solar}} \). Finally, to obtain the normal direct solar irradiance (value if detector was normal to the sun), the direct solar irradiance is divided by the cosine of the sun zenith angle according to \( E_{\text{direct normal}} = E_{\text{direct solar}} / \cos(\phi) \). Four measurements at each band pass are averaged and reported in one minute intervals (Figure 3.10). In addition to these irradiance measurements, an attached weather station recorded wind speed, wind direction, air pressure, temperature, and relative humidity as a function of time.

![Image of irradiance measurements](image-url)

**Figure 3.9:** The SBR rotates the shadow band to capture 4 irradiance values for each of its six bands. These measurements consist of the total irradiance (top left), the shadowed irradiance (bottom left), and two adjacent diffuse irradiance measurements (top right and bottom right).

### 3.4.4 Hyperspectral Goniometer

The Goniometer at the Rochester Institute of Technology (GRIT)[39] measures the BRDF of materials in the field and in laboratory settings. GRIT sweeps a spectrometer through 360 degrees of azimuth and 60 degrees of zenith in order to characterize the reflectance distribution of light over the hemisphere for a specific sun-material geometry (see Figure 3.11). GRIT uses
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Figure 3.10: Minute interval measurements of the solar (sun-normal) irradiance (top) and diffuse irradiance (bottom) as recorded by the SBR. Plotted are a subset of the 6 wavelengths on top of vertical black lines that mark the HSI image acquisitions. The irregularities around 2pm are due to increased cloud cover.

A radiometrically calibrated ASD FR 4 high-resolution spectrometer that records 2151 radiance values from 350-2500 nm in 1 nm intervals. The radiometer foreoptic is mounted inside a sensor carriage that traverses the zenith plane using a stepper motor that crawls up and down a quarter circle arm. The arm, in turn, is mounted on a ring rotary stage that employs another stepper motor to traverse every azimuthal position. Sampling density is selected by the user and GRIT’s integrated software automatically moves to the necessary angular configurations and records attitude information using two mounted IMUs. The first IMU, a VectorNav 100, is mounted on the sensor carriage and provides roll and pitch information while the second IMU, a VectorNav 300 IMU/GPS, utilizes two GPS antennas to report accurate position, and heading data.[39]

One in situ BRDF measurement can take up to 30 minutes. During this period of time the scene illumination can vary considerably due to changing atmospheric conditions, such as clouds or haze [94]. To capture this temporal illuminant variation, GRIT uses a second spectrometer of the same make and model as the first that stares downward normal to a white Spectralon panel [94]. The second radiometer is referred to as the base station and is usually placed closely enough to the goniometer that both share the same incident irradiance but far enough that its presence does not contaminate the goniometer measurements. Without this second
radiometer simultaneously capturing spectral radiance, it would be impossible to decouple a change in illumination from a change in the material BRDF as the sensor scans across azimuth and elevation.

The two spectrometers take measurements in parallel, acting as a single dual beam spectrometer [94]. Because both the material of interest and the white panel share the same incident irradiance, the BRDF equations for both can be combined such that one BRDF can be described as a function of the other BRDF and the ratio of both radiance measurements. To show this relationship, first the definition of the mean BRDF ($\rho$) across time ($t$) is given as

$$\rho(\lambda, \theta_i, \phi_i, \theta_r, \phi_r) = \frac{1}{p} \sum_{t=1}^{p} \frac{L_{r,\text{truth}}(t, \lambda, \theta_r, \phi_r)}{E_{i,\text{truth}}(t, \lambda, \theta_i, \phi_i)},$$  \hspace{1cm} (3.2)

where $L_{r,\text{truth}}$ is the true reflected irradiance, $E_{i,\text{truth}}$ is the true incident radiance, and $(\theta_i, \phi_i, \theta_r, \phi_r)$ represent the incident and reflected azimuth and zenith angles respectively. Next, per wavelength calibration and location gain differences are accounted for between the two spectrometers by assuming unknown spectral calibration coefficients $k(\lambda)$ that affect the measured radiance ($L_m$), and unknown spectral correction coefficients $f(\lambda)$ that account for differences in incident irradiance between the two radiometers by correcting to a common irradiance ($E_c$), producing the two equations

$$L_m(t, \lambda, \theta_r, \phi_r) = k(\lambda)L_{\text{truth}}(t, \lambda, \theta_r, \phi_r) \hspace{1cm} (3.3)$$

$$E_c(t, \lambda, \theta_{\text{sun}}, \phi_{\text{sun}}) = f(\lambda)E_{\text{truth}}(t, \lambda, \theta_{\text{sun}}, \phi_{\text{sun}}). \hspace{1cm} (3.4)$$

Now the equations for the BRDF of the material of interest and the white panel are given with
respect to measured radiance and a common irradiance:

\[
\rho_m(\lambda, \theta_{sun}, \phi_{sun}, \theta_r, \phi_r) = \left( \frac{f_g(\lambda)}{k_g(\lambda)} \right) \frac{1}{p} \sum_{t=1}^{p} \left( \frac{L_{g,m}(t, \lambda, \theta_r, \phi_r)}{E_c(t, \lambda, \theta_{sun}, \phi_{sun})} \right)
\]  

(3.5)

and

\[
\rho_{w_b}(\lambda, \theta_{sun}, \phi_{sun}, \theta_b, \phi_b) = \left( \frac{f_b(\lambda)}{k_b(\lambda)} \right) \frac{1}{p} \sum_{t=1}^{p} \left( \frac{L_{b,w_b}(t, \lambda, \theta_b, \phi_b)}{E_c(t, \lambda, \theta_{sun}, \phi_{sun})} \right)
\]  

(3.6)

where the subscripts \(g\) (goniometer) and \(b\) (base station) are used to differentiate between the two radiometers and the subscripts \(w\) (white panel) and \(m\) (material of interest) differentiate between the two material types. The final BRDF equation [94] that is invariant to sub optimal sky conditions is achieved by combining Equations (3.5) and (3.6) and yields

\[
\rho_m(\lambda, \Theta_r) = \left( \frac{f_g k_b}{f_b k_g} \right) \frac{1}{p} \sum_{t=1}^{p} \left( \frac{L_{g,m}(t, \lambda, \theta_r, \phi_r)}{L_{b,w_b}(t, \lambda, \theta_b, \phi_b)} \right) \rho_{w_b}(\lambda, \Theta_b)
\]  

(3.7)

where \(\Theta_r = [\theta_{sun}, \phi_{sun}, \theta_r, \phi_r]\) and \(\Theta_b = [\theta_{sun}, \phi_{sun}, \theta_b, \phi_b]\).

Assuming both radiometers are perfectly calibrated \((k_b(\lambda) = k_g(\lambda))\) and the incident irradiance is equal \((f_g(\lambda) = f_b(\lambda))\), the reflectance measurement would simply be a per band ratio of the reflected radiance of the material over the reflected radiance of the white panel multiplied by the BRDF of the white panel with respect to the sun/base station geometry. If these equality conditions do not hold, the BRDF measurements taken will be relatively accurate with respect to each other but off by a factor of \((f_g(\lambda)k_b(\lambda)/f_b(\lambda)k_g(\lambda))\) with respect to the absolute truth.

To account for the calibration and irradiance factors, Bachmann et. al construct a “transfer” function by simultaneously measuring the radiance of a white panel with the goniometer and a second white panel with the base station [94]. This conversion factor then allows for the transfer from base station BRDF to goniometer BRDF. The concept of operation of the GRIT system therefore consists of a white panel measurement followed by all necessary azimuth/elevation measurements concluded by a final white panel measurement to facilitate optimal transfer function interpolation [94].

The goniometer white panel measurement adds a third BRDF equation similar to Equations (3.5) and (3.6):

\[
\rho_{w_g}(\lambda, \Theta_b) = \left( \frac{f_g(\lambda)}{k_g(\lambda)} \right) \frac{1}{q} \sum_{t=1}^{q} \left( \frac{L_{g,w_g}(t, \lambda, \theta_b, \phi_b)}{E_c(t, \lambda, \theta_{sun}, \phi_{sun})} \right)
\]  

(3.8)

Equations (3.6) and (3.8) are then combined to produce the desired transfer function

\[
\rho_{w_g}(\lambda, \Theta_b) = \left( \frac{f_g(\lambda)k_b(\lambda)}{f_b(\lambda)k_g(\lambda)} \right) \frac{1}{q} \sum_{t=1}^{q} \left( \frac{L_{g,w_g}(t', \lambda, \theta_b, \phi_b)}{L_{b,w_b}(t', \lambda, \theta_b, \phi_b)} \right) \rho_{w_b}(\lambda, \Theta_b)
\]  

(3.9)

where the parameter \(t\) is replaced by \(t'\) because the white panel/white panel measurements are made at a different time than the material/white panel measurements. This transfer function is then used to remove the material BRDF measurement dependence on \(f_g(\lambda), f_b(\lambda), k_g(\lambda), k_b(\lambda),\) and \(p_{w_b}\) from the previously established temporally invariant reflectance equation (Eq 3.7). This
new functional form of BRDF that incorporates the constructed transfer function (Eq 3.9) into the original function (Eq 3.7) is

\[
\rho_m(\lambda, \Theta_r) = \frac{1}{q} \sum_{t'=1}^{q} \left( \frac{L_{b,w_b}(t', \lambda, \theta_b, \phi_b)}{L_{g,w_g}(t', \lambda, \theta_b, \phi_b)} \right) \frac{1}{p} \sum_{t=1}^{p} \left( \frac{L_{g,m}(t, \lambda, \theta_r, \phi_r)}{L_{b,w_b}(t, \lambda, \theta_b, \phi_b)} \right) \rho_{w_g}(\lambda, \Theta_b). \tag{3.10}
\]

Figure 3.12: GRIT was used to measure the BRDF of both the asphalt parking lot (left) and the grass adjacent to the SUV (right) in order to characterize the secondary photon bounce effect in support of the earth shine experiment. The polar BRDF plots are at 555 nm and for time considerations, only the forward scattering spherical quadrant was measured. The spectral plots are a function of zenith angle and sampled from the principal plane.

The final BRDF measurement of the material, \( \rho_m \), is therefore only dependent on in-scene spectral measurements of radiance and the BRDF of the goniometer white panel, \( \rho_{w_g} \) [94]. The results of using GRIT to collect the BRDF of the grass and asphalt as part of the background adjacency experiment (see Section 3.2.3) are shown in Figure 3.12. This white panel BRDF value is measured in the laboratory under controlled illumination conditions. For this study the panel BRDF is assumed to be Lambertian, thus only a nadir laboratory measurement is utilized. To reduce error in future studies, the illumination and GRIT fore-optic orientations, \((\lambda, \theta_{sun}, \phi_{sun}, \theta_b, \phi_b)\), could be more precisely accounted for in the laboratory, after recording the radiance data in-scene. In addition, the Bidirectional Reflectance Factor (BRF) can be used in Equation (3.10) for both \( \rho_m \) and \( \rho_{w_g} \) by adhering to the relationship \( \rho_{BRDF} = \rho_{BRF}/\pi \) [31].

The final BRDF measurement of the material is invariant to changing irradiance caused by sub-optimal sky conditions, differences in irradiance between the goniometer and base station,
and calibration errors between either of the two radiometers used [94]. Each unique azimuth elevation data point is reported as an array of BRFs in 1nm intervals.

### 3.4.5 Portable Spectroradiometer

The SVC HR-1024i Portable Spectroradiometer made by Spectra Vista Corporation [95] was used to take directional hemispherical reflectance (DHR) measurements of in-scene materials as part of the data collection. The instrument records 1024 bands from 350-2500 nm and features low noise, cooled indium gallium arsenide (InGaAs) detectors [95]. The radiometer was outfitted with a fiber optic contact probe which provides spectral measurements of DHR. The roof, side, hood, tire, hub cap, and trim of each of the four vehicles were measured as well as other in-scene materials such as the felt panels, vertical and horizontal calibration targets, the focus target, grass, and asphalt. A subset of these measurements are shown in Figure 3.13.

![Figure 3.13: A portable spectroradiometer was used to measure the spectra of in-scene materials such as the hoods of the four target vehicles (left) and the four felt panels (right).](image)

### 3.4.6 GPS Surveyor

During and shortly after the HSI collection, a Trimble Pro 6H [96] receiver mounted on a 1.3m pole was used to capture the three dimensional coordinates of strategic scene locations. The antenna/receiver was attached by wire to a Trimble Recon portable computer running TerraSync V5.70 and all points were later post processed using differential correction. Over one hundred measurements were taken per coordinate resulting in 94% of the coordinates with reported accuracies between 5 and 15cm. The data is reported as latitude, longitude, and height above the WGS-84 ellipsoid and converted into East-North-Up (ENU) coordinates based on an established scene center. The position data is used for measuring vehicle position (see Sect. 3.5.1) and GRIT orientation (see Sect. 3.4.4).

### 3.4.7 Time Lapse Photography

A Canon EOS Rebel T2i RGB camera [97] took photographs in six second intervals of an area that encompassed all targets during the collection. The camera uses a CMOS sensor to record 18 megapixel, 5184x3456 pixel images taken at f/10 with a 55mm focal point. The photos are registered and used to extract vehicle positions and provide a documented account of the collection, as discussed in Section 3.5.1.
3.5 Data Processing

3.5.1 Vehicle Position Extraction

The vehicles were continuously repositioned into four orientations by volunteer drivers during the data collect. The drivers oriented the vehicles with respect to guide marks on the parking lot which resulted in a large variance in vehicle orientation due to human error. Therefore the absolute orientation of each vehicle differed from the planned orientation and had to be directly measured. To perform this measurement, it was decided that photogrammetric techniques would optimally maximize the accuracy of the vehicles’ measured position in 3D space while minimizing the time needed for measurement.

To extract the 3D coordinates of the vehicles for each HSI acquisition, tennis balls were sliced into two halves and used as fiducial markers. These markers were placed on the top front and rear of each vehicle after it was re-positioned. Two 2cm x 2cm pieces of black electrical tape were permanently placed on each vehicle for the duration of the collect as guides for the two fiducial markers in order to ensure consistent fiducial marker placement between images. The markers were left on the vehicles for approximately twelve seconds and then removed for the HSI image acquisition, a period of time long enough to ensure at least one RGB time-lapse image was taken of both fiducial markers of each vehicle (see Section 3.4.7). In addition to these fiducials, points on the parking lot were established as control points and measured with the GPS surveyor (see Section 3.4.6). The pixel coordinates of the fiducials and control points were manually selected in the time-lapse imagery providing the 2D image coordinates for all control points (see Figure 3.14). The locations of the control points in both pixel space and ENU coordinate space were used to form a pixel to parking lot plane transfer function using a 2D Direct Linear Transformation (DLT) and linear least squares.

The equations of colinearity form the basis for many photogrammetric techniques and describe the projection from a 3D object coordinate system through a central point or perspective center into a 2D camera coordinate system [98]. The functional relationship between these two coordinate systems can be expressed as a coordinate translation, rotation, and scaling as expressed by

\[
\begin{bmatrix}
    x - x_0 \\
    y - y_0 \\
    z
\end{bmatrix} = \frac{1}{m} \begin{bmatrix}
    r_{11} & r_{12} & r_{13} \\
    r_{21} & r_{22} & r_{23} \\
    r_{31} & r_{32} & r_{33}
\end{bmatrix} \begin{bmatrix}
    X - X_0 \\
    Y - Y_0 \\
    Z - Z_0
\end{bmatrix},
\]

(3.11)

where \((x,y)\) are the pixel coordinates, \((X,Y,Z)\) are the object space coordinates, \(\{r_{i,j}\}\) are the \(i\)th and \(j\)th components of the 3x3 rotation matrix needed to align the two coordinate systems, \((X_0,Y_0,Z_0)\) is the perspective center, \((z,x_0,y_0)\) are interior camera parameters, and \(m\) is a scale factor [98]. The equations of colinearity are derived by rewriting Equation 3.11 in terms of the pixel coordinates \((x,y)\) and eliminating the scaling parameter \(m\) such that

\[
x = x_0 + z \frac{r_{11}(X - X_0) + r_{12}(Y - Y_0) + r_{13}(Z - Z_0)}{ r_{31}(X - X_0) + r_{32}(Y - Y_0) + r_{33}(Z - Z_0)}
\]

(3.12)

\[
y = y_0 + z \frac{r_{21}(X - X_0) + r_{22}(Y - Y_0) + r_{23}(Z - Z_0)}{ r_{31}(X - X_0) + r_{32}(Y - Y_0) + r_{33}(Z - Z_0)}.
\]
In order to solve for the unknown system parameters \( \{r_{i,j}, X_0, Y_0, Z_0, z, x_0, y_0\} \), a 2D plane to 2D plane technique called a 2D-DLT is utilized due to the fact that the 3D space is weakly characterized since the parking lot control points lie on a plane. This assumption allows the variable \( Z \) to be set to zero. These equations can then be rearranged to obtain a linear system with respect to the unknown parameters, leading to

\[
\begin{align*}
x - L_1X - L_2Y - L_3 + L_7xX + L_8xY &= 0 \\
y - L_4X - L_5Y - L_6 + L_7yX + L_8yY &= 0,
\end{align*}
\]

where \( L_i \) are linear coefficients \([98]\).

The process of solving this linear system to characterize the projective transformation from object space to pixels is called a direct linear transformation. In the 3D DLT case, the new linear coefficients \( L_i \) can be used to solve for the original parameters in Equation 3.12. The 2D case, however, creates an underdetermined system and the transformations are used without solving for the underlying parameters. In both cases, however, the solved parameters allow the mathematical transformation between pixel coordinates and real-world coordinates.

The pixel to plane transfer function was used to project each fiducial marker onto the parking lot plane (plane \( 1 \)). To obtain the actual position of the marker, the height above ground was
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Figure 3.15: Diagram outlining the geometry used to facilitate the retrieval of 3D coordinates using a 2D direct linear transformation. The vehicle height and line of sight vector are used to determine the actual location of the fiducial marker from its projected location on the parking lot plane (plane $1$).

Figure 3.16: The final data product of performing vehicle position extraction are absolute positions of all vehicles in 3D space for each HSI acquisition. Shown are the extracted vehicle coordinates associated with HSI image #13 taken at 2:26pm. The units of the above plot are meters and the displayed vehicle positions correspond to the image in Figure 3.14.

measured for each fiducial point for each vehicle. This height was then used to form a new plane (plane $2$) unique to each marker, parallel to the parking lot. The position of the marker was then solved by finding the intersection of plane $2$ and the vector from the RGB camera to the projected fiducial coordinate (see Figure 3.15). The resulting data products are the ENU coordinates of each fiducial marker for all vehicles as seen in each HSI image (see Figure 3.16).

An example of how these coordinates can be utilized is shown in Figure 3.17 where facet models of the three vehicle types are rendered according to the real world coordinates of the vehicles and camera. Correctly positioned facet models can aid the comparison of the HSI cubes and synthetic imagery in order to evaluate forward models and simulation tools.

3.5.2 Atmospheric Characterization

During the data collect, two instruments recorded the downwelled irradiance: the shadow band radiometer (see Section 3.4.3) and the GRIT Basestation (see Section 3.4.4). The data from both sensors is shown in Figure 3.18.

Both instruments provide a piece of information that the other does not, and both are therefore utilized in characterizing the illumination during the HSI acquisitions. The SBR
collects data in five band passes with full width half max (FWHM) values on the order of 10nm and records the measurements in 1 minute intervals. The SBR data are used to extract the optical depth coefficients that determine atmospheric scattering and absorption as a function of wavelength by measuring both downwelled and solar irradiance. In order to accomplish this with the highest accuracy, the SBR was placed on the top of the roof so that it would have an unobstructed view of the sky. This placement allots the sensor a full hemispherical view of the sky and avoids downwelling shape factor effects and adjacency effects caused by the red brick buildings. These effects will be present, however, in the imagery as all the targets are on the ground (see Figure 3.1). Essentially there are two illumination profiles for any given moment: an unobstructed view of the sky from the top of the roof and an obstructed partial view of the sky from the collection area of interest. Unlike the SBR, the GRIT Basestation (see Section 3.4.4) was placed on the ground near the area of interest and therefore captured an irradiance profile that better represents the incident illumination of the imaged scene. This instrument also records data at a higher temporal resolution, a higher spectral resolution, and a wider total bandwidth than the SBR, reporting irradiance data at 1nm increments from 400 to 2500 nm at 1.5 second intervals. This instrument only measures total irradiance, however, and was only operating between 10:30AM and 12:30PM (six of the twenty three HSI acquisitions).

The two illumination profiles (roof and ground) are evident in the constant differences between the SBR and GRIT Basestation as seen in figure 3.18. Assuming both instruments are adequately calibrated, the residual gain and bias must be explained by a difference in diffuse lighting. Note that the magnitude of the difference between the GRIT and SBR data is wavelength dependant and is more prevalent in the shorter wavelengths bands, commensurate with a standard downwelled irradiance spectrum. This leads to the hypothesis that the difference in diffuse light can be explained by a simple shape factor $F$ that accounts for the blocking of diffuse “sky-light” by the buildings.

In order to quantify this difference it is assumed that the solar illumination measured by the GRIT Basestation and SBR are equal. This is a good assumption given that throughout the duration of the collection the GRIT Basestation maintained a clear line-of-sight to the...
sun and was never shadowed by the surrounding buildings or trees. Therefore, given that the total irradiance is a sum of the diffuse and solar irradiance \( E_{\text{total}} = E_{\text{diffuse}} + E_{\text{solar}} \), the diffuse irradiance is given as \( E_{\text{diffuse}} = E_{\text{total}} - E_{\text{solar}} \). The diffuse irradiance of the GRIT Basestation, spectrally integrated using the response function of the SBR, is therefore given as \( E_{\text{GRIT,diffuse}} = E_{\text{GRIT,total}} - E_{\text{SBR,solar}} \). A diffuse transfer coefficient \( F(\lambda) \) is defined as the ratio of the GRIT diffuse irradiance over the SBR diffuse irradiance as

\[
F(\lambda) = \frac{E_{\text{GRIT,diffuse}}(\lambda)}{E_{\text{SBR,diffuse}}(\lambda)}.
\] (3.14)

The coefficient captures both the shape factor decrease in the hemispherical sky light and the additional illumination added to the scene from the surrounding buildings and other tall objects. This model is simplistic, however, and fails to capture solar illumination dependant changes of the in-scene diffuse illumination. The results of these transfer coefficient calculations are shown in Figure 3.19 and show that there is a non-linear dependence on wavelength to the transfer coefficients. This means the surrounding buildings are not just removing a portion of the skylight but are also contributing significantly to the ambient radiance in the scene. This is likely due to the red brick that constitutes the building walls. From 0.4um to 1.2um red brick
Figure 3.19: For each of the 6 SBR bands the solar term is subtracted from the GRIT Basestation values to produce 6 GRIT diffuse terms. Each of these terms are divided by the SBR terms in order to determine the downwelled shape factor.

has a near linear climb in reflectance from 0 to 0.6 [99]. This combined with the prevalence of healthy vegetation in the scene can explain why the shape factor is functionally dependant on wavelength.

As stated, the SBR data was used to characterize the Rayleigh scattering, aerosol loading, and water column vapor of the atmosphere during the day of the collection. This data, taken at 6 short band passes was then used to derive full spectral profiles of solar and diffuse irradiance from 0.4 to 2.5 µm. This atmospheric characterization procedure, explained by Richtsmeier through email correspondence, is a multi-step process that starts with the calculation of the top of atmosphere irradiance and ends with a unique MODTRAN spectrum for each HSI image acquisition [100].

First, Langley plots were made to extract the per band optical depth \( \tau \) and top of atmosphere solar irradiance \( E_0 \) using linear regression of the Beer-Lamber-Bouger equation for the first five bands,

\[
E = E_0 e^{-\delta / \cos(\theta)},
\]

(3.15)

where \( E \) is the observed irradiance, \( E_0 \) is the top of atmosphere solar irradiance, \( \delta \) is the optical depth, and \( \theta \) is the solar zenith angle. Taking the natural log of both sides linearizes the equation with respect to \( \delta \) and \( \ln(E_0) \) yielding

\[
\ln(E) = \ln(E_0) - \frac{1}{\cos(\theta)} \delta.
\]

(3.16)

As seen in Figure 3.20, the data start clean and linear in the morning as the sun is rising but experience a significant amount of variation as clouds pass between the SBR and the sun. This variation results in the assumption of a cloudless sky in Equation 3.15. The variation is mitigated however using a more robust form of curve fitting, such as an iteratively re-weighted least squares approach [101].

Next, a MODTRAN run with the measured temperature and pressure (from the time of the collection) provides the Rayleigh optical depth \( \delta_r \) for each band. Assuming the total optical depth is composed of an aerosol and Rayleigh component for the 412.9 nm and 868.2 nm bands,
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Figure 3.20: For SBR bands 1-5, the top of atmosphere irradiance and total optical depth is calculated by fitting a line to the linearized form of the Beer-Lamber-Bouger equation. A normal least squares solution is vulnerable to disruptions due to clouds. The iteratively re-weighted least squares solution uses bi-square weights.

\[ \delta = \delta_r + \delta_a \] (see Table 3.3), subtracting the Rayleigh from the total optical depth yields the aerosol optical depth \( \delta_a = \delta - \delta_r \) for bands 1 and 5. These two data points are then used to find the Angstrom coefficient \( \alpha \) of the Angstrom formula

\[
\frac{\delta_A(\lambda)}{\delta_A(\lambda_0)} = \left( \frac{\lambda}{\lambda_0} \right)^{-\alpha},
\]

where a value of \( \lambda_0 \) is selected to be 550nm to allow the coefficients to be used in MODTRAN as input. To solve for the Angstrom coefficient, the Angstrom formula is linearized yielding

\[
\ln (\delta_A(\lambda)) = \ln (\delta_A(\lambda_0)) + \alpha \ln \left( \frac{\lambda_0}{\lambda} \right).
\]

The coefficient is then found using linear regression, or if there are only two data points, fitting a line as shown in figure 3.21a. After the coefficient is solved for, the aerosol loading for the remaining bands are calculated. From the aerosol and Rayleigh scattering optical depths, all other assumed optical depth contributors can be solved, as shown in table 3.3.

Finally, the column water vapor is solved for \([102]\) based on the irradiance recorded in band 6. This band is strategically placed on a strong water absorption feature. First, the top-of-atmosphere solar irradiance is determined assuming a square-root curve-of-growth extinction due to the water column vapor \([103]\). The absorption model is

\[
\ln(E) = \ln(E_0) - \sec(\theta)(\delta_A + \delta_R) - k \sec(\theta)^{0.5},
\]

where \( k \) and \( E_0 \) are solved for using the same linear regression techniques used in the Langley plots. From this regression the total absorption for band 6 is known for any given time. These
last data complete the parametric representation of the atmospheric absorption/scattering for any given point in time over the six SBR bands. The results of deriving these parameters for 12:53pm are shown in Table 3.3. As explained by Richtsmeier, the MODTRAN tape5 input file incorporates the derived Angstrom coefficient ($\alpha$, Equation 3.18), the calculated solar zenith angle, and the time dependant measurements of temperature, pressure, and relative humidity [100]. The last step of the process involves the manual manipulation of the water column vapor until the MODTRAN reported optical depth of band six matches the calculated optical depth [100].

Figure 3.21: The line fit to the two aerosol optical depth data points (red) is used to determine the aerosol optical depth at all other wavelengths (yellow) according the Angstrom formula. Shown are the (a) linearized and (b) normal representations of the Angstrom formula (see Equations 3.17 and 3.18).

Figure 3.22: A spectral atmospheric transmission profile prediction based on the described atmospheric characterization process is shown in blue with the measured irradiance values recorded by the SBR in red. The curve is based on data collected in conjunction with image number eight at 12:53pm.
Once the atmosphere has been parametrically characterized as a function of time, MODTRAN is used to generate a continuous spectrum of atmospheric irradiance and transmission for both solar and diffuse sources. This is accomplished by using the Angstrom coefficients as input along with the temperature, pressure, and solar zenith angle of a specific time during the collect. Using these known inputs, a range of column water vapor parameters are used in order to best match the total optical depth of Band 6 with the calculated optical depth for the specified time. The final results of the solar MODTRAN output for 9:55am are compared to the observed solar SBR data in Figure 3.22.

Table 3.3: Atmospheric loading summary (image #8, 12:53pm)

<table>
<thead>
<tr>
<th>Band</th>
<th>Center [nm]</th>
<th>FWHM [nm]</th>
<th>Absorption Contributors</th>
<th>$E_{TOA}$ [W/m$^2$/nm]</th>
<th>$\delta_{total}$</th>
<th>$\delta_R$</th>
<th>$\delta_A$</th>
<th>$\delta_{O_3}$</th>
<th>$\delta_{H_2O}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>412.9</td>
<td>10.1</td>
<td>$\delta_A, \delta_R$</td>
<td>1.607</td>
<td>0.351</td>
<td>0.311</td>
<td>0.040</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>494.9</td>
<td>9.3</td>
<td>$\delta_A, \delta_R, \delta_{O_3}$</td>
<td>1.864</td>
<td>0.185</td>
<td>0.147</td>
<td>0.031</td>
<td>0.007</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>613.3</td>
<td>10.4</td>
<td>$\delta_A, \delta_R, \delta_{O_3}$</td>
<td>1.598</td>
<td>0.118</td>
<td>0.061</td>
<td>0.024</td>
<td>0.034</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>671.4</td>
<td>10.0</td>
<td>$\delta_A, \delta_R, \delta_{O_3}$</td>
<td>1.437</td>
<td>0.074</td>
<td>0.042</td>
<td>0.021</td>
<td>0.011</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>868.2</td>
<td>11.3</td>
<td>$\delta_A, \delta_R$</td>
<td>0.893</td>
<td>0.030</td>
<td>0.015</td>
<td>0.015</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>937.4</td>
<td>10.7</td>
<td>$\delta_A, \delta_R, \delta_{H_2O}$</td>
<td>0.912</td>
<td>1.162</td>
<td>0.011</td>
<td>0.013</td>
<td>0</td>
<td>1.137</td>
</tr>
</tbody>
</table>

This atmospheric characterization process results in idealized cloudless representations of the atmosphere at the specified time. Therefore, there will be disagreement in the produced MODTRAN spectrum and the measured SBR data; this is especially true when cloud cover increases. The physically ideal MODTRAN spectra must be compensated, therefore, to more exactly match the measured SBR data.

A novel correction process is used to compensate the ideal MODTRAN spectra. First, the direct solar and downwelled MODTRAN spectra are spectrally integrated according to the SBR spectral response curves. Next, the six band direct solar and downwelled spectra are used as basis vectors for the real SBR data. Linear least squares regression is used to determine the basis vector loadings which best fit the 6 band basis vectors to the measured data. These basis vector loadings are finally applied to the original direct and downwelled MODTRAN spectra.

This ideal MODTRAN spectrum compensation routine fits the measured data well and corrects lingering errors from the atmospheric characterization process described above. The process can be explained physically by considering that the water droplets that constitute cloud cover are of a size which permits the treatment of geometric optics to describe the scattering functions. These droplets therefore refract both direct solar and downwelled illumination regardless of their hemispherical location. The results of this process for both illumination extremes of cloud cover are shown in Figure 3.23. Image 8 was taken during minimal direct solar illumination transmission loss conditions due to cloud cover, resulting in a perfect MODTRAN fit with very little ideal spectrum compensation required (see top of Figure 3.23). Image 20, however, was acquired during heavy solar illumination transmission loss conditions due to heavy cloud obscuration in the solar illumination path. Even in this extreme example, the ideal MODTRAN
atmosphere is properly compensated, resulting in good fits between the measured SBR and the compensated spectra (see bottom of Figure 3.23).

With the atmospheric illumination characterized for the entire spectrum (0.4\(\mu m\) to 2.5\(\mu m\)), the difference in diffuse irradiance between the top of the building and the ground can be re-visited. Rather than comparing only six discrete bands however, now the entire spectrum can be examined. As previously stated, if the solar irradiance of the SBR and GRIT Basestation are assumed to be equal, the GRIT Basestation diffuse irradiance can be calculated as \(E_{GRIT,\text{diffuse}}(\lambda) = E_{GRIT,\text{total}}(\lambda) - E_{SBR,\text{solar}}(\lambda)\). The same principal is now applied for all \(\lambda\). This assumes an accurate representation by MODTRAN of the direct solar irradiance. The resulting difference in the diffuse spectra are therefore assumed to be attributed to the differences in-scene illumination, as previously discussed. A subset of the available diffuse spectra are shown in Figure 3.24, and it is evident there are temporally persistent structural differences.

As shown before with the six discrete bands, a diffuse transfer function can be calculated using Equation 3.14. And when multiplied with the MODTRAN diffuse spectrum, yields an estimate of the in-scene diffuse spectrum. This diffuse transfer equation is calculated for a small subset of the total possible measurements; measurements that correspond to the time stamps of
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Figure 3.24: The (a) diffuse irradiance and (b) diffuse irradiance normalized by the total irradiance for three times selected from the overlapping SBR and GRIT data set. Plots are based on the assumption that the GRIT solar irradiance is equal to MODTRAN generated solar irradiance.

The mean and variance of the resulting transfer functions are shown in Figure 3.25. The variance exhibited by the transfer functions is heavily dependant on the diffuse SNR, therefore reasonable estimates are only available in the VIS and NIR wavelengths. In order to filter this transfer function and make it stable and usable, a variance filter is applied that only keeps values that have low variance and pulls values with high variance closer to one. The filter function used is

\[
g(\lambda) = \frac{2}{1 + \exp\left(-\frac{\sigma^2}{K}\right)} - 1 \quad (3.20)
\]

\[
f(\lambda) = (1 - g)(\lambda) + g, \quad (3.21)
\]

such that \(g(\lambda)\) is closer to zero when the variance is small, resulting in the original transfer function and \(g(\lambda)\) is closer to one when the variance is large in order to lesson the effects of the transfer function. Because the transfer function is applied using element-wise multiplication, one is the “do nothing” or default value. \(K\) in Equation 3.20 is a constant that alters the strength of
Figure 3.25: Shown is the standard deviation of the raw diffuse transfer function about the mean (blue), standard deviation with no bias (red), the filtered diffuse transfer function (black), and the original SBR diffuse transfer coefficients for the 6 bands (green).

the filtering process. A $K$ value of one was used in this research. The filtered transfer function is also plotted in Figure 3.25. The diffuse irradiance and diffuse irradiance ratios are corrected using the filtered transfer function and shown in Figure 3.26.

Again, it is important to point out that any errors in the SBR or Grit Basestation radiometric calibration and any errors in the MODTRAN spectra will propagate into the diffuse transfer function and appear as changes in the diffuse illumination. It is clear, however, that there is temporally persistent, spectrally dependant structure in just the 6 transfer coefficients seen in Figure 3.19 that aligns with the full spectrum transfer function, so there is likely signal amongst the possible noise.
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3.6 Summary

The vehicle BRDF sampling hyperspectral data collect conducted at RIT involved the continuous rotation and imaging of four vehicles over a diverse set of sun-target-sensor geometries. During the collection three experiments were conducted: (1) create a vehicle reacquisition test data set for the testing of hyperspectral reacquisition and tracking algorithms, (2) determine the contributions of vehicle shape, color, and orientation to the effective vehicle BRDF, and (3) quantify the magnitude of the background adjacency effects on a white vehicle. During the collection a goniometer measured in-scene BRDF measurements, an SBR collected 6 strategic bands of solar and downwelled irradiance, a nadir starring hyperspectral radiometer collected total irradiance, an RGB camera collected time-lapse imagery, a GPS surveyor collected the exact position of in-scene fiducial, and a portable spectroradiometer collected in-scene material DHR. After the data collection, the time-lapse imagery and GPS data were used to retrieve the exact positions of all vehicles for each HSI image. The SBR data was used in conjunction
with MODTRAN to characterize the atmosphere for the entire VNIR-SWIR spectrum. This characterization enabled the calculation of a diffuse transfer function and an in-scene diffuse ratio function to determine the ratio of solar to downwelled irradiance in-scene.

The data from this collection will aid in understanding the phenomenological dependencies of sun position, vehicle orientation, vehicle material, and vehicle shape on the observed imagery of vehicles in the hyperspectral domain. Additionally, the vehicle BRDF sampling of four different vehicles across a wide range of these parameters will provide a useful data set for testing vehicle reacquisition and tracking algorithms. The high spatial and spectral resolutions of this data set will facilitate the testing of algorithms across a wide range of imaging domains from close proximity, vehicle to vehicle systems to aerial sub pixel vehicle tracking systems. Lastly, this data and the effects studied will aid in the validation of synthetically generated imagery and lead to better models and better vehicle target detection algorithms.
Chapter 4

Calibration

4.1 Introduction

The role of calibrating a remote sensing instrument is to convert the digital count (DC) or digital number signal into a scientifically meaningful quantity such as radiance. This quantity, defined as the radiometric flux per unit projected area per unit solid angle, accounts for both the spatial and angular power intensity of light entering and leaving a surface relative to the surface geometry. Radiance exhibits the property of path length invariance in that it remains constant as it propagates through a lossless media and is therefore ideal to characterize the spectral power leaving a target and entering the camera aperture [31]. The steps taken to convert the raw digital count VNIR and SWIR images into single radiance images are given in the below list. Each step is described in detail in the following chapter.

1. Dark Frame Subtraction
2. Bad Pixel Removal
3. Division by Integration Time
4. VNIR SWIR Registration
5. VNIR Gain Correction
6. Calibration Target Spectra Extraction
7. Calibration Target Reflectance Factor Regression
8. Compute and Apply Linear Response Functions (Digital Counts to Radiance)
9. VNIR and SWIR Fusion

4.2 Preliminary Processing

4.2.1 Dark Frame Subtraction

The first step of processing the raw digital count images into calibrated radiance images is to subtract the dark frames from the raw digital count frames. This is done to remove fixed pattern
noise caused by electronic sources such as dark current or dark noise. Two example dark frames are shown in Figure 4.1.

Figure 4.1: Dark frames of the (a) VNIR and (b) SWIR camera focal planes in units of raw digital counts. The x-axis of the focal plane as shown maps to wavelength and the y-axis maps to line number or vertical spatial distance.

4.2.2 Bad Pixel Removal

The next step is the removal of bad or dead pixels. This is accomplished by applying a 3x3 spatial median filter for each wavelength for both the VNIR and SWIR images. A 3x3 median filter sets the value of each pixel to the median of the surrounding 3x3 neighborhood pixels.

4.2.3 Integration Time Normalization

The goal of this data collect was to capture the BRDF effects of vehicles. These effects can vary greatly and depending on the sun-vehicle-sensor geometry, bright glints can be present in the scene during image acquisition. In order to capture the full range of glints, great care was undertaken to prevent pixel saturation. A saturated pixel would truncate the captured range of the BRDF and would result in a partial characterization of the vehicles’ BRDFs. Setting the dynamic range of the camera too high, however, washes out the detail of the rest of the image. A careful balance was undertaken by the camera operators of adjusting the integration times of the cameras based on scene illumination and the previous image. A plot of the integration time as a function of the time of day is shown in Figure 4.2. Smaller integration times are correlated with less scene illumination and larger integration times are correlated with more scene illumination. This can be seen by comparing Figure 4.2 to Figure 3.10.

The effect of changing the integration time, however, changes the ratio of digital counts per unit radiance. To obtain a measure globally proportional to radiance across all images, the digital count images are divided by the integration time. The benefit of this division is seen in the following camera model equation

\[
S(\lambda) = \frac{\Delta t A_{det} R(\lambda)}{G} L(\lambda),
\]

(4.1)
which defines how a simple camera model converts an aperture radiance \( L \) to digital counts \( S \) where \( A_{det} \) is the area of a detector, \( R \) is the detector responsivity, \( G \) is the camera G-number, and \( \Delta t \) is the integration time. As seen in this equation, the division of both sides by \( \Delta t \) yields a raw measure proportional to radiance assuming the optics, responsivity, and detector area remain constant throughout the data collection. The results are images in units of digital counts per millisecond,

\[
\frac{S(\lambda)}{\Delta t} = \frac{A_{det} R(\lambda)}{G} L(\lambda). \tag{4.2}
\]

During the calibration procedure the linear relationship between \( S(\lambda)/\Delta t \) and \( L(\lambda) \) is learned through regression without solving for the underlying parameters \( A_{det}, R(\lambda) \), or \( G \).

### 4.2.4 Registration

The next processing step is the registration of the SWIR and VNIR images. Although many algorithms exist to perform automated registration, due to the registration of two different modalities, the parallax created from two different look angles, and the human knowledge of where the important in-scene objects of interest are, manual registration was performed. An average of 65 control points were selected for each of the 23 pairs of images. For each image pair, a 2x6 affine transform matrix was computed for transforming the SWIR image coordinates to the VNIR image coordinates according to

\[
\begin{bmatrix}
  x_{vnir} \\
  y_{vnir}
\end{bmatrix} =
\begin{bmatrix}
  \alpha_{11} & \alpha_{12} & \alpha_{13} \\
  \alpha_{21} & \alpha_{22} & \alpha_{23}
\end{bmatrix}
\begin{bmatrix}
  x_{swir} \\
  y_{swir} \\
  1
\end{bmatrix}. \tag{4.3}
\]

The matrix was calculated using linear least squares regression. The result of applying this transformation is to rotate, shear, scale, and translate the input image (in no particular order). The resulting mean registration error was 3.63 VNIR pixels. The larger IFOV SWIR pixels were stretched and interpolated using bicubic interpolation to match the higher resolution VNIR images when constructing the data cubes.
4.3 VNIR Gain Correction

This section addresses a calibration issue discovered in the VNIR images. It was observed that there was a brightening towards the top of the VNIR images that was not present in the SWIR images and could not be explained by any natural phenomena (see Figure 4.3) [104]. Based on a discussion between Spectral Sciences Inc, Headwall Photonics Inc, and the owner/operator of the camera at the University of Massachusetts, it is believed that the gain issue was caused by using new optics on the VNIR camera without undergoing the necessary calibration [104]. This section details the steps taken to correct for this identified VNIR brightening effect. This correction procedure follows the outlines of a process described by Adler-Golder [104].

![Figure 4.3: The uncorrected VNIR image (left) and the VNIR image with the gain correction applied (right) taken at 10:23am.](image)

The VNIR and SWIR camera share a small overlapping bandpass between 900nm and 1000nm at which both cameras should be recording the same data. Although the in-scene illumination at this bandpass is strong and results in usable images compared to the low SNR images of strong atmospheric absorption regions, the spectral range is at the limits of both camera’s operational capacity. The foundational assumption made to correct for the VNIR brightening effect is that the SWIR camera is properly calibrated spatially. This was confirmed visually. The overlap region can therefore be used to quantify the amount of gain in the VNIR signal. The second assumption made is that gain is constant spectrally for all wavelengths of the VNIR image. This assumption was also confirmed visually by panning through each image of the VNIR cube and observing a constant brightening effect.

The first step is to baseline the images using dark pixel subtraction in order remove any lingering dark current or stray light effects. This is done by assuming that 0.05% of the pixels are dark pixels. Given the amount of heavy shadowing in the scene that occurs underneath the vehicles, the retrieval of legitimate dark pixel samples is achieved for each shot. The dark pixels are averaged and subtracted from the images. The dark pixels do not exhibit any of the "brightening" or "gain" effects as seen in Figure 4.4, so removing them from the images is similar to removing the bias from a linear system, such that only the gain remains. In these images,
the dark pixels were averaged horizontally (samples) and plotted as function of their vertical position (line number) and wavelength to demonstrate the signal independence to line number.

![Figure 4.4](image1.png) **Figure 4.4:** The dark pixels as a function of wavelength and line number for the VNIR image (left) and SWIR image (right) taken at 10:23am.

The SWIR bands have larger FWHM values and are spaced further apart spectrally than the VNIR bands. This results in 60 VNIR bands in the overlap region but only 11 SWIR bands. The SWIR bands are over sampled using cubic spline interpolation to match the 60 VNIR bands. The gain ratio is next calculated by rationing each of the 60 VNIR bands over each of the 60 interpolated SWIR bands. Due to misalignment in the registration and parallax between the two images, the raw ratio data is very noisy. Every VNIR pixel that did not exactly align with the same scene content as its corresponding SWIR pixel will report an erroneous gain ratio. The smoothly transitioning scene content, however, such as the grass, parking lot, and correctly registered vehicles, can absorb a few pixel registration errors and will report valid gain ratio values. To eliminate bad gain ratio values, first a 5x5 median filter is applied to remove the small error sources. Next, outlier pixels are identified by assuming a Gaussian distribution and setting a sigma threshold of 10. The median of the data is used as the distribution center and $(1.4826) \times \text{median absolute deviation}$ is used as a robust estimation of sigma. Any pixels with standard deviations larger than the threshold are put into a 2D bad pixel bitmap. Finally, to create a more comprehensive bad pixel mask, the bad pixels identified by the sigma threshold are used as seeds for two morphological operations. As expressed in the equation

$$Mask = ((Seeds) \oplus SE) \cdot SE,$$

first an image dilation is performed, followed by an image closing, with both operators using a disk structuring element. The resulting mask and filtered gain ratio are shown in Figure 4.5 where the gain ratio displayed has been spectrally averaged across the 60 bands.

To test the hypothesis that the gain ratio is constant across all wavelengths, the gain ratios of the 60 common bands are averaged spatially across the samples (horizontally) and shown in Figure 4.6. These images show the structure of the gain ratio and its constancy across the wavelengths of the common bandwidth. The curve of the structure supports the idea that the cause of the brightening effect is due to the optics in that the pattern is symmetric across the focal plane and suggestive of some sort of unaccounted for cosine falloff.
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Figure 4.5: The bad pixel map dictating noisy gain ratios (left) and the resulting average gain ratio image with the bad pixel map applied (right) for the images taken at 10:23am.

Figure 4.6: The gain ratios are averaged spatially across the horizontal samples and plotted as a function of wavelength and line number (based on the VNIR and SWIR images taken at 10:23am).

The gain ratios of each of the VNIR-SWIR image pairs are averaged both spatially across the sample and spectrally to produce a single gain ratio curve as a function of line number per image pair. The application of any one curve to its corresponding VNIR image to correct the gain brightening effect results in visible striations across the image. Each individual correction curve is noisy while the underlying gain signal is a smoothly varying function of line number. The effect is also persistent across all image pairs, allowing the gain curve from each to be used in the regression of a global gain function. Using iteratively re-weighted least squares regression, a smooth gain ratio curve is calculated that uses the basis functions $f(x) = x^i$ for $i = 0..5$. The individual local gain ratio curves are shown in Figure 4.7 along with the global gain ratio line of best fit. The final result of applying the inverse of the global gain ratio curve is shown in Figure 4.3.
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4.4 Target Spectra Extraction

The spectra of the in-scene calibration targets are extracted from the digital count images using a region of interest (ROI) tool. This tool allows a user to select a polygon border around an ROI and returns the enclosed pixels. The distribution of spectra of each calibration target for each image acquisition are extracted using this tool. The RGB rendering of the hyperspectral ROIs are shown in Figure 4.8 where the highlighted portion represents the selected ROI. During the selection process only the middle of the calibration targets were used in order to avoid spatial contamination from the surrounding materials (grass/blacktop) that result from atmospheric scattering and optical point spread functions. These spectra distributions will be used in the radiometric calibration processes described in the following sections.
4.5 Spectral Calibration Verification

There was concern that the propagation of light inside the VNIR spectrometer that lead to the VNIR gain issue may have changed both the magnitude and spatial distribution of light on the focal plane since the camera was last calibrated. For this reason, it was necessary to check the spectral calibration to assure that the detectors where absorbing the correct wavelength of photons in accordance with the wavelengths reported by the camera. To quickly check this issue, the raw digital counts of the white panel ROI were chosen based on the high and constant reflectivity of the measured white panel in-scene reflectance. This mean of the white panel digital counts for a single frame were compared to the total irradiance measure by the Grit Basestation to assure that all the spectral features due to atmospheric absorption lined up (see Figure 4.9).

The first derivative is a useful operator when looking to compare the higher frequency (higher order) spectral features between two signals whose magnitudes differ as function of wavelength by low frequencies (lower order). This is because the first derivative is functionally equivalent to a high-pass filter in the frequency domain. Using Fourier analysis, this is proved in that the Fourier transform of the derivative operator $F(d/dx)$ is the high pass filter $2\pi i \xi$. The normalized derivative therefore removes the lower frequency structure that disagreed because both signals are not radiometrically calibrated, but retains the higher frequency structures that can be used to compare atmospheric absorption features. The first derivative is used in Figure 4.10 to again compare the raw digital counts to the measured total irradiance. It was subjectively determined during this analysis that the all spectral absorption features matched and that further spectral calibration was not necessary.
Figure 4.9: The raw digital count values of the white panel (taken at 11:35am) are normalized and plotted against the predicted radiance values. With no processing the spectral features clearly match up even though the normalized magnitudes do not.

Figure 4.10: The normalized first derivatives of the white panel digital count image taken at 11:35am by the VNIR camera (top) and the SWIR camera (bottom). The first derivative operates acts as a high pass filter in the frequency domain, removing the lower order spectral structure.
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4.6 Reflectance Factor Regression

To perform in-scene radiometric calibration, the measured reflectance spectra of the calibration panels are combined with the measured total irradiance to produce a predicted at sensor radiance. The radiance model assumed for the images is

\[ L_{\text{sensor}}(\lambda, t) = L_{\text{target}}(\lambda, t) + L_u(\lambda, t), \]  

(4.5)

where \( \lambda \) is wavelength, \( t \) is time, and \( L_u \) is the upwelled path radiance. The radiance digital count model is

\[ DC(\lambda, t) = m_0(\lambda)L(\lambda, t) + \tilde{b}_0(\lambda) + DN(\lambda, t) + SL(\lambda, t), \]  

(4.6)

where \( DC \) is digital counts or digital numbers, \( DN(\lambda) \) is any residual dark current left after dark frame subtraction, \( SL(\lambda) \) is the stray light, and \( m_0 \) and \( \tilde{b}_0 \) are the gain and offset. To mitigate the contributions due to these three terms, dark pixel subtraction is first performed in digital counts. This subtraction aims to achieve constant calibration coefficients across all 23 images that remain valid despite changes in-scene illumination, scattered light, and path radiance. The digital count dark pixel model based on Equation 4.6 is

\[ DC_{\text{dark}}(\lambda, t) = m_0(\lambda)L_u(\lambda, t) + \tilde{b}_0(\lambda) + DN(\lambda, t) + SL(\lambda, t), \]  

(4.7)

and the model for the dark pixel subtracted images is therefore

\[ DC(\lambda, t) - DC_{\text{dark}}(\lambda, t) = m_0(\lambda)L_{\text{target}}(\lambda, t). \]  

(4.8)

The cameras are therefore calibrated to target leaving radiance and not sensor reaching radiance. The line of sight distance from the camera to all in-scene targets is short and constant between all frames, so this distinction is inconsequential but worth noting. Finally, Least Squares regression is used to determine the gain and offset that convert digital counts to target leaving radiance. Although the model shown in Equation 4.8 only uses a gain with no offset, in reality, the dark pixels are not perfectly dark, so there is still a small residual offset that must be accounted for in the linear regression. Thus, the final model used is

\[ DC_{\text{target}}(\lambda, t) = m_0(\lambda)L_{\text{target}}(\lambda, t) + b_0(\lambda), \]  

(4.9)

which can be inverted to

\[ L_{\text{target}}(\lambda, t) = m_1(\lambda)DC_{\text{target}}(\lambda, t) + b_1(\lambda). \]  

(4.10)

The initial model used to represent the target leaving radiance assumed Lambertian targets and a projected area adjustment to the total irradiance based on the sun-target geometry. This initial Lambertian target model is

\[ L_{\text{tgt}}(\lambda, t) = \left( \frac{\cos(\phi_{\text{tgt}}(t))\,E_{\text{tot}\perp}(\lambda, t)}{\cos(\phi_{\text{sun}}(t))} \right) \left( \frac{\rho_{\text{DHR,tgt}}(\lambda)}{\pi} \right), \]  

(4.11)

where \( E_{\text{tot}\perp} \) is the ground normal total irradiance recorded by the GRIT Basestation, \( \rho_{\text{DHR}} \) is the diffuse hemispherical reflectance recorded by the portable spectroradiometer, \( \phi_{\text{sun}} \) is the...
zenith angle of the sun, and $\phi_{tgt}$ is the angle between the target normal vector and the sun. This initial model proved to be unstable across all 23 images in that it only produced linear results for each individual frame but not for all the frames combined. Obtaining stable across-frame coefficients was important because the GRIT Basestation data was only available for a subset of 23 frames and this study observes vehicle BRDF as a function of time. For these reasons, frame independent calibration was not desirable. In addition, because the camera settings and optics remained constant throughout the data collect it was deduced that the inter-frame disagreement on the calibration coefficients must be caused by phenomenology not captured by the model.

The next model used the SBR data and the SBR diffuse transfer function described in Section 3.5.2 to separate the GRIT Basestation signal into a diffuse and solar component. A shape factor was also calculated for each of the targets based on the targets’ geometry. This new model is

$$L_{tgt}(\lambda, t) = \left[ \cos(\phi_{tgt}(t))E_{sun}(\lambda, t) + (SF_{tgt})(E_{dif}(\lambda, t)) \right] \frac{\rho_{DHR,tgt}(\lambda)}{\pi},$$

where $SF_{tgt}$ is the diffuse shape factor, $E_{sun}$ is the direct solar irradiance, and $E_{dif}$ is the ground normal irradiance contribution form the downwelled skylight. The new model still failed to produce inter-frame, consistent coefficients, meaning the model was still not able to fully characterize the observed radiance. Upon further reflection, it was decided that the Lamber-tian target assumption is a poor BRDF estimate for a collection scenario in which the sun transitions across 27 degrees of zenith and 98 degrees of azimuth and some of the targets are illuminated by direct solar radiation at small angles of incidence. This is problematic, however, since simultaneously solving for radiance and reflectance is difficult.

Figure 4.11: The vertical calibration panels are fully illuminated by the sun at 11:39am (left) but by 2:43pm the panels are self-shadowed and only illuminated by the diffuse downwelled and grass reflected illumination (right).

The simultaneous calibration and reflectance calculation is tractable for this scenario for two specific reasons. The first reason is that the SBR provides information on how to split up the total irradiance recorded by the GRIT Basestation into diffuse and solar illumination. The second reason is that there are three calibration panels (black, grey, and white) in the scene that were placed vertically in such a way that the fronts become completely self shadowed after a certain point in the data collection (see Figure 4.11). These ELM targets only illuminated with diffuse light and the knowledge of the exact quantity of diffuse light provides an initial estimation of the sensor calibration curves from which all other quantities can be calculated.
The non-Lambertian model used is

\[ L_{tgt}(\lambda, t) = [(RF_{tgt}(t)) \cos(\phi_{tgt}(t)) E_{sun}(\lambda, t) + (SF_{tgt})(E_{dif}(\lambda, t))] \frac{\rho_{DHR,tgt}(\lambda)}{\pi}, \quad (4.13) \]

where \( RF_{tgt} \) is the target reflectance factor adjustment for the given sun-target-sensor geometry such that \( r_f = (\rho_{DHR})(RF) \) where \( r_f \) is the target reflectance factor [31]. For simplicity, the reflectance factor adjustments are forced to be constant as a function of wavelength, but for more complex regressions, these factors can be a linear combination of any number of basis functions. When the digital counts are calibrated and converted to target leaving radiance the model becomes

\[ m_1(\lambda)DC(\lambda, t) + b_1(\lambda) = [RF(t) \cos(\phi_{tgt}(t)) E_{sun}(\lambda, t) + (SF)(E_{dif}(\lambda, t))] \frac{\rho_{DHR}(\lambda)}{\pi}, \quad (4.14) \]

where the \( tgt \) subscript has been removed from some variables for space. This model does not account for the irradiance reflected from the grass onto the vertical calibration panels shown in Figure 4.11. To mitigate errors introduced by this background adjacency illumination, the calibration panel ROIs shown in Figure 4.8 are taken from the upper portion of the panels.

The reflectance factor adjustments \( RF_{tgt}(t) \), gain coefficients \( m(\lambda) \), and offset coefficients \( b(\lambda) \) are jointly solved for using constrained linear least squares in which the constraint is that the reflectance factor adjustments must be positive. As mentioned, more complicated models can be used for the reflectance factors in order to make the values functions of wavelength. This would be equivalent to solving for a spectrally varying BRDF function rather than a spectrally constant function. Each degree of freedom, however, adds complexity to the positivity constraint across the spectrum of interest. For example, if the reflectance factor is linear with respect to wavelength, two constraints must be added per target (one for each edge of the function), and if the reflectance factor is quadratic, there are three constraints, one for each end of the function and one for the inflection point. Additionally, the shape factor can also be jointly solved for by using this technique as it would only add one additional free parameter per target type. Care must be taken, however, in that additional free parameters run the risk of lowering the accuracy of the final answers and even creating a rank deficient matrix that cannot be solved.

The size of the matrix used for solving this system of equations is large and a sparse matrix representation is recommended. The final size of the matrix is \((\text{targets})(\text{frames})(2^*\text{wavelengths})\) by \((\text{targets})(\text{frames})+(2^*\text{wavelengths})\). Each target ROI for each frame is composed of 100’s of pixels, and if each pixel were used individually the matrix size would be 100x to 1000x larger. For this reason, the median of the target ROI is used as an estimate of the spectrum digital count value. In contrast, for the final calibration discussed in the next section, each pixel is used to determine the calibration coefficients because a different independent regression is used for every wavelength.

The spectrum generated using MODTRAN and the SBR measurements, as described in Section 3.5.2, was used only to learn the reflectance factor adjustment variables because this data was available for 20 of the 23 frames, whereas the GRIT Basestation data is only available for 6 of the 23 frames. Once the reflectance factor adjustment variables are determined using the SBR/MODTRAN spectra, the GRIT Basestation measurements are used to determine the gain and offset coefficients as described in the next section. Unsurprisingly, the final answers do not vary significantly, showing that this method can be used to fully calibrate the system in one
Figure 4.12: The reflectance factor adjustment results for the felt calibration targets (top), vertical calibration panels (bottom left), and horizontal calibration panels (bottom right). The dashed lines are the results of interpolating the last three frames which have no SBR/MODTRAN data.

The linear form of the equation used in the regression with unknown parameters in bold typeface is

\[
(SF)(E_{dif}(\lambda,t))\frac{\rho(\lambda)}{\pi} = m_1(\lambda)DC(\lambda,t) + b_1(\lambda) - RF(t)\cos(\phi_{tgt}(t))E_{sun}(\lambda,t)\frac{\rho(\lambda)}{\pi}. \tag{4.15}
\]

The solution converges quickly and produces logical results. The reflectance factor adjustments are shown in Figure 4.12 as a function of sun azimuth angle. The larger sun azimuth angles are related to image acquisitions later in the day when the sun is most opposite the camera and closest to the principal scattering plane in which the BRDF effects of the targets would be maximized. This trend is clearly seen in the felt panels that lay flat in the grass away from other objects. They clearly exhibit constant BRDF behavior, except for a sharp rise in their effective reflectance toward the end of the day. This matches the initial hypothesis that the in-scene targets are not perfectly Lambertian. The black vertical calibration target appears to have some anomalous behavior as the sun drives towards smaller incidence angles in preparation
Figure 4.13: Shot 19 taken at 3:30pm shows the heavy diffuse shadowing and near solar shadowing of the horizontal calibration panels.

for its transition from in front of the panel to behind the panel. This anomalous behavior can be explained either by stray light entering the side of the target between the wood and the material, or unaccounted for upwelled/scattered light. Given that the black panel is a very weak reflector and much more susceptible to unaccounted for light added to the total received signal, either hypothesis is valid. In addition, as $\cos(\phi_{tgt})$ becomes smaller and smaller this effect is more pronounced, as seen in the data.

There are also interesting characteristics in the reflectance factors of the horizontal calibration panels towards the end of the data collect. These characteristics can be explained by the close

Figure 4.14: Gain and offset results of the reflectance factor adjustment regression. Shown are the gain coefficients $m_1(\lambda)$ for the VNIR (top left), and SWIR (bottom left) as well as the offset coefficients $b_1(\lambda)$ for the VNIR (top right) and SWIR (bottom right) cameras.
proximity shadowing of the horizontal calibration panels during these image acquisitions. As seen in Figure 4.13, all three panels are very nearly shadowed even though they have been given values of 1 for their shape factor (model was told these panels have a clear view of the sky). The regression, therefore, is trying to correct for this lack of illumination with low reflectance factor values. This is evidence that more free parameters could be entered into the model, such as shape factor, that may provide better results. Fortunately, the felt target reflectance factor adjustment curves are well behaved, so using all targets together should yield adequate calibration estimates. The spectrally independent slope and offset terms \( (m_1(\lambda), b_1(\lambda)) \) that were calculated in the described reflectance factor regression process are shown in Figure 4.14.

### 4.7 Calibration

To perform radiometric in-scene calibration, the SBR diffuse ratio function and diffuse transfer function are incorporated into the GRIT Basestation data in order to estimate the proportion of the total measured in-scene irradiance that emanated from the downwelled/diffuse skylight, as opposed to the direct solar illumination (see Section 3.5.2). Next, using the reflectance factor adjustment terms solved for in Section 4.6, Equation 4.13 is solved for—this is the predicted radiance. Target reflectance spectra and irradiance spectra are carefully sampled using the appropriate spectral response curves of the VNIR and SWIR cameras: 5 nm and 10 nm FWHM, respectively.

This predicted radiance calculation produces a single radiance value per target per frame, yet there are 100's of pixels (digital counts) that constitute a single target for a given frame. Rather than taking the mean or median of the target ROI, all pixels are used in the regression by appropriately weighting them such that each target is weighted equally regardless of the number of pixels that constitute its ROI. This is accomplished using a weighted linear least squares solver where the weight of each data point is defined as \( w_{tgt,i} = 1/n_{tgt,i} \) where \( i \) is the frame index and \( n \) is the total number of pixels in the specified ROI. The radiance, digital count values, and weights are used to solve the per wavelength gain and offset coefficients in accordance with Equation 4.9 rather than 4.10 because the weighted least squares algorithm produces a solution which minimizes errors in the independent variable, or Y-axis. Finding the solution to the model described in Equation 4.9, therefore, better conforms to the real-world model in which errors are assumed to be more prevalent in the digital count values rather than the predicted radiance point estimates.

As previously stated, the GRIT Basestation data was only available from 10:23am to 1:00pm, so the calculation of the gain and offset coefficients was based on six VNIR-SWIR image pairs. Although the GRIT Basestation was on station for a shorter period of time than the SBR, the GRIT data has higher spectral and temporal resolution and was placed in-scene rather than on the roof (see Section 3.5.2). For these reasons, the GRIT Basestation data was selected for the final radiometric calibration.

The calculated spectral gain and offset coefficients for the VNIR and SWIR imagery are shown in Figure 4.15. These plots are very similar to the calibration coefficients calculated during the reflectance factor regression, shown in Figure 4.14. This similarity of calculated coefficients suggest that the reflectance factor regression calibration coefficients could be used to produce a valid estimate of target leaving radiance. Another noteworthy similarity is between
the VNIR calibration gain term in Figure 4.15 and the VNIR/SWIR Gain Ratio plot (see Figure 4.6). The similarity of shapes suggests there is a similar power falloff on the camera focal plane in both the spectral and spatial dimensions.

The linear response of the VNIR and SWIR cameras over the six frames for a subset of the total wavelengths is shown in Figure 4.16. Also plotted are the linear response curves calculated using the weighted least square regression. Similar plots are shown in Figure 4.17 in which the data points are colored by target type.

The sensor noise of both cameras are shown in Figure 4.18. The noise is calculated by taking the standard deviation of the target ROIs in digital counts and scaling by the spectral gain function determined by the calibration process. The noise shown here is not just a function of the camera noise because the images of the targets were not perfectly homogeneous. Texture in the targets resulted in small amounts of self-shadowing, especially for the felt panels and vertical calibration panels at small solar incidence angles. Also shown in Figure 4.18 is the observed SNR of the ROIs. These values are calculated by dividing the predicted radiance values for each target by the sensor noise. While the sensor noise is spectrally varying for any one material with more noise at shorter wavelengths, the SNR exhibits less variation across the spectrum.

The predicted radiance calculated using Equation 4.13 is compared to the calibrated radiance determined by applying the calibration coefficients to the digital count images (see Figure 4.19). In these images the width of the calibrated radiance line is equal to two standard deviations (+/- $\sigma$). Error between the predicted radiance and calibrated radiance in these images is attributed to calibration errors and is proportional to the distance between the linear calibration lines in Figures 4.16 and 4.17 and the point estimates of predicted radiance. In order for these radiance values to match perfectly, the data points in Figures 4.16 and 4.17 would need to be perfectly
linear. The large standard deviation present in the imaged radiance of the black calibration panel, despite the near constant SNR (see Figure 4.18), suggests calibration issues at the lower reflectance values. Two possible explanations of this observed phenomena are either a non-linear VNIR camera response or stray light not accounted for that additively combines with the black panel leaving radiance.

To relate the target leaving radiance model given by Equation 4.13 to the classical diffuse facet model target leaving radiance described in Section 2.5, a modification is made to \( \rho_{DHR} \) and all the incident irradiance terms are combined into \( E_{\text{tot}} \) such that

\[
L(\lambda, t) = \left[ RF(t) \cos(\phi_{\text{tgt}}(t)) E_{\text{sun}}(\lambda, t) + (SF)(E_{\text{dif}}(\lambda, t)) \right] \frac{\rho_{DHR}(\lambda)}{\pi},
\]

(4.16)

and

\[
L(\lambda, t) = E_{\text{tot}}(\lambda, t) \, RF_{\text{eff}}(\lambda, t) \frac{\rho_{DHR}(\lambda)}{\pi},
\]

(4.17)

where

\[
E_{\text{tot}}(\lambda, t) = \cos(\phi_{\text{tgt}}(t)) E_{\text{sun}}(\lambda, t) + (SF)(E_{\text{dif}}(\lambda, t))
\]

(4.18)

and \( RF_{\text{eff}} \) is the effective reflectance factor adjustment. By restating the equation in this form, all incident irradiance terms are decoupled from the reflectance terms allowing the division of one to yield the other. The effective reflectance factor adjustment \( RF_{\text{eff}} \) can be related to the previously defined reflectance factor adjustment \( RF \) via the diffuse irradiance ratio \( d_r \) defined as

\[
d_r(\lambda, t) = \frac{(SF)(E_{\text{dif}}(\lambda, t))}{E_{\text{tot}}(\lambda, t)}.
\]

(4.19)

Using this diffuse irradiance ratio, the effective reflectance factor can be written as

\[
RF_{\text{eff}}(\lambda, t) = d_r(\lambda, t) + RF(t) - RF(t)d_r(\lambda, t).
\]

(4.20)

The ground normal diffuse irradiance ratio is a specific case of the diffuse irradiance ratio defined in Equation 4.19 where there is no shape factor obstructing the view of the hemisphere and the
target is flat and parallel to the ground, as is the case with the GRIT Basestation measurements. This ground normal diffuse irradiance ratio is defined as

\[ d_r(\lambda, t) = \frac{E_{dif}(\lambda, t)}{E_{tot}(\lambda, t)} \]  

(4.21)

where

\[ E_{tot}(\lambda, t) = E_{dif}(\lambda, t) + \cos(\phi_{tgt}(t))E_{sun}(\lambda, t) \]  

(4.22)

The ground normal diffuse irradiance ratio \( d_r \) can be used to derive the diffuse irradiance ratio \( d_r \) using the formula

\[ d_r(\lambda, t) = \left[ 1 + \frac{\cos(\phi_{tgt}(t))}{\cos(\phi_{sun}(t))SF} \left( d_{r \perp}(\lambda, t)^{-1} - 1 \right) \right]^{-1} \]  

(4.23)

The diffuse irradiance ratios are equal when the target has the same geometry as a flat, ground parallel target: in other words, when \( SF = 1 \) and \( \cos(\phi_{tgt}) = \cos(\phi_{sun}) \), \( d_r = d_{r \perp} \).

An example of how this irradiance reflectance separation can be used is shown in Figure 4.20, where the calibrated radiance images are divided by the in-scene measured irradiance \( E_{tot} \) and multiplied by \( \pi \). The resulting reflectance values were then compared to the in-scene measured...
reflectance $\rho_{DHR}$ multiplied by the effective reflectance factor adjustment $RF_{eff}$. The resulting figures highlight how calibration errors due to noise and non-linearities propagate to error in absolute in-scene reflectance. For example, the blue felt digital counts are systemically below the linear calibration lines in Figure 4.17. This calibration non-linearity results in calibrated reflectance values that consistently fall just short of the measured in-scene reflectance values in Figure 4.20.
Figure 4.19: The digital count images are calibrated using the gain and offset calibration coefficients and compared to the predicted target leaving radiance. The calibrated images are in blue (VNIR) and red (SWIR) and the predicted radiance is in yellow. These images were generated from the VNIR and SWIR images taken at 11:35am and provide a metric of how well the images were calibrated at every wavelength.
Figure 4.20: The calibrated images are divided by the total irradiance measured by the GRIT Bases- tation and compared to a modified version of the in-scene measured reflectance. The observed reflectance is in blue (VNIR) and red (SWIR) and the modified measured reflectance is in yellow. These images were generated from the VNIR and SWIR images taken at 11:35am and demonstrate how radiometric calibration errors propagate to errors in absolute in-scene reflectance.
4.8 VNIR and SWIR Fusion

The result of applying the calibration coefficients to the digital count images are VNIR and SWIR images in units of target leaving radiance. The final step is to combine both images to create a single hyperspectral image. Both images are already registered and interpolated to the same pixel instantaneous field of view (IFOV), therefore the images only need to be concatenated spectrally. To accomplish this, the VNIR cubes were truncated from the first wavelength to 922.8nm (inclusive) while the SWIR cubes were truncated from 932.8nm to the last wavelength (inclusive). These two truncated HSI cubes were then spectrally concatenated with no spectral interpolation in order to best preserve the original data. The wavelengths of concatenation were selected in order to create a sudden transition from 1.5nm increments in wavelength to 10nm increments in wavelength.

4.9 Summary

Using the calibration process laid out in this chapter, raw digital count frames were transformed into calibrated radiance frames. This process first invokes dark frame subtraction, bad pixel removal, and integration time normalization. Next, the VNIR and SWIR digital count images were manually registered by interpolating the smaller image, larger pixel, SWIR image to the VNIR image using an affine transformation. Next, the identified VNIR “brightening” calibration problem was compensated for by using overlapping VNIR and SWIR spectral bands to generate a VNIR gain adjustment. Next, the reflectance factor adjustments that account for the non-Lambertian BRDFs of the calibration targets were solved for using a constrained linear least squares regression. Measured in-scene reflectance and irradiance data were then used to predict target leaving radiance. This allowed for the calculation of the calibration coefficients using linear regressions between that predicted radiance and target digital counts. Finally, the application of the calibration coefficients generated VNIR and SWIR radiance images which were then fused into a single hyperspectral image. The result of the processes laid out in this chapter are 23 calibrated hyperspectral radiance images taken between 10:23am and 4:18pm.
Chapter 5

Vehicle BRDF Analysis

5.1 Introduction

The four vehicles were imaged across a six hour period window starting at 10:23am and ending at 4:18pm. During this period of time, the sun traversed 27 degrees of zenith and 98 degrees of azimuth, starting the day illuminating the vehicles from the front and ending the day back lighting the vehicles from the rear. This diversity in illumination geometry, combined with the non-Lambertian characteristics of shiny vehicle paint, generates a range of perturbations in the spectra of each vehicle. Characterizing, understanding, and modeling this spectral variability is important in increasing the accuracy of a sub-pixel spectral reacquisition task.

The goal of the BRDF analysis conducted in this section is to study this vehicle spectral diversity. This section explores the underlying spectral model complexity, the contribution of vehicle shape, color, and orientation on the spectral variations, and the effect of background adjacency effects on the spectral signatures. First, the total ground normal irradiance is extracted from the hyperspectral images. Next, the images are normalized by this extracted irradiance to produce reflectance images. Finally these reflectance images are cropped according to two different collection scenarios and the mean value of the cropped ROIs is used as the reflectance spectrum.

5.2 Irradiance Retrieval

The goal of irradiance retrieval is to utilize the calibration targets to determine the total ground normal irradiance of the scene for every image acquisition, even those for which there was no available GRIT Basestation data. The procedure is similar to the process used to determine the calibration coefficients in which the target reflectance and the total in-scene irradiance was used to predict target leaving radiance (see Section 4.7). For the irradiance retrieval procedure, the target reflectance and target leaving radiance are used to predict the total in-scene irradiance. If the simple diffuse target model were used, this equation would simply be $E_{tot} = L_{tgt} \pi / \rho$ and a linear regression of $L_{tgt}$ and $\rho / \pi$ would yield an estimate of $E_{tot}$. For consistency, however, the same forward model used for calibration is used for irradiance retrieval (see Equation 4.13).

The radiance in Equation 4.13 is a function of both diffuse and solar irradiance. When these
two irradiance terms are separated, the equation takes on the form

\[ L(\lambda, t) = \frac{SF \rho_{DHR}(\lambda)}{\pi} E_{diff}(\lambda, t) + \frac{\cos(\phi_{tgt}(t))RF(t)\rho_{DHR}(\lambda)}{\pi} E_{sun}(\lambda, t). \]  

(5.1)

In order to only solve for one irradiance value, the ground normal diffuse irradiance ratio \( d_{r\perp}(\lambda, t) \) term defined in Equation 4.21 is used to define the diffuse irradiance in terms of the solar irradiance

\[ L(\lambda, t) = \frac{SF \rho(\lambda) d_{r\perp}(\lambda, t) \cos(\phi_{sun}(t))}{1 - d_{r\perp}(\lambda, t)} E_{sun}(\lambda, t) + \frac{\cos(\phi_{tgt}(t))RF(t)\rho(\lambda)}{\pi} E_{sun}(\lambda, t). \]  

(5.2)

This diffuse irradiance ratio is based on the SBR/MODTRAN data with the applied diffuse irradiance transfer function (see Section 3.5.2). The terms are combined to yield radiance as a linear function of solar irradiance, expressed as

\[ L(\lambda, t) = \left(\frac{\rho(\lambda)}{\pi} SF d_{r\perp}(\lambda, t) \cos(\phi_{sun}(t)) \right) E_{sun}(\lambda, t) + \cos(\phi_{tgt}(t))RF(t) \frac{\rho(\lambda)}{\pi} E_{sun}(\lambda, t). \]  

(5.3)

The solar irradiance term is solved for using the same weighted least squared regression used to determine the calibration coefficients (see in Section 4.7). The solar irradiance term is then used to find the total ground normal irradiance \( E_{tot\perp} \) using the formula

\[ E_{tot\perp}(\lambda, t) = \frac{\cos(\phi_{sun}(t))E_{sun}(\lambda, t)}{1 - d_{r\perp}(\lambda, t)} , \]  

(5.4)

derived from Equations 4.21 and 4.22. The results of fitting a line to Equation 5.3 are plotted in Figure 5.1 where everything in parentheses of Equation 5.3 is called the solar reflectance and plotted in the x-axis. The slopes of the lines are the direct solar irradiance.

![Radiance vs Reflectance](image)

**Figure 5.1:** The results of plotting calibrated radiance vs solar reflectance (terms in parentheses in Equation 5.3) for a subset of the total wavelengths for the image taken at 11:35am. The slope of the lines are used to determine the total in-scene ground normal irradiance at the time of image acquisition.
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Figure 5.2: The retrieved irradiance is plotted along with the irradiance measured in-scene by the GRIT Basestation and Shadow Band Radiometer (SBR) for images taken at 12:53am (top) and 3:09pm (bottom). These two images were selected to show that the accuracy of the irradiance retrieval process is invariant to changes in total irradiance magnitude and the process is valid for images not used in the determination of calibration coefficients.

The process of retrieving the total irradiance from the imagery is performed for all images. The retrieved total irradiance spectra align closely with the measured GRIT Basestation spectra and SBR data as seen in Figure 5.2. Shown are the SBR data points (no diffuse transfer function applied) along with the retrieved irradiance for two extremes in total irradiance magnitude caused by the moderate cloud cover later in the day. The agreement between the retrieved irradiance and SBR data shows that the irradiance retrieval accuracy is invariant to changes in total irradiance magnitude. The agreement also demonstrates that the calibration procedure, which used only images taken while the GRIT Basestation was active, is also valid much later in the day for frames that were not used for calibration. This agreement across frames implies that the calibration coefficients and forward model parameters are valid throughout the duration of the data collection.

5.3 Simulated Vehicle BRDF Analysis

In order to better understand the observed vehicle BRDF spectra imaged as part of the data collection described in Chapter 3, a small study using simulated spectra was conducted in order
to better understand the phenomenology of non-Lambertian BRDF observations. In this study, in-scene measured irradiance and MODTRAN derived irradiance were divided into direct solar and downwelled/diffuse components and combined with a DHR reflectance to produce a target leaving radiance and BRDF spectrum. A distribution of spectra were generated for each material by adjusting the direct solar component to simulate different perspectives of a material’s specular lobe.

The downwelled and direct solar irradiance spectra were calculated using both a GRIT Basestation derived spectra and MODTRAN mid-latitude summer derived spectra. The MODTRAN spectra were calculated using a 10% reflectance background, space starring scenario with a solar zenith angle of 60 degrees. In order to calculate the measurement derived spectra, the GRIT Basestation total ground normal irradiance was divided into a direct solar component and a downwelled/diffuse component using the SBR/MODTRAN derived diffuse ratio function and diffuse transfer function. This process is similar to the process used in the radiometric calibration of the cameras described in Section 4.7. The MODTRAN derived irradiance spectra were combined with an ideal reflector (DHR=1), while the GRIT Basestation derived spectra were combined with in-scene measured vehicle roof DHR reflectance spectra. Both produce a target leaving radiance according to the equation

\[
L(\lambda) = (kE_{sun \perp}(\lambda) + E_{dif \perp}(\lambda)) \left( \frac{\rho_{DHR}(\lambda)}{\pi} \right) \left[ \frac{W}{m^2 \text{sr nm}} \right],
\]

where the parameter \( k \) adjusts the direct solar irradiance term.

This solar irradiance variation simulates a collection scenario in which the sensor is sweeping across any part of the specular lobe of the material. This can happen if the sensor is static but the sun is moving (as was the case in this data collect) or if the sensor is moving relative to the material. In either case, the specular lobe radiance is caused by both diffuse and solar illumination sources, but only the solar illumination changes as a function of sun-target-sensor geometry (assuming the diffuse illumination is approximately constant). The simulated observed radiance is calculated by normalizing Equation 5.5 by the total ground normal irradiance leading to the simulated BRDF formulation of

\[
\rho_{BRDF}(\lambda) = \left( \frac{kE_{sun \perp}(\lambda) + E_{dif \perp}(\lambda)}{E_{tot \perp}(\lambda)} \right) \left( \frac{\rho_{DHR}(\lambda)}{\pi} \right) [\text{sr}^{-1}].
\]

The purpose of this simulation is not to exactly replicate the observed BRDF spectra but to observe the characteristics of the spectral distributions generated by a rough approximation of a non-Lambertian material. The materials in this case are the vehicle roofs. This part of the vehicle was selected due to its relevance to Section 5.4. The purpose of including MODTRAN based calculations is to verify that certain characteristics are physically derived and not due to low SNR or sensor calibration issues. The MODTRAN derived spectra therefore act as a control in deconstructing the observed spectra characteristics. Nominal values for \( k \) were chosen to be \( k = 0, 0.2, ... 1.8, 2.0 \) and the GRIT Basestation derived irradiance spectra was measured at 11:35 am in conjunction with the fourth HSI image of the data collect. The simulated radiance, BRDF, and normalized BRDF are shown in Figures 5.3, 5.4, and 5.6, respectively.

The simulated radiance spectra are shown in Figure 5.3. From these images it’s not clear that there is both a gain and a bias \( (k = 0) \); there only appears to be a gain difference between the
Figure 5.3: Simulated radiance spectra using the roof measured DHR of the blue car (top left), red car (top right), white car (center left), and white truck (center right), and using a DHR of one (bottom). Spectra calculated using Equation 5.5 without dividing by $E_{\text{tot} \perp}$ various spectra (i.e. no apparent change in color). In addition, the MODTRAN based radiance spectra with unity DHR are directly proportional to the downwelled irradiance in the limiting case of $k = 0$, and the spectra are directly proportional to the total irradiance when $k = 1$.

The simulated BRDF spectra (Figure 5.4) again appear to only deviate with respect to a gain term and thus there is no apparent change in color. This color difference does not become evident until the spectra are Euclidean normalized. Despite this, there are two interesting features that become visible in the reflectance domain. These features are centered at 940nm and 1130nm and correspond to strong water absorption features. These features are caused by relative differences in water absorption between the diffuse downwelled irradiance and the direct solar irradiance. The original propose of adding the MODTRAN control spectra to this study was to make sure that these features were not due to low SNR characteristic of water absorption regions. The assumption is that if a feature is prevalent in the control spectra, there is a radiative-transfer, physics based explanation for it. The MODTRAN based spectra with unity DHR at the bottom of Figure 5.4 show both features, validating their existence.

Further investigation into the two water absorption features leads to the plot shown in Figure 5.5. This shows the ratio of the downwelled irradiance to total irradiance for two MODTRAN simulations: one with a solar zenith angle of 30 degrees and one with a solar zenith angle of 60 degrees. This downwelled irradiance ratio term, initially defined in Equation 4.21, is expressed
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Figure 5.4: Simulated BRDF reflectance spectra using the roof measured DHR of the blue car (top left), red car (top right), white car (center left), and white truck (center right). And simulated BRDF reflectance spectra using a DHR of one (bottom).

\[ d_{r,\perp}(\lambda) = \frac{E_{\text{diff}}(\lambda)}{E_{\text{diff}}(\lambda) + E_{\text{sun,\perp}}(\lambda)}. \]  

(5.7)

From this figure it is evident that at the two features of interest, 940nm and 1130nm, there is a larger contribution in irradiance from the downwelled skylight than directly from the sun (small bumps in the plots). This difference, however, is dependant on the amount of atmosphere between the sun and the target of interest, in that more atmosphere leads to a greater amount of transmission loss due to atmospheric water absorption. This effect is evident when contrasting the diffuse ratio of the 30 and 60 degree solar zenith angles. At a solar zenith angle of 30 degrees, the features at 940nm and 1130nm completely disappear due to the shorter solar atmospheric path length.

The dependence of these relative water absorption features on the observed BRDF is conveyed with the following thought experiment: if an observer has a view of the specular lobe that results in very little solar specular lobe radiance contribution (small \( k \)), the total observed radiance spectrum will have these water absorption features. This is because when normalizing by the total irradiance, which includes the solar irradiance term, either too much or too little irradiance was contained in the denominator of Equation 5.6 at the water absorption bands, relative to the neighboring bands. Through reciprocity, the reverse is true of a strong specular
Figure 5.5: The downwelled/diffuse ratio of total irradiance (see Equation 5.7) for two MODTRAN simulations, one with a solar zenith angle of 30 degrees (blue) and one with a solar zenith angle of 60 degrees (red). Both executions used a Mid-Latitude Summer atmospheric profile and a 10% background reflectance.

For a mathematical departure into how relative water absorption between the downwelled and solar direct irradiance creates these features in the BRDF, consider the equation for the diffuse irradiance ratio defined in Equation 5.7. It can be shown that using this ratio, the simulated BRDF, defined in Equation 5.6, can be redefined in terms of the ratio as

$$\rho_{BRDF}(\lambda) = (K + d_{r\perp}(\lambda) - K d_{r\perp}(\lambda)) \left( \frac{\rho_{DHR}(\lambda)}{\pi} \right) [sr^{-1}].$$

(5.8)

From this mathematical definition, it is now clear how relative differences at these water absorption bands shown in Figure 5.6 manifest as features in the simulated BRDF spectra. Notice that at the limiting case of $k = 0$, $\rho_{BRDF} = d_{r\perp} \rho_{DHR}/\pi$. Similarly, in the case where $k = 1$, $\rho_{BRDF} = \rho_{DHR}/\pi$ and in case of $k > 1$, the shape of the identified water absorption features flip.

After isolating the source of the 940nm and 1130nm features and demonstrating their dependence on the relative water absorption between the solar direct and downwelled irradiance spectra, the direction of the features are considered. At these features, if the downwelled irradiance accounts for a greater proportion of the total irradiance relative to the entire spectrum, as is the case in Figure 5.5, the features will have a positive, upward peak at low specular lobe contribution geometries, and as the sun-target-sensor geometry changes such that the specular lobe contribution to total observed radiance increases, the direction of the features will decrease. Likewise, if the direct solar irradiance accounts for a greater proportion of the total irradiance at the wavelengths of interest relative to the entire spectrum, the features will have a negative, downward peak at low specular lobe contribution geometries. And as this contribution increases, the direction of the feature will increase towards a more positive, upward shape. Therefore, the correlation between the direction and changing magnitude of this feature and the changing magnitude of the entire reflectance spectra reveal fundamental information about the relative water
absorption and cloud cover of the direct and downwelled illumination.

An interesting application of this functional relationship is using multiple observations of the BRDF, or a priori knowledge of the diffuse irradiance ratio $d_{r,\perp}$, to derive knowledge about the relative amounts of direct solar and downwelled irradiance contributions to the observed BRDF. Adhering to the simple model in Equation 5.8, this would be equivalent to solving for $k$. This would facilitate the remote probing of a vehicle BRDF without the need to pass through multiple points of the specular lobe. In addition, because of the narrow width of these features, a smoothly varying reflectance assumption would allow the removal of a free parameter. For example, if solving for $k$ in Equation 5.8, with known $d_{r,\perp}$, unknown $\rho_{DHR}$, and only one reflectance spectra, the assumption that $\rho_{DHR}$ is constant on and just off the feature at 1130 nm creates two or more BRDF values with only two variables to solve for. Finally, these spectral features could be utilized for shadow detection techniques: a $k$ of zero likely means the sun is fully obstructed. As shown in the 30 degree solar zenith simulation of Figure 5.5, however, this spectral feature might not be available to exploit. In addition, its usefulness is in its low, but non zero signal, caused by a low but but non zero path transmission at these water absorption bands. This will inherently result in lower SNR values in these bands which could possibly limits the usefulness of these features.

![Figure 5.6: Simulated Euclidean normalized BRDF reflectance spectra using the roof measured DHR of the blue car (top left), red car (top right), white car (center left), and white truck (center right), and using a DHR of one (bottom).](image-url)
In order to view the color change that results from adding various relative amounts of direct solar target leaving radiance, in accordance with a non-Lambertian material, the reflectance spectra from Figure 5.4 are Euclidean normalized and plotted in Figure 5.6. Euclidean normalization treats the spectra as vectors and divides them by their respective magnitude ($L^2$-Norm) such that each spectrum has unity magnitude. The interesting characteristic that appears in these normalized reflectance spectra is a node point in which many of the spectra overlap. The wavelength at which this node exists appears to be dependant on the reflectance, given that the point shifts when comparing the normalized reflectance spectra of the different car roofs. The spectral color shift about this node is due to the variations of the direct solar irradiance contribution term ($k$). The higher the value of $k$, the more red shifted the spectrum becomes, because the downwelled spectra has a stronger skewness towards blue than the solar direct spectrum. Likewise, the lower the value of $k$, the more blue shifted the spectrum becomes until $k = 0$, at which point the normalized spectrum looks like a normalized Rayleigh scattering distribution. This node point is a clear indicator that the material is non-Lambertian since it signifies a variation in direct solar irradiance, indicative of a specular lobe. Upon further investigation, this node point seems to coincide with the centroid of the element-wise multiplication of the solar irradiance spectrum and the reflectance spectrum, but the values do not match exactly—further investigation is needed.

5.4 Nadir Vehicle BRDF Analysis

For a remote sensing scenario in which the view of a vehicle is primarily viewed from directly above (nadir viewpoint), the majority of the spectral signature contribution emanates from the upper vehicle surfaces such as the hood, roof, windshield, and trunk. As opposed to spectra from vehicle sides, the upper vehicle surfaces are less likely to be self-shadowed and experience less spectral contributions from the road surfaces or nearby surfaces, such as vegetation. The nadir vehicle viewpoint, therefore, is hypothesized to be simpler than an oblique viewpoint in that a forward model describing the reflected light would be simpler.

The vehicles imaged as part the experiment described in Chapter 3 were done so at shallow view angles between 30 and 40 degrees. In order to establish a proxy to the nadir view scenario from the non-nadir imagery, the roofs of each vehicle are cropped out and the mean of the resulting spectra are used as a single spectrum (see Figure 5.7). The resulting spectra are representative of a hyperspectral camera with a GSD on the order of 1-2 meters and the pixels are representative of a single roof pixel in terms of model complexity. Although the underlying sun-target-sensor geometry is still that of a shallow view angle, for some viewing angles the half angle vectors formed by bisecting the target-sun and target-sensor vectors are valid for nadir viewing scenarios. In addition, because most vehicles are dominated by one homogeneous material, i.e. painted panels, understanding the BRDF effects of the vehicle roofs, even at extreme viewing geometries, provides insight into vehicle BRDFs at all viewing scenarios. This nadir assumption was also made by Bartlett et. al., who assumed the spectral BRDF measurements of a flat vehicle panel were representative of a nadir viewing scenario when implanted into hyperspectral imagery [59].
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5.4.1 Nadir Reflectance Variability and Feature Analysis

After the vehicle spectra are cropped out of the hyperspectral imagery, the mean of the spectra is taken to collapse them into a single spectrum representing a single pixel or sub pixel component. Shown in Figure 5.8 is the radiance spectra of the four vehicles’ roofs taken from 21 of the 23 hyperspectral images. The two samples removed were due to changing illumination conditions during the image acquisition, resulting in images with varying total irradiance as a function of horizontal position (sample number). Note the stark contrast in radiance magnitude between the white vehicles and the blue/red vehicles.

The reflectance spectra are found by dividing the vehicle radiance spectra by the retrieved total ground normal irradiance, found using the irradiance retrieval method described in Section 5.2. This operation yields a measure of the vehicles’ reflectance, or samples of the vehicles’ BRDF, governed by the equation

\[ \rho_{BRDF}(\lambda, \theta_i, \phi_i, \theta_r, \phi_r) = \frac{L(\lambda, \theta_r, \phi_r)}{E_{tot,\perp}(\lambda, \theta_i, \phi_i)}. \]  

These reflectance spectra are shown in Figure 5.9. While the variation of radiance spectra can be attributed to changes in illumination conditions, the purpose of normalizing by the incident irradiance is to achieve an illuminant invariant measure of reflectance. This measurement is an
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Figure 5.8: The spatial mean of the total target leaving radiance of the roofs of the blue car (top left), red car (top right), white car (bottom left) and white truck (bottom right).

Based on the measured vehicle paint BRDFs reported by Gunther et al. [55] and the large range of sampled geometries, the more likely scenario is that the diffuse reflectance accounts for a much larger proportion of the DHR in the white vehicle paints when compared to the darker vehicle paints (see Section 2.3). This quality, the degree of relative diffuse scattering in automotive paint, is further examined by incorporating the multi-lobe Cook-Torrance BRDF parameters reported by Gunther et al. [55] (see Section 2.4) for common automotive paints, and hemispherically integrating the BRDF to determine the total material DHR, according
to Equation 2.2, for normal incident irradiance. In order to calculate a metric of relative paint diffuseness, the diffuse scattering DHR term in the reported Cook-Torrance models is divided by the total integrated DHR. This revealed a weak linear correlation between the overall brightness of vehicle paint (DHR) and the described diffuse scattering ratio. This trend is shown in Figure 5.10, where the mean DHR and mean diffuse scattering ratio are displayed. The mean values were used because the models reported by Gunther et. al. [55] generated three BRDFs for the red, green, and blue color channels.

At the two extreme ends of the diffuse scattering ratio are the black and white paint samples seen in the bottom left and top right corners of Figure 5.10. These samples have diffuse scattering ratios of 0.15 (black) and 0.98 (white) and the normalized principal plane BRDF of both are shown in Figure 2.4. This stark contrast in diffuse scattering ratios is counter-intuitive when viewing the paint sample renderings [55] in Figure 5.10. Even though the white sample is quantitatively more diffuse than the black sample, it appears just as glossy in the rendered images. This is the result of the sharp gloss lobe shown in the principal plane graphs of Figure 2.4. As explained in Section 2.3, the likely physical explanation for this difference in specular lobe width is the glitter scattering mechanism caused by the small metal flakes. The data set shown in Figure 5.10 is obviously small, but the correlation is supported by the observations made in this data collect. More automotive paint samples should be collected however, in order to draw stronger and broader conclusions about this trend and to determine its applicability to the global population of real-world commercial vehicles. In order to generate diffuse scattering ratios using NEFDS paint samples, where parameters are reported according to a modified Beard-Maxwell BRDF model, the two volumetric scattering terms (diffuse scattering and multiple scattering) should be divided by the total reported DHR [57,67].

In addition to the trends in overall reflectance spectra magnitude variability, the water ab-
Figure 5.10: The Cook-Torrance multi-lobe BRDF parameters reported by Gunther et. al. [55] were hemispherically integrated to calculate the total DHR and the diffuse scattering ratio for the eight paint samples (top). The parameters were derived from imaged spheres that were professionally painted by an automotive paint shop. Gunther et. al. made renderings of the eight samples (below) [55].

Absorption features described in Section 5.3 are clearly visible in the reflectance spectra shown in Figure 5.9. The fact that the features face downward (negative direction) and increase in magnitude with increases in reflectance spectra magnitude suggest that the direct solar irradiance path experienced a greater amount of water absorption attenuation than the downwelled irradiance during the data collection. This conclusion agrees with the large solar zenith angles associated with a northern hemisphere October data collect: the average solar zenith angle was 55 degrees. In addition, observed partial cloud cover in the solar path also substantiates this conclusion—the effect was more noticeable later in the day when solar transmission loss due to cloud obscuration increased.

In order to observe magnitude independent differences in reflectance, the reflectance spectra are Euclidean normalized to have unit magnitude, as shown in Figure 5.11. This technique further eliminates changes in spectra due to magnitude and aids in the comparison of the spectral “color” as a function of sun-target-sensor geometry variations. Note the asymmetry in the relative ordering of the spectral magnitudes about the 900nm point, similar to the asymmetry features found in the simulated normalized reflectance spectra in Section 5.3. Larger spectral reflectance values to the left of this node point tend be the smallest values to the right of the
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Figure 5.11: The spatial mean of the BRDF of the roofs are normalized such that the spectra have unit magnitude. Displayed are the normalized BRDF of the blue car (top left), red car (top right), white car (bottom left) and white truck (bottom right).

Node point and vise versa. This trend appears to hold true for all the vehicles, but is most apparent in the red and blue car spectra due to the larger normalized variability. In the red car normalized BRDF plot, the yellow colored spectrum is largest to the left of the node point but smallest to the right. Likewise, the dark blue spectrum is smallest to the left of the node point but largest to the right. This behavior exactly matches the simulated BRDF behavior and is a clear sign that the variation is due to the amount of reflected solar illumination. The solar illumination magnitude profile has a first moment (mean) around 900nm and has a strong positive third moment (skewness) that accounts for normalized variations.

The radiance spectra of the four vehicles associated with the hyperspectral images taken at 1:36pm and 4:15pm are shown in Figure 5.12. The two sets of images were selected so that the vehicles are facing the same direction in both images (southwest), the images are separated by more than three hours, and the later image was taken with the camera close to the principal scattering plane of the vehicle roofs. The associated reflectance spectra are also shown in Figure 5.13. In both figures it is clear that the pixel variance increases as the camera moves closer to the forward scattering lobe of the vehicles’ roofs. This increase in variance does not appear to be due to a change in spectra magnitude; instead the increase in variance is due to the increase of forward scattering vehicle elements. The discontinuities in the 99th percentile spectra are another interesting feature. These spectra are associated with the brightest pixels and report the radiance for these pixels. The discontinuities, such as the those seen in the red and white car reflectance, suggest potential calibration issues at extreme pixel magnitudes or pixel saturation effects. Either way, these effects at extreme pixel values should be taken into consideration as sources of error in the mean spectra values.
Figure 5.12: Mean radiance spectra of the roofs of the four vehicles taken from the hyperspectral images acquired at 1:36pm (left) and 4:14pm (right). Shown are the mean, median, standard deviation, and 99th percentile spectra of the blue car (top row), red car (second row), white car (third row), and white truck (bottom row).
Figure 5.13: Mean reflectance spectra of the roofs of the four vehicles taken from the hyperspectral images acquired at 1:36pm (left) and 4:14pm (right). Shown are the mean, median, standard deviation, and 99th percentile spectra of the blue car (top row), red car (second row), white car (third row), and white truck (bottom row).
5.4.2 Nadir Integrated Reflectance Magnitude Analysis

To visualize the magnitude change in total spectral reflectance as a function of time, the vehicle roof spectra were spatially averaged and spectrally integrated. By averaging in the spatial dimension and spectrally integrating, an HSI ROI image is reduced to a scalar broadband reflectance value. The spectrally integrated reflectance value is plotted as a function of sun azimuth in Figure 5.14 where each vehicle direction (north, south, southwest, and southeast) is represented by a single line. Given that the sun azimuth angle that places the camera in the principal scattering plane is roughly 260 degrees, it is clear that the mean spectral magnitude of the darker vehicles is increasing as a function of principal plane proximity. The closer the camera gets to a position directly across from the sun, the brighter the spectral reflectance of the dark vehicles. Unlike the red and blue vehicles, the reflectance magnitude of the white vehicles does not share the same characteristics. This was seen in Figures 5.9 and 5.11 where the spectral variations of the darker vehicles were greater than those of the white vehicles. This is further evidence that the white vehicles are proportionally more diffuse than the blue and red vehicles in that the diffuse scattering terms account for a greater ratio of the total reflected light. As mentioned in Sections 2.3 and 5.4.1, this is likely due to difference in the glitter scattering mechanisms.

![Figure 5.14: The reflectance spectra of the vehicle roofs are averaged spatially and spectrally and plotted as a function of sun azimuth. Each vehicle direction (north, south, southwest, and southeast) is represented by a single line and the lines are colored by vehicle. The approximate time of day is also shown on the bottom x-axis.](image)

5.4.3 Nadir Reflectance Orientation Analysis

For a nadir imaging scenario, the sun-target-sensor geometry is minimally changed with a vehicle rotation and the BRDF of smooth car panels is isotropic, meaning that there is no dependence on the surface orientation. Therefore, changes in vehicle orientation in the nadir imaging scenario
should have a negligible effect on the observed BRDF. This is observed in the vehicle roof reflectance spectra of the blue car, white car, and white truck as seen in Figure 5.15, in which the BRDF spectra are colored by direction. In an attempt to isolate the vehicle orientation effects, the four BRDF samples shown in these figures were selected to minimize the time between the first and last sample in order to lesson the time-varying BRDF effects caused by changing solar position and cloud cover. While the blue car, white car, and white truck undergo minimal change as a function of vehicle orientation, the red car BRDF exhibits a strong functional dependence on vehicle orientation. One possible explanation for this behavior is that the roof of the red car is less parallel to the ground plane than the other vehicles, meaning a rotation of the red vehicle results in a larger change in sun-target-sensor geometry. This feature of the red car can be seen in Figure 3.4. Another possible explanation for the red car BRDF variability is that even over a small window of time the sun’s position changes, altering the vehicle BRDF. As seen in Figures 5.16 and 5.17, there is a strong functional relationship between BRDF magnitude and time, especially for the red car.

Figure 5.15: Four consecutive nadir vehicle roof reflectance spectra are colored by vehicle orientation and shown for the blue car (top left), red car (top right), white car (bottom left), and white truck (bottom right).

The vehicle roof reflectance spectra are directionally sorted and colored by both vehicle and acquisition time for the north and south facing vehicles in Figures 5.16 and 5.17. The figures of both directions demonstrate the BRDF magnitude dependence on time/solar azimuth seen in Figure 5.14.

5.4.4 Nadir Reflectance Principal Components Analysis

Using principal components analysis, the ordered eigenvectors of the vehicle roof reflectance spectra are calculated and shown in Figure 5.18. Again, the red car and blue car share characteristics separate from the white vehicles. The first eigenvector of every vehicle is positive,
Figure 5.16: All vehicle roof reflectance spectra of the north facing vehicles are plotted and colored by vehicle (top). The north facing spectra are also sorted by vehicles and colored by acquisition time for the blue car (second row), red car (third row), white car (fourth row), and white truck (bottom row).
Figure 5.17: All vehicle roof reflectance spectra of the south facing vehicles are plotted and colored by vehicle (top). The north facing spectra are also sorted by vehicles and colored by acquisition time for the blue car (second row), red car (third row), white car (fourth row), and white truck (bottom row).
smoothly varying, and loosely matches the shape of the mean spectrum. This implies that the first principal component captures the broadband magnitude variations of the reflectance spectra. The second set of eigenvectors appear to capture the asymmetry about the node point described in Sections 5.3 and 5.4.1. The second eigenvector of the red vehicle and the second eigenvector of the blue vehicle cross the origin around 900nm, in conjunction with the location of the BRDF node points seen in Figure 5.11.

![Figure 5.18:](image)

Figure 5.18: The first three eigenvectors of the vehicle roof reflectance spectra are plotted as well as the mean of the spectral distribution for the blue car (top left), red car (top right), white car (bottom left), and the white truck (bottom right).

As seen in Figure 5.19, the first three eigenvectors of the blue and red car account for 99.77% and 99.71% of the total variability, respectively. Given that a portion of the overall variability is due to noise, the data models of the dark vehicles can be well represented with a low dimensional subspace. There also exists similarity in the dimensionality of the two white vehicles. With seven eigenvectors, the white car and white truck principal component data models account for 99.75% and 99.71% of the spectral variability, respectively. In addition, the first three eigenvectors of the white vehicle subspaces are objectively similar. The white vehicles similarity in model complexity and eigenvector shape suggests that the white vehicles share a similar subspace, regardless of the fact that the vehicles are different shapes. In addition, there are some similarities between the blue and red car principal components. This analysis suggests that in a nadir imaging scenario, the subspace model representing the BRDF is more dependant on vehicle paint surface features (paint BRDF) than vehicle shape (truck vs car).
Finally, the similarities in data models for the white vehicles suggests the possibility of transfer learning between the vehicles, a concept that would be extremely useful for acquiring vehicles not previously characterized.

![Cumulative Eigenvector Explanation of Variability](image)

**Figure 5.19:** The cumulative explanation of variability as a function of the number of eigenvectors in the subspace model for the vehicle roof spectra distributions.

### 5.5 Off-Nadir Vehicle BRDF Analysis

The data collection was naturally off-nadir, so no special assumptions need to be made. In this scenario, as seen in Figure 5.20, the body of each vehicle is cropped, rather than just the roofs. And unlike the nadir ROI spectra, the spectra of these ROIs cover many different materials, such as the paint, glass, tires, trim, and even vehicle interior. Additionally, as opposed to the nadir ROIs where all the IFOV of each pixel is solar illuminated, the IFOV of these pixels contain both shadowed and non-shadowed materials. Finally, while the nadir ROI radiance was almost exclusively cause by single photon bounces, the off-nadir radiance is the result of both single bounces originating from direct solar and downwelled illumination sources and secondary and tertiary photon bounces for the surrounding asphalt, grass, and other vehicles. Due to the increase in material diversity, shadowing effects, and non-linear reflectance mixtures caused by adjacency effects, the forward model underlying these reflectance spectra is much more complicated than the nadir scenario of Section 5.4.

#### 5.5.1 Off-Nadir Reflectance Variability and Feature Analysis

The vehicle radiance spectra are shown in Figure 5.21 and the reflectance spectra in Figure 5.22. As expected, the reflectance spectra of the entire vehicle ROIs exhibit greater variations across the data collect than the nadir reflectance spectra. One potential source of this increased variation is glints. While the nadir reflectance spectra typically did not contain any glints in the images, the entire vehicle spectra do encapsulate these high reflectance areas of the vehicle. These glints can cause erratic behavior in the pixels due to both saturation effects and
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Figure 5.20: To study BRDF effects of an off-nadir collection scenario, the vehicles are cropped out of the hyperspectral imagery. The left column image was taken at 2:26pm, the middle column image was taken at 2:35pm, and the right column image was taken at 3:09. The cropped regions are brightened for visual clarity.

non-linearities in the pixel response functions; these effects can materialize as discontinuities in the radiance and reflectance spectra. The normalized reflectance spectra shown in Figure 5.23 again show the same asymmetry about the 900nm node point, similar to those seen in the nadir reflectance spectra and simulated reflectance spectra, providing evidence of a non-Lambertian BRDF. The water absorption features are also visible in the off-nadir reflectance spectra. While the magnitude and direction of these features were smoothly varying in the nadir reflectance spectra as a function of sun azimuth, the features in the off-nadir reflectance spectra are unpredictable and no clear correlation with solar azimuth exists. An explanation for this disorder lies in the self-shadowing dependence on vehicle orientation. As mentioned in Section 5.3, the magnitude of these features increases in either strong or weak direct solar contributions to the target leaving radiance. The self-shadowing effects coupled with the heavy afternoon cloud coverage cause large variations in the amount of relative water absorption and direct solar contribution to the observed radiance.

Individual radiance and reflectance spectra are shown in Figure 5.24 and 5.25, respectively. Here the 99th percentile, mean, and median spectra are plotted to gauge the effects of the brightest glint pixels on the mean spectra. For example, there is a clear discontinuity in the 99th percentile blue car radiance spectrum in the 1:36pm image (top left) at the wavelength where the VNIR and SWIR images were fused together (920nm). This discontinuity in radiance
Figure 5.21: The spatial mean of the total target leaving radiance of the blue car (top left), red car (top right), white car (bottom left) and white truck (bottom right).

Figure 5.22: The spatial mean of the vehicle BRDF of the blue car (top left), red car (top right), white car (bottom left), and white truck (bottom right).

can also be seen in the reflectance spectrum but is isolated to a small spatial region of the vehicle and does not alter the mean in a meaningful way. In the red car reflectance spectrum from the 1:36pm image (left column), an example is shown of how a small number of pixels can disrupt the mean value, pulling its values towards the outlying pixels. The mean value is shifted to such a degree, in both the reflectance and radiance spectra, that the median falls outside of one
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Figure 5.23: The spatial mean of the vehicle BRDF spectra are normalized such that the spectra have unit magnitude. Displayed are the normalized BRDF spectra of the blue car (top left), red car (top right), white car (bottom left) and white truck (bottom right).

standard deviation about the mean. As was seen in the nadir vehicle spectra, the variance of the right column reflectance spectra is greater than the left column due to the spatial variability in radiance caused by the specular surfaces and principal plane sensor proximity.

5.5.2 Off-Nadir Integrated Reflectance Magnitude Analysis

The mean reflectance is plotted as a function of sun azimuth and time for the entire vehicle off-nadir ROI spectra (see Figure 5.26). The structure of the integrated reflectance curves, and how the curves vary with respect to solar azimuth and orientation, are significantly different than the corresponding nadir, roof only ROI spectra plot (see Figure 5.14). The dominating factor effecting the overall magnitude of these spectra is the self shadowing effect driven by the sun’s movement across the sky, which shifts from illuminating the vehicles from the front (sun behind sensor) to back lighting the vehicles (sun opposite sensor). While the self-shadowing accounts for the decrease in magnitude, the increase in magnitude near the end of the data collect can still be attributed to the decreasing distance between the camera and the principal scattering plane of the vehicle surfaces.

Another interesting divergence in structural characteristics between the nadir and off-nadir versions of the integrated reflectance vs solar azimuth plot is the difference between the various directions of any one vehicle. The nadir, roof only ROI spectra exhibited no self-shadowing and maintained a consistently flat, ground-parallel, homogeneous surface. Therefore, the reflectance curve of every direction followed the same pattern and overlaid each other on the plot (see Figure 5.14). In contrast, the off-nadir ROI spectra exhibit significant variations based on direction, caused by self-shadowing, complex-geometries, and multiple materials (see Figure 5.26). Interestingly, the relative magnitude and shape of the directional variations in reflectance
Figure 5.24: Mean radiance spectra of the four vehicles taken from the hyperspectral images acquired at 1:36pm (left) and 4:14pm (right). Shown are the mean, median, standard deviation, and 99th percentile spectra of the blue car (top row), red car (second row), white car (third row), and white truck (bottom row).
Figure 5.25: Mean reflectance spectra of the four vehicles taken from the hyperspectral images acquired at 1:36pm (left) and 4:14pm (right). Shown are the mean, median, standard deviation, and 99th percentile spectra of the blue car (top row), red car (second row), white car (third row), and white truck (bottom row).
Figure 5.26: The reflectance spectra of the vehicles are averaged spatially and spectrally and plotted as a function of time/sun azimuth. Each vehicle direction (north, south, southwest, and southeast) is represented by a single line and the lines are colored by vehicle.

appear to be consistent within any single vehicle. As seen in the top of Figure 5.27, for each of the four vehicles the relative ordering of integrated reflectance amongst the four directions remains consistent throughout the data collect, with some few exceptions. For each vehicle, the southwest direction produces the brightest integrated mean reflectance, followed by the southeast direction, the south direction, and lastly, the north direction consistently has the weakest reflectance.

The similarity of the relative ordering of reflectance magnitude across vehicles is likely due to the fact that each of the vehicles possesses the same geometric features such as the hood, windshield, and roof. The south facing reflectance spectra likely have a greater mean reflectance than the north facing spectra due to the southerly path of the sun during the experiment, from southeast to southwest (135 to 236 degrees azimuth). When the vehicles faced south, they presented the sun with sloped downward angled hoods and windshields, providing surfaces more conducive to brighter BRDFs with a greater probability of glints than the vehicle rears. One possible explanation for the relative ordering amongst the south facing vehicle reflectance magnitudes is that the southwest facing vehicles presented the sun and sensor with the greatest amount of vehicle side surface area, followed by the south and southeast facing spectra. Another possible explanation for the relative ordering is that the southwest facing vehicles generated the least amount of self-shadowing, followed by the south and southeast facing spectra. The relative similarity of reflectance magnitude between the two Chevrolet Spark vehicles (white and blue car), seen in the bottom graph of Figure 5.27, fits with the idea that directional differences in spectral distributions are based on the sun and vehicle surface geometry. While the vehicles are different colors, and the white car is likely more diffuse than the blue car, the relative structure of the spectra intensity is the same due to the exact same vehicle shape. This demonstrated importance of vehicle shape suggests the possibility of characterizing the full vehicle reflectance of a single make and model and functionally manipulating the model to fit any other color. This
Figure 5.27: The reflectance spectra of the vehicles are averaged spatially and spectrally and plotted as a function of time/sun azimuth. Each vehicle direction (north, south, southwest, and southeast) is represented by a single line and the lines are colored by direction. The first plot consists of all four vehicles (top) and the second plot is the same data plotted for only the two Chevy Spark vehicles (bottom).

Type of transfer learning between car colors would be representative of shifting the white car curves shown in Figure 5.27 to fit the blue car curves, or vice versa.

5.5.3 Off-Nadir Reflectance Orientation Analysis

Four consecutive off-nadir BRDF reflectance spectra taken at different vehicle orientations are shown in Figure 5.28 for each of the four vehicles. These spectra were selected in order to minimize the time interval between the first and last image acquisition in order to mitigate the time varying BRDF effects. The relative ordering seen in the integrated reflectance plots is
again seen in these figures, but it is apparent that the ordering reverses between the VNIR and SWIR parts of the spectra. The relative ordering in the SWIR portions is consistent with the relative ordering shown in Figure 5.27; however, the relative order in the VNIR is the opposite. This relative ordering reversal is likely due to the same mechanism responsible for node points observed in the normalized reflectance plots, the contribution of direct solar illumination to the observed spectral radiance.

In Figures 5.29 and 5.30 the opposite trend of the nadir, roof ROI spectra shows that instead of increasing, the intensity of the spectra is decreasing as a function of time. This behavior, supported by the reflectance vs time plots of Figures 5.26 and 5.27, occurs in the spectra of all the vehicles, not just the dark vehicles. This is further evidence that geometric contributions such as self-shadowing dominate the variations in spectrum magnitude in the off-nadir domain, rather than the BRDF of the surface materials.

### 5.5.4 Off-Nadir Reflectance Principal Components Analysis

The first three eigenvectors of the off-nadir collection scenario spectra are shown in Figure 5.31 and the cumulative explanation of variability is shown in Figure 5.32. Again, the first eigenvectors capture the overall wide band spectral intensity and the subsequent eigenvectors appear to capture the dominating spectral features, such as the vehicle color in the visible portion of the spectrum. In addition, the higher order eigenvectors have peaks and troughs that correlate to the previously discussed atmospheric absorption features at 940nm and 1130nm. This shows that the magnitude and direction of these features plays a significant role in the observed BRDF variability. Finally, using only four eigenvectors to model the vehicle spectra captures 99.7%, 99.9%, 99.8%, and 99.8% for the blue car, white car, red car, and white truck,
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Figure 5.29: All vehicle reflectance spectra of the north facing vehicles are plotted and colored by vehicle (top). The north facing spectra are also sorted by vehicles and colored by acquisition time for the blue car (second row), red car (third row), white car (fourth row), and white truck (bottom row).
Figure 5.30: All vehicle reflectance spectra of the south facing vehicles are plotted and colored by vehicle (top). The north facing spectra are also sorted by vehicles and colored by acquisition time for the blue car (second row), red car (third row), white car (fourth row), and white truck (bottom row).
respectively.

**Figure 5.31:** The first three eigenvectors of the vehicle reflectance spectra are plotted as well as the mean of the spectra for the blue car (top left), red car (top right), white car (bottom left), and the white truck (bottom right).

**Figure 5.32:** The cumulative explanation of variability as a function of the number of eigenvectors in the subspace model for the vehicle spectra.
5.6 Vehicle Background Adjacency Contribution Analysis

In a sub-pixel target collection scenario in which a vehicle constitutes a single pixel as the sensor vantage point becomes more oblique, there will be a greater contribution from the vehicle sides to the observed radiance and less contribution from the vehicle’s top horizontal surfaces, such as the roof and hood. In this collection scenario, it is paramount to consider the spectral radiance contributions from the road and nearby surfaces to the sensor reaching spectral radiance. These background adjacency effects are caused by secondary and tertiary photon bounces (sun-background-vehicle-sensor and sun-vehicle-background-vehicle-sensor) and create non-linear mixing effects that impact the final spectrum. The goal of the background adjacency experiment was to quantify this effect for two different surfaces and show how the perceived vehicle BRDF of a white vehicle changes as it moves through such an environment. The results of this study will demonstrate the importance of accounting for the road surface and background adjacency effects when measuring the hyperspectral spectrum of a vehicle in an off-nadir viewing scenario.

The two background surfaces selected for this study were grass and asphalt. For both scenarios, hyperspectral images were taken of the vehicle with and without a large black panel (1.22m x 1.02m) placed on the ground in front of the vehicle’s side (see Figures 5.34 and 5.38). Both pairs of image were taken minutes apart in order to minimize differences caused by solar position changes—the grass images were separated by 3 minutes and the asphalt images were separated by 6 minutes. During these short intervals, the irradiance magnitude shifted a small amount due to changing illumination conditions. To eliminate these differences in incident irradiance, the radiance images were divided by their respective scene extracted, total ground normal irradiance and then multiplied by the average irradiance. The radiance images are therefore relative radiance based on a common irradiance spectrum and expressed as

\[
L(\lambda, t) = \left( \frac{L_{\text{observed}}(\lambda, t)}{E(\lambda, t)} \right) \left( \frac{E(\lambda, t) + E(\lambda, t')}{2} \right) .
\]  

(5.10)

Figure 5.33: The reflectance spectra of the black panel (blue), grass (red), asphalt (yellow), and truck side (purple) are shown. The black panel and truck reflectance spectra were measured using the portable spectroradiometer (see Section 3.4.5) and the grass and asphalt reflectance spectra were measured using GRIT (see Section 3.4.4). The estimated geometry used for the GRIT measured spectra is 0 degrees relative azimuth and 45 degrees zenith.
Figure 5.33 shows the principal reflectance spectra associated with the vehicle background adjacency experiment. The reflectance profiles of the grass and asphalt were taken from the GRIT BRDF data collection (see Section 3.4.4) by estimating the correct azimuth and elevation geometry (zero degree relative azimuth and 45 degrees zenith) for the black panel and vehicle. The reflectance profiles of the truck and panel were measured in-scene using the portal spectroradiometer (see Section 3.4.5). The truck reflectance spectra was sampled from the white paint on the side of the truck.

5.6.1 Grass Background Analysis

The grass image pairs and cropped door panel images are shown in Figure 5.34. The hyperspectral door panel images correspond to the grass only images and they are rendered to both RGB (red, green, & blue) and NRG (near infrared, red, & green) spectral response channels. The door panel images show the implicit background adjacency effects on the side of a white vehicle when it is parked next to grass. The heightened green and NIR presence in the door panel color is due to the application of a linear 2% stretch. The green peak and red-edge can also been seen in the mean observed spectra shown in Figure 5.37.

The difference images formed by subtracting the black panel radiance image from the grass only radiance image are shown in Figure 5.35. In addition to being shown in their entirety, the difference images are also cropped to different ROIs and rendered to both RGB and NRG spectral response channels. Again, each image has a linear 2% stretch applied. The bright squares in front of the vehicle are caused by the radiance reflected from the grass that was not reflected from the black panel. Because the reflectance of the black panel is so much lower than the grass (see Figure 5.33), the difference images are representative of a scenerio in which the vehicle was only illuminated by a 1m x 1m patch of grass.
Figure 5.35: The radiance difference images of the white truck next to grass rendered to RGB (left column) and NRG (right column). The difference images are shown in their entirety (top row), cropped using the large ROI (middle row), and cropped using the small ROI (bottom row). Images have a 2% linear filter applied that maintains the correct color ratio.

The spatial intensity profile of the square patch of grass, reflected from the vehicle side, reveals the specularity of the vehicle BRDF. If the white paint were perfectly specular, the reflection of the grass patch in the vehicle would be perfectly square and the remaining side of the vehicle would be very dark. Conversely, if the vehicle’s surface were perfectly diffuse, the reflected image would resemble a rectangle with a convolution kernel and cosine falloff mask applied where the kernel is in the shape of the GRIT measured BRDF (see Section 3.4.4), centered according to the appropriate geometry, and the cosine falloff mask accounts for the projected area based on the indent angle between the grass patch and the side of the vehicle. Based on the soft edge of the grass patch reflection and the illumination across the entire vehicle side, the difference images are further evidence that the white truck paint exhibits behavior more closely aligned with a diffuse reflector than a specular reflector.

The radiance difference image of the door panel is also shown as a percent difference image in Figure 5.36. The total radiance percent difference of the small ROI difference image is calculated by dividing the total radiance difference image by the average of the two total radiance images and scaling the resulting values by 100. The total radiance of the ROI difference images is calculated by integrating spectrally: i.e. integrating out the 1/nm term in the radiance units. The accompanying histogram shows that most of the pixels have a percent difference of 3-5%. According to Table 5.1, the percent difference of the mean spectra of this ROI is 4.40%.

This 4.40% difference value is significant given that the adjacency effect results from only
a single 1m x 1m patch of grass. As seen in Figure 5.34, the black panel sits beside the front
car door with an equally large spot available next to the rear car door. Assuming a symmetric
illumination profile from this rear patch of grass (as compared to the observed patch) and linear
mixing, the percent difference values should double as a result of illuminating the vehicle with
both patches of grass, raising from 4.40% to 8.80%. Additionally, when more black panels are
laid in more available grass patches, the percent difference should continue to rise, however,
additional panels would not have the same linear/additive effects at the first two. The further
away a panel, the more attenuated the adjacency effect. The fact that a 4% difference is observed
from only a 1m x 1m patch of background suggests that background adjacency effects play a
significant role in the observed radiance and reflectance spectra of a vehicle near vegetation.

The mean observed reflectance spectra of the grass only image and the grass+panel image
are shown in Figure 5.37. Present in both spectra is a significant deviation from the truck
reflectance spectrum caused by grass adjacency effects: there is a green peak around 550nm and
a red-edge around 700nm. The mean observed reflectance difference spectrum is also shown in
Figure 5.37 along with the grass-panel spectrum, truck spectrum, and a spectrum reminiscent
of a sun-grass-truck-sensor propagation path.

5.6.2 Asphalt Background Analysis

The two images used to create the asphalt difference images are shown in Figure 5.38 along with
RGB and NRG rendering of the door panel ROIs. The radiance difference images in Figure 5.39
exhibit the same background adjacency effect as the grass scenario. Again, the entire side of
the vehicle is illuminated by the small 1m x 1m patch of asphalt. Although the effect is more
spectrally flat than the grass scenario and commensurate with the reflectance spectrum of the
asphalt measured by GRIT, there is still a greenish hue in the RGB rendering that is supported
by a green peak in the mean difference spectrum plotted in Figure 5.41. This suggests that
enough of the light follows the propagation path of sun-grass-asphalt-truck-sensor or even sun-
grass-truck-asphalt-truck-sensor that there is a detectable peak around 550nm in the difference
reflectance.
Figure 5.37: Above is the mean reflectance spectrum of the small ROI for the grass only image (blue), grass+panel image (red), and the difference image (yellow). Below is the normalized reflectance spectra of the mean reflectance difference of the small ROI (blue), the grass and panel reflectance difference (red), the truck reflectance (yellow), and a reflectance spectrum representative of a sun-grass-truck-sensor propagation path (purple).

In both the grass and asphalt difference images (Figures 5.35 and 5.39), the tops of the vehicle surfaces are very dark. This evidence supports the hypothesis that the road surface and nearby vegetation adjacency effects are isolated to the sides of a vehicle. The importance of the background adjacency effect is therefore dependant on the zenith look angle of the sensor. The more nadir the viewpoint, the less important it is to consider background adjacency effects. In contrast, the more off-nadir the view point, the greater the background adjacency effect influences the measured vehicle spectrum.

Similar to the grass background imagery, the radiance percent difference for the asphalt background is calculated for each pixel of the small ROI and displayed in Figure 5.40. Again there is an observable rectangular shape at the bottom of the image. While the peak percent difference is around 40%, the percent difference of the mean total radiance is 16.62%, as reported in Table 5.1.

The mean reflectance spectra of the small ROI (door panel) for both asphalt background images is shown at the top of Figure 5.41. When compared to the grass version of this figure (see Figure 5.37), it is clear that the magnitude of the original asphalt spectra are smaller than the grass spectra. Below this plot is the normalized mean difference reflectance spectra of the small ROI for the asphalt background. The reflectance curve closely follows the truck paint reflectance curve except for the noted green peak, potentially caused by nearby grass. Given the
spectrally flat shapes of both the white car paint and asphalt background around 550nm (see Figure 5.33), the nearby vegetation is the only possible explanation for the introduction of this green peak.

5.6.3 Results

The total mean difference metric is calculated by integrating the pixels spectrally and taking a spatial mean in either order. The total mean difference metric is then divided by the average total mean metric and multiplied by 100 to yield the percent difference. This operation is performed for both the radiance and reflectance spectra of both the large ROIs (the entire side of the truck) and the small ROIs (just the front and rear doors). The radiance and the reflectance results are shown in Table 5.1. The percent difference of the small ROI is consistently greater than the large ROI because the illumination caused by the 1m x 1m patch is concentrated in the region of the truck doors. Also, the percent difference of the asphalt background is consistently larger than the grass background, while the magnitude of the average integrated radiance and reflectance is greater under the grass adjacent conditions. One possible explanation for this is that because the grass spectral magnitude is brighter, the black panel is brighter in the grass images than the asphalt images. The brighter panel in the grass images translated to lower intensity difference images and therefore lower percent difference values. This effect is confirmed by taking the mean integrated reflectance of the black panel for both the grass and asphalt images: 6.2% and 4.4% reflectance, respectively.
Figure 5.39: The radiance difference images of the white truck on asphalt rendered to RGB (left column) and NRG (right column). The difference images are shown in their entirety (top row), cropped using the large ROI (middle row), and cropped using the small ROI (bottom row). Images have a 2% linear filter applied that maintains the correct color ratio.

The mean reflectance spectra of the small ROI for all four images is shown in Figure 5.42. While illumination geometry between these two images changes due to a separation in acquisition time of 105 minutes, the calibrated radiance images are normalized by the corresponding scene extracted ground normal total irradiance. The difference in the reflectance spectra is therefore due primarily to the background adjacency effects. The stark intensity difference between the grass and asphalt reflectance spectra is significant given that the vehicle was only moved the length of a parking space between both images. Moving the vehicle from the asphalt to the grass adjacent parking spot results in an integrated reflectance magnitude increase of 3.97 for the small ROI and 2.45 for the large ROI, or a 250% to 400% difference in reflectance, depending on pixel size. This result, and accompanying mean reflectance spectra, demonstrates the broadband importance of accounting for the background adjacency contribution to vehicle reflectance.

The goal of this study is to demonstrate the importance of accounting for the road surface and background adjacency effects when measuring the hyperspectral spectrum of a vehicle in an off-nadir viewing scenario. While the difference images and spectra provide a qualitative
Figure 5.40: The total radiance percent difference image of the asphalt image pair (left) and the intensity histogram of the image (right).

Table 5.1: Background adjacency study percent difference results

<table>
<thead>
<tr>
<th>Material</th>
<th>ROI Size</th>
<th>Radiance Percent Difference</th>
<th>Reflectance Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grass</td>
<td>Large</td>
<td>3.26%</td>
<td>5.13%</td>
</tr>
<tr>
<td>Grass</td>
<td>Small</td>
<td>4.40%</td>
<td>5.41%</td>
</tr>
<tr>
<td>Asphalt</td>
<td>Large</td>
<td>8.03%</td>
<td>17.51%</td>
</tr>
<tr>
<td>Asphalt</td>
<td>Small</td>
<td>16.62%</td>
<td>23.97%</td>
</tr>
</tbody>
</table>

assessment in understanding these adjacency effects, the percent difference metrics demonstrate the quantifiable importance of accounting for the vehicle background. This study shows that when tracking a vehicle using the hyperspectral reflectance spectrum in an off-nadir viewing scenario, spectrum will vary significantly as the vehicle traverses different road surfaces and passes nearby patches of vegetation. Incorporating spatial knowledge about the road surfaces and nearby background, therefore, should increase tracking and reacquisition accuracies when compared to the assumption that the reflectance spectrum is temporally constant. In this manner, by modeling and accounting for these spatial-spectral variations in road surfaces and background, the adjacency effects measured in this study could be compensated for, in order to achieve an illuminant invariant reflectance spectrum.
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Figure 5.41: Above is the mean reflectance spectrum of the small ROI for the asphalt only image (blue), asphalt+panel image (red), and the difference image (yellow). Below is the normalized reflectance spectra of the mean reflectance difference of the small ROI (blue), the asphalt and panel reflectance difference (red), the truck reflectance (yellow), and a reflectance spectrum representative of a sun-asphalt-truck-sensor propagation path (purple).

Figure 5.42: The mean reflectance spectrum of the small ROI for the asphalt only image (blue), asphalt+panel image (red), grass only image (yellow), grass+panel image (purple).
5.7 Summary

The irradiance retrieval closely matched the recorded in-scene irradiance taken by the GRIT Basestation, which suggests the reflectance images and derived spectra are accurate. The retrieved irradiance was then utilized to transform the calibrated radiance images into reflectance images. The reflectance images were then cropped according to two possible scenarios: nadir and off-nadir. The data collection was intrinsically an off-nadir collection, so for the off-nadir scenario, the entire outline of the vehicle was used. The roofs of the vehicles were cropped to represent the overhead vehicle vantage point of a nadir collections scenario. The mean reflectance spectra of the cropped ROIs was utilized to represent a single or several pixel vehicle target size collection scenario in which the sensor GSD is approximatly the size of the vehicle or larger. This is a reasonable assumption because the more contiguous wavelengths into which a system divides the aperture reaching photons, the larger the GSD must be in order to retain a similar SNR.

In order to understand the BRDF distributions of a non-Lambertian material, simulated BRDF samples were constructed using real measured reflectance and irradiance data in addition to MODTRAN derived irradiance data. Examination of the BRDF distributions lead to the understanding of two BRDF characteristics of non-Lambertian materials: a node point about which the spectra vary asymmetrically and water absorption features which yield information about the amount of solar radiance contribution to the observed BRDF.

Through reflectance magnitude analysis, it was shown that the darker vehicles (red and blue) exhibit much greater BRDF variation effects than the white vehicles. This is in line with the results of previous experiments (Gunther el. al. [55]) that characterized the BRDF of multiple vehicle paints and showed that white vehicles are more diffuse than dark vehicles. This effect was greater for the nadir/roof spectra because these signatures exhibited no self-shadowing, no background adjacency effects, and were made of only one material. The principal components subspace models representing these spectral distributions also show a large degree of similarity between the two dark vehicle and the two white vehicles. This suggests that there are two distinct underlying models representing the behavior of the spectra: a white model and a dark model. This is an important realization for practical vehicle tracking applications in which vehicles new to an algorithm (i.e. not trained on or characterized) must be tracked or reacquired. In this scenario, knowledge of a color dependency on BRDF would help aid in the transfer learning between BRDF models.

When the off-nadir spectra were considered, there was a noticeable dependence on BRDF effects towards the end of the day when the camera was closer to the principal scattering plane of the vehicle paint. However, the main contribution to reflectance magnitude was discovered to be the vehicle shape and its interactions with the sun geometry that lead to self-shadowing and glints. In this scenario, vehicle shape and direction were most influential in that the directional dependence on relative reflectance magnitude as a function of time was very similar for all four vehicles, and nearly identical for the two Chevy Sparks. The directional dependence on reflectance at any given point in time has implications for the ability of vehicle tracking and reacquisition algorithms to determine the direction of a vehicle based on a single reflectance spectrum. In addition, knowledge of how a spectrum varies with direction could be leveraged to search for a vehicle, using the directional spectral dependence knowledge in order to perform the
reacquisition/tracking task. For example, if a vehicle came to a four way intersection, the current spectra could be manipulated for each of the three possible directions in order to reacquire the vehicle.

Lastly, the background adjacency effect, resulting from vehicle radiance contributions from the road surface and local environment, was qualitatively shown and quantitatively measured. The effect, which is more important in off-nadir viewing scenarios, was shown to account for a significant amount of the perceived vehicle reflectance spectrum. The scattered light from a small 1m x 1m patch of pavement was shown to alter the mean reflectance spectrum of the entire side of a white truck by 17.5% and the scattered light from a small 1m x 1m patch of grass was shown to alter the reflectance by 5.1%. Additionally, when the white truck was moved the length of a parking space, the reflectance spectra magnitude of the vehicle side changed by 240%. These results demonstrate the importance in accounting for spatial variations in road surfaces and nearby vegetation with respect to a spectrally based vehicle tracking and reacquisition algorithm. If a tracking algorithm failed to account for the 240% magnitude change and spectral shape change caused by moving a white truck into a parking spot near vegetation (per the conducted experiment), tracking accuracies could decline and the vehicle could be lost.
Chapter 6

Sub Pixel Reacquisition and BRDF Learning

6.1 Introduction

In a hyperspectral sub-pixel vehicle tracking and reacquisition scenario, one or more previously imaged vehicle spectra are utilized as an established target feature space in order to spatially localize the same vehicle in subsequent frames. As mentioned in Chapter 1, the spectral vehicle reacquisition problem is a subset of the vehicle tracking problem in which spatiotemporal information is not considered and only spectral measures of similarity are used to derive the new vehicle location. The spectral reacquisition problem is therefore useful in imaging scenarios with both high frame rates and low frame rates (WAMI assets) or low revisit rates (space based assets). This chapter focuses on the sub-pixel vehicle reacquisition scenario in which the sensor GSD is comparable to the size of a vehicle, or larger, such that entire portions of the vehicle are contained within a single pixel. In order to determine the most effective algorithms for performing the spectral vehicle reacquisition task, the observed BRDF reflectance signatures described in Sections 5.4 and 5.5 are implanted into hyperspectral imagery, and various detection algorithms are tested in this artificial environment. Sub-pixel subspace algorithms and graph-based SVM detectors are compared to algorithms that attempt to learn the geometrical structure of vehicle BRDFs using a novel eigenvector loading regression technique.

6.2 Hyperspectral Target Detection Testing Environment

In the field of remote sensing, the term hyperspectral target detection describes an algorithm that calculates a measure of spectral similarity between an established target spectral feature space and the spectrum of a test pixel. These detection algorithms typically require information about both the target and background spectra and produce metrics that indicate the likelihood that a pixel contains the specified target (see Section 2.10). The results of these detection algorithms are reported as receiver operating characteristic (ROC) curves in order to report score-threshold ($\xi$, Equation 2.25) independent detection results; better algorithms typically have larger areas under the curve [85].
In order to test the effectiveness of various sub-pixel hyperspectral target detection algorithms in identifying pixels that contain a specified vehicle, an algorithm test environment is constructed in which target vehicle spectra are implanted into wide area hyperspectral imagery. The idea for this type of algorithm test environment was derived from a paper by Perkins et. al. [61] and the technique is also used by Sundberg et. al. [62] and Bartlett et. al. [59]. The technique is referred to as implantation because the target reflectance spectra are combined with background reflectance spectra from the imagery using a linear mixing model and a specified pixel fill percentage. In this research, only pixel-wise spectral similarity operators are considered and so the pixels are not actually implanted into the imagery; the imagery is vectorized and used as a pool of background pixels.

Four total imaging scenarios are considered in the testing of the target detection algorithms. The two geometrically diverse viewing scenarios (nadir and off-nadir) are combinatorially combined with two methods of temporally dividing the time series reflectance spectra into a training set and testing set. The two different viewing scenarios are described in detail in Sections 5.4 and 5.5. The two temporal sub-division methods are a random assignment method and an AM-PM assignment method. In the random assignment method the reflectance spectra are randomly assigned to training and testing data sets. And in the AM-PM assignment method algorithms are trained on the reflectance spectra imaged during one half of the collect and tested on the reflectance spectra of the other half of the collect. The AM-PM assignment method tests the capability of a detection algorithm to generalize to new reflectance signatures different than those in the training set. As shown in Sections 5.4 and 5.5, due to the temporal correlation in the spectrum variation, the difference between the testing and training reflectance sets are maximized with an AM-PM assignment method. In addition to testing algorithms’ generalization capabilities, the AM-PM reacquisition scenario is an important detection task with practical implications. Training on the AM data set and testing on a PM data set has clear applications in reacquiring vehicles, while training on a PM data set and testing on an AM data set is applicable in WAMI imaging methodologies in which post-event forensics is used to back-track vehicles from a specific incident, effectively tracking a vehicle backwards in time[9].

In the four imaging scenarios tested, k-fold cross validation is used to generalize the reported detection results given the small target set size. For the random target division method, 4-fold cross validation is used, resulting in a training-test data set assignment breakdown of 75% (training) and 25% (testing) for both the background and target pixels. For the AM-PM division method, 2-fold cross validation is used resulting in a 50%/50% breakdown in training set test set size.

Classical hyperspectral target detection algorithms are not typically employed with a breakdown of pixels into testing and training sets. To incorporate this rigid bifurcation into established detectors like ACE, a set of simple rules were followed in the construction of the statistics used in these detectors. If an operation could be performed on all the data without any need to know the class labels, this operation is performed jointly on both the test and training set. Two examples of such operations are the mean subtraction used in the ACE detector and the PCA based dimensionality reduction. However, if class label knowledge is required to perform the operation, only the training set is used to prepare the detector. For example, the creation of a background covariance matrix requires the labeled background pixels, therefore this operation is only performed on the training set. If, however, all the pixels are used to form the background
covariance matrix, the operation can be used across the test and training data sets. This distinction is important when comparing the ROC curves shown in this chapter, generated using labeled training and testing data sets, to other ROC curves in literature. Most ROC curves report the performance associated with detecting a signature using the same signature as the reference spectrum. In this test environment, however, none of the test signatures can be used as the reference spectra, causing the detectors to search for spectra they have never seen before.

Two different sets of hyperspectral imagery taken with two different sensors are used as background pixels in order to create two scene-implant test environments. The first set of imagery was taken of the RIT campus by SpecTIR of Reno, NV on July 29, 2010 as part of the SpecTIR Hyperspectral Airborne Rochester Experiment (SHARE) 2010 data collect [105]. This imagery, shown in Figure 6.2, consists of five passes over the RIT campus taken at a 1m GSD with a 360 band pushbroom imaging spectrometer with a nominal FWHM spectral resolution of 5nm and a spectral range of 390-2450 nm [106, 107]. In order to use the scene implantation method, an atmospheric compensation method was necessary to convert the radiance imagery into reflectance imagery.

For the RIT images, quick atmospheric correction (QUAC) [108] was applied to bring the images into a similar reflectance domain. Next, the empirical line method (ELM) [31] was used in those images in which the calibration panels, with known reflectance, were visible (two of the five images). The ELM coefficients from these two images were then used on the remaining three according to the image acquisition timestamps. The reflectance images were then down-sampled to a GSD of 2m using bicubic interpolation, closer to a sub-pixel imaging regime. The application of QUAC is a necessary pre-processing step in order to use the calculated ELM coefficients across all images and construct a consistent data set. The background pixels do not need to be perfectly accurate, just relatively consistent, in order to test the relative effectiveness of different target detection schemes.

The second hyperspectral data set was taken of the University California, Davis campus and University Airport by HyMap Hyvista Corp. of Sydney Australia on May 31, 2003 [109]. This imagery, shown in Figure 6.3, was taken at a 2.8m GSD with a 126 channel imaging spectrometer with a FWHM spectral resolution of 16nm and a spectral range of 450-2500 nm [109]. The UC Davis imagery was provided by Spectral Sciences Inc. to aid in this study. The FLAASH [32] atmospheric compensation routine was used to calculate reflectance imagery from the calibrated radiance imagery. In total, there are 909,920 RIT background pixels and 1,409,536 UC Davis background pixels available after processing. Statistics for the two sets of background pixels are shown in Figure 6.1.

When the reflectance spectra are “implanted” into the background spectra, great care is taken to assure that higher spectral resolution reflectance spectra are properly sampled according the spectral response functions of the background images. In addition, the $\rho_{BRDF}$ spectra calculated as part of Sections 5.4 and 5.5 are multiplied by $\pi$ according to Equation 2.8 in order calculate a measure of $\rho_{DHR}$ consistent with the reflectance imagery.

There are several intrinsic problems with this type of target implantation test environment. The first problem is the placement of vehicles over unrealistic backgrounds, such as building roofs, water, and vegetation. This problem could be rectified by identifying road pixels and using a mask that only allows implantation at these pixels. This is a tedious task, however, and difficult to perform with larger GSD imagery. The second problem is that the cropped
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Figure 6.1: The standard deviation, mean, and median of the hyperspectral imagery taken of the RIT campus (top) and the UC Davis campus and University Airport (bottom).

Off-nadir vehicle spectra have a significant amount of asphalt and/or grass signal contribution to the observed reflectance spectra due to the background adjacency effect studied in Section 5.6.3. When the reflectance spectrum is “implanted” into the background imagery, it will therefore have an incorrect background adjacency contribution. The third problem is a lack of compensation for the observed vehicle projected area. The amount of sub pixel fill should physically vary with the orientation of a vehicle due to changes in the observed vehicle surface area. When a constant pixel fill percentage is used, these subtle differences in fill factor are lost. This problem could also be corrected with additional book-keeping in the reflectance spectra generation process. The problem is mitigated in this study by giving the algorithms no *a priori* knowledge or assumptions about the pixel fill percentage.

Despite the identified problems with this target detection algorithm test environment, it remains a useful tool in exploring the relative performance between multiple detection algorithms. The goal of the test environment is not to make absolute predictions of algorithm performance for a real-world imaging task, but rather to make relative assessments of algorithm performance in a simulated environment representative of a real-world scenario. Essentially the purpose of the background is to provide a collection of pixels that cause false alarms and allow the comparison of multiple algorithms. For this reason its not imperative that the target implantation process be physically accurate in order to provide a useful algorithm evaluation tool.
Figure 6.2: Hyperspectral imagery taken by SpecTIR over RIT as part of the SHARE 2010 data collect rendered to RGB. The imagery has 360 spectral bands and a GSD of 2m. Shown are 909,920 pixels.
Figure 6.3: Hyperspectral imagery taken by HyMap Hyvista Corp. over UC Davis and University Airport rendered to RGB. The imagery has 126 spectral bands and a GSD of 2.83m. Imagery was provided by Spectral Sciences Inc. Shown are 1,409,536 pixels.
6.3 Subspace Target Detection Results

Several subspace target detection algorithms were tested using the target pixel scene implantation algorithm test environment described in Section 6.2. The tested subspace detectors were the Subspace Spectral Matched Filter (SS-SMF, Equation 2.50), the Subspace Adaptive Coherence/Cosine Estimator (SS-ACE, Equation 2.52), the Subspace Sub-Pixel Generalized Likelihood Ratio Test (SS-SPGLRT, Equation 2.54), and the Subspace Adaptive Generalized Likelihood Ratio Test (SS-AGLRT, Equation 2.55).

In addition to these target subspace detectors, two graph-based manifold learning dimensionality reduction algorithms were used: an unsupervised Laplacian Eigenmap (LE) algorithm and a semi-supervised Schrodinger Eigenmap (SE) algorithm (see Section 2.8). The lower dimensional output of both graph-based functions was followed by a support vector machine which used Gaussian radial basis functions as the kernel (see Section 2.9). The eigenmap functions used a value of $k = 20$ in the KNN search, $\sigma = 0.25$ for the weight calculations, $\beta = 0.25$ for combining the Graph Laplacian and Schrodinger potential matrix, and a dimensionality of 60 was used as input into the SVM. Additionally, the total number of connections used in the Schrodinger potential matrix $M$ were capped to just 1% of the total pixels due to computing resource limitations. This low value explains why the LE and SE results look so similar. The goal of including these graph-based SVM detectors is to see if there are obvious non-linear manifolds upon which the BRDF data resides that would be easily separated using a non-linear graph-based transformation of the data.

For each of the algorithm tests, k-fold cross validation is utilized by averaging the probability of detection for each probability of false alarm. In addition, a background dimensionality was chosen by setting the PCA dimensionality reduction threshold of cumulative variation to 99.95%, resulting in a background dimensionality of 52 for the 360 band RIT imagery and 17 for the 126 band UC Davis imagery. PCA was also used to create the target subspaces by taking the top three eigenvectors weighted according to their eigenvalues. A constant pixel fill percentage of 50% was chosen to adequately test the best performing algorithms while preventing the worse performers from visually collapsing together on the graphs. Finally, a constant value of 5% was chosen as the ratio of target pixels to background pixels.

For brevity, only the results for the blue car and white truck implanted into the RIT imagery are shown in this chapter. These vehicles were selected because they demonstrate the best and worse cases for the BRDF learning algorithm introduced in Section 6.4. In addition, these vehicles are good surrogates for the variety of vehicle BRDFs seen in Chapter 5. The algorithm results for every vehicle implanted into both background images are displayed in Appendix A.

6.3.1 Nadir Scenario

In the nadir imaging scenario, the blue car reflectance varied more than the white truck reflectance (see Section 5.4.2). As seen if Figure 6.4, the SS-ACE detector had a considerably more difficult time detecting the large reflectance shift of the blue car than the more diffuse white truck. In addition, the SS-AGLRT, LE, SE detectors performed consistently better than the SS-SMF and SS-SPGLRT detectors. This relative ordering in algorithm performance will be seen throughout this chapter. One possible explanation is that the SS-ACE and SS-AGLRT
detectors are normalized by a measure of the test pixels amplitude whereas the SS-SMF and SS-SPGLRT detector are not. The normalized detectors are therefore more invariant to changes in broadband spectrum magnitude, characteristic of a distribution of spectra generated by multiple looks of a vehicle’s BRDF. Finally, when comparing the random 4-fold cross validation to the AM-PM 2-fold cross validation, all algorithms show the same relative ordering in performance.

![Figure 6.4](image.png)

**Figure 6.4**: Shown are the sub-pixel subspace algorithm detection results tested on the RIT background imagery using a random 4-fold cross validation target set assignment for (from top to bottom) the blue car, red car, white car, and white truck.

### 6.3.2 Off-Nadir Scenario

In the off-nadir imaging scenario, where the vehicle BRDF was dominated by the vehicle shape and self shadowing effects, all the reflectance spectra exhibited similar, temporally consistent variations. This similarity in variations is reflected in the similarity in algorithm performance between the blue car and white truck off-nadir reflectance spectra seen in Figure 6.5. In this off-nadir scenario, again, the SS-AGLRT, LE, and SE algorithms outperform all other detectors with the SS-AGLRT yielding more consistently superior results than the graph-based SVMs. In both nadir and off-nadir scenarios, the SS-SMF and SS-AGLRT are clearly the worst detectors for this application.
Figure 6.5: Shown are the sub-pixel subspace algorithm detection results tested on the RIT background imagery using an AM-PM 2-fold cross validation target set assignment for (from top to bottom) the blue car, red car, white car, and white truck.

6.4 Eigenvector Loading Regression

The subspace detection algorithms use target subspaces to simultaneously solve for the pixel fill and the eigenvector loadings. These algorithms use techniques like eigendecomposition and end-member determination to model the target signature variability with multiple basis vectors. These models, however, don’t take into account the sun-target-sensor geometry of the BRDF observations. If a detector could incorporate knowledge of where the BRDF observation took place, it could use previous, geometrically similar observations to predict what the reflectance spectrum would look like. BRDF input geometry is a four dimensional space \( \{ (\theta_i, \phi_i, \theta_r, \phi_r) \} \in \mathbb{R}^4 \), Equation 2.1) where a change in vehicle orientation can also be thought of as a rotation in both \( \phi_i \) and \( \phi_r \). Therefore, non-Lambertian reflectance observations could be populated into a four dimensional BRDF look up table and new observations could use interpolation over previous observations. The vehicle BRDF would therefore be characterized, or learned.

In the data collect described in Chapter 3, the source BRDF geometry \( (\theta_i, \phi_i) \) was smoothly varying as a function of time while the sensor geometry was static \( (\theta_r, \phi_r) \), ignoring changes in vehicle orientation. Because the sun never returns to the same position in a given day, the BRDF sampling geometry was a one dimensional manifold embedded in the two dimensional space \( \{ (\theta_i, \phi_i) \} \in \mathbb{R}^2 \). This one dimensional BRDF sampling geometry function can be parametrized as a function of time for this specific collection scenario. Therefore, in the data driven BRDF learning technique described in this Section, time is used as a proxy for geometry with the understanding that the equations can be generalized to use the polar coordinate geometry for more complex BRDF observation scenarios.

During this research it was observed using DIRSIG that the principal component loadings were smoothly varying functions of the BRDF geometry in a vehicle sub-pixel imaging scenario.
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For example, the rotation of a vehicle by a full 360 degrees produces smoothly varying concentric figure eights in the eigenvector “rotated” data space. The phenomena is caused by the smoothly varying changes of relative reflectance contributions as the polar coordinate geometry of the BRDF observations changes. This characteristic of non-Lambertian BRDFs is leveraged by introducing a novel data drive BRDF learning algorithm that performs linear regression across the principal component loadings of the leading eigenvectors (by eigenvalue) of the BRDF observations. This BRDF learning algorithm will be referred to as Eigenvector Loading Regression (ELR), and the steps that describe its execution are as follows:

1. Perform eigendecomposition on the vehicle reflectance data. Truncate the leading n eigenvectors (sorted by eigenvalue).

2. Project the vehicle reflectance training data set onto the n leading eigenvectors to reduce the dimensionality of each reflectance measurement to n dimensions or n eigenvector loadings.

3. For each of the n dimensions, parametrize the eigenvector loadings as a function of time using linear regression.

4. For each reflectance spectrum in the testing data set, use the time-stamp as input into the parametrized eigenvector loading functions to generate a point estimate of the reflectance spectrum in the n dimensional space.

5. Expand the reflectance spectrum estimate to the original dimensionality by multiplying the eigenvector loadings with their associated eigenvectors and adding each component.

6. Use classical hyperspectral matched-filter detectors to search for the estimated spectrum.

If the BRDF geometry samples were not a one dimensional function of time, ELR could be performed across the geometrical polar coordinates themselves. For example, if the source was static and the sensor made reflectance observations across many different azimuths and zeniths, the ELR would be a regression across two variables \( \theta_r, \phi_r \in \mathbb{R}^2 \) and the result would be a smoothly varying two dimensional function. In addition, the dimensionality of the four dimensional BRDF representation could be reduced by using techniques leveraged by standard BRDF models. One technique, for example, describes BRDF relative to the angle between the source mirror direction and observer viewpoint while another technique describes BRDF relative to the angle between the source-observer bisection vector and the surface normal (Ngan et al. recommend the latter [110]).

The results of performing ELR across all the reflectance spectra for the blue car and white truck are shown in Figures 6.6 and 6.7. These results demonstrate the validity of the ELR process by showing how the reflectance spectra smoothly vary as a function of time in lower dimensional space. While these regression results used all the reflectance spectra, during the algorithm execution in the scene implantation test environment only 75% and 50% of the reflectance spectra were used in the 4-Fold Random and 2-Fold AM-PM test cases, respectively. The ELR results indicate that the leading eigenvector loadings are usually positive and greater in magnitude than the loadings of the subsequent eigenvectors. This is because the leading eigenvectors are
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Figure 6.6: Eigenvector loading regression was performed on all test samples for the nadir image scenario. Shown are the normal (left) and normalized (right) regression results for the first three eigenvectors (ordered by eigenvalue). The solid lines are the original eigenvector loadings and the dotted lines are the regression results.

usually associated with broadband intensity changes in the spectral distributions. In addition, in the nadir viewing scenario, the leading eigenvector loading total variation of the blue car is greater than that of the white truck, reflecting previous observations that show the white truck relatively more diffuse than the blue car.

One interesting difference between the nadir and off-nadir ELR results is the smoothness of the first eigenvector loading function. This difference mirrors the results shown in Figures 5.14 and 5.26, and demonstrates a greater reflectance magnitude dependence on the vehicle orientation in the off-nadir imaging scenario. Seen in the first eigenvector loadings of this off-nadir scenario (see Figure 6.7), jumping between orientations introduces error in the form of a non smoothly varying loading function. If more data samples were available, a separate ELR could be performed for each vehicle orientation; however, because of the limited sample size orientation is ignored and error is introduced into the ELR algorithm.

Both physics based and data driven vehicle BRDF learning methodologies attempt to structure a series of BRDF observations into a model used to predict reflectance spectra at new, previously unseen sun-target-sensor geometries. Learning the subspace basis vector loadings is a data driven vehicle BRDF learning technique that requires no physics based assumptions about underlying light interactions. Rather than physics based forward modeling methods that attempt to generate a BRDF-vehicle forward model, eigendecomposition requires no radiative transfer model or target knowledge. This is an advantage in that no vehicle BRDF contribution
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Figure 6.7: Eigenvector loading regression was performed on all test samples for the off-nadir image scenario. Shown are the normal (left) and normalized (right) regression results for the first three eigenvectors (ordered by eigenvalue). The solid lines are the original eigenvector loadings and the dotted lines are the regression results.

component can possibly be left out of a data driven model (for example, there will not be any unaccounted for radiation paths). A data driven model attempts to blindly capture all target variations. There are certain instances, however, where a physics based forward model would be more advantageous in a vehicle tracking and reacquisition scenario. For example, if using a physics based model, a vehicle model and road surface model could be separately maintained such that when a vehicle passes over different road conditions, the adjacency effects measured in Section 5.6.2 could be accounted for by changing only the parameters for the road surface model. Another example of a physics based modeling advantage would be the ability to predict target signature fluctuations due to changes in vehicle orientation, even when those orientations have not been previously imaged. If the vehicle approached a four-way stop, a physics based model could perturb the established reflectance spectrum for each of the possible new directions in order to determine which way the vehicle traveled without having previously observed those orientations. A data driven BRDF model is constrained to information it has observed, and separating out the various contribution factors (the inverse problem) is not feasible. There may be vague correlations between ordered eigenvectors and physical phenomena, but unlike a physics based forward model, the relationships are non-deterministic.

The goal of this section is to investigate the validity of this ELR BRDF learning technique. Iterative least squares regression using bi-square weights is used to determine the polynomial coefficients of degree four that fit lines to the eigenvector loadings as a function of time. The
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three algorithms tested that use the spectrum generated by the eigenvector loading regression process are the Spectral Matched Filter (SMF, Equation 2.33), the Adaptive Coherence/Cosine Estimator (ACE, Equation 2.38), and the Adaptive Generalized Likelihood Ratio Test (A-GLRT, Equation 2.43). For each of these algorithms, ELR is performed using one, two, three, and four leading eigenvectors, and based on these results the optimal number of eigenvectors for each algorithm are selected.

The SMF-ELR results are shown in Figures 6.8 and 6.12, the ACE-ELR results are shown in Figures 6.9 and 6.13, and the AGLRT-ELR results are shown in Figures 6.10 and 6.14. For each of these figures, the ELR results are compared to the corresponding subspace detector and graph-based SVM results. From these ROC curves, and the ROC curves based on the other vehicles and background imagery (see Appendix A), it was determined that the optimal number of leading eigenvectors for the ELR algorithms is dependant on the detection scenario and reflects the benefits and downsides of over fitting and under fitting a data driven BRDF model. For example the 4-fold random set assignment method is best suited for three target subspace basis vectors while the 2-fold AM-PM application is best suited for only one basis vector. This is because the AM-PM method requires the BRDF model to generalize more than the random assignment method in order to detect previously unseen target spectra. In contrast, the random assignment method includes all possible spectral variations within enough random samples, and therefore the model can be closely fit to the training set. The detector results from these optimal ELR detectors and their corresponding subspace variants are then shown together in Figures 6.11 and 6.15.

6.4.1 Nadir Scenario ELR Detection Results

As seen in Figure 6.8, all 4-fold SMF-ELR algorithms outperform the 4-fold SS-SMF for detecting both vehicles, with the exception of a low probability of false alarm scenario for the white truck. For the 2-fold detection scenario however only the simpler target subspace models outperform the SS-SMF detector. This behavior is repeated for both the SS-ACE/ACE-ELR and SS-AGLRT/AGLRT-ELR plots. In each case the simpler BRDF models are the highest performing detectors for the 2-fold AM-PM assignment method while detectors with more leading eigenvectors perform better in the 4-fold random method.

While a majority of SMF-ELR detectors outperformed their corresponding SS-SMF detectors, in both the ACE-ELR and AGLRT-ELR algorithms (see Figures 6.9 and 6.10), the subspace variants of the two algorithms outperform the ELR variants in detecting the white truck. In contrast, for the blue car, similar to the SMF-ELR algorithm, the ELR variants generally outperform their subspace counterparts. This difference in algorithm performance between detecting the blue car and white truck is likely due to the relative difference in sampled BRDF variability observed in the nadir imaging scenario (see Section 5.4.2) in which the BRDF of the white truck varied less than the blue car. Therefore, it appears that the ELR algorithms are best suited to compensate for large changes in vehicle reflectance caused by the vehicle BRDF. An interesting downside of the ELR algorithm is its inability to generalize outlying target reflectance spectra. This can be seen in the non-unity probability of detection for very low probabilities of false alarm, seen in the AGLRT-ELR algorithms for both vehicles (see Figure 6.10). This is likely due to the type of regression chosen for the ELR algorithms which uses re-weighted bi-square
weights to prevent outliers from influencing the smoothness of the regression. The plots of each subspace detector with the optimal ELR variant are shown in Figure 6.11. This figure shows that the AGLRT-ELR algorithm performed best for the blue car target and the SS-ACE performed best for the white truck target.

Figure 6.8: Shown are the SMF-ELR detector results for the nadir reflectance spectra of the blue car (top) and white truck (bottom). The target spectra were implanted into the RIT imagery.

Figure 6.9: Shown are the ACE-ELR detector results for the nadir reflectance spectra of the blue car (top) and white truck (bottom). The target spectra were implanted into the RIT imagery.
Figure 6.10: Shown are the AGLRT-ELR detector results for the nadir reflectance spectra of the blue car (top) and white truck (bottom). The target spectra were implanted into the RIT imagery.

Figure 6.11: Shown are the best detector results for the nadir reflectance spectra of the blue car (top) and white truck (bottom). The target spectra were implanted into the RIT imagery.
6.4.2 Off-Nadir Scenario ELR Detection Results

The real benefit of a data driven vehicle BRDF model is shown in off-nadir viewing scenarios in which the physics based forward models become increasingly complex. In the nadir viewing scenario, the upper vehicle surfaces could be modeled as flat vehicle paint panels. However, in the off-nadir viewing scenario, as discussed in Section 5.5, more complex self-shadowing and background adjacency effects come into play. As seen in Figures 6.12, 6.13, and 6.14, the ELR algorithm variants consistently outperform their subspace counterparts in the off-nadir viewing scenario. This consistent ELR advantage, with the exception of the SMF-ELR at low probabilities of false alarm, is because the ELR algorithms handle non-Lambertian BRDF caused reflectance variability better than the subspace detection schemes. This was also seen in the nadir scenario (see Section 6.4.2) in which the ELR algorithm variants did a better job of modeling reflectance spectra with more variability than the subspace variants. In the nadir scenario, this was observed by contrasting the blue car and white truck detection results. The plots of each subspace detector with the optimal ELR variant are shown in Figure 6.15. From this plot, it is clear that the AGLRT-ELR algorithm performs best when detecting the blue car target and performs equally well as the SS-AGLRT for the white truck target results.

![Graphs showing detection results](image)

**Figure 6.12:** Shown are the SMF-ELR detector results for the off-nadir reflectance spectra of the blue car (top) and white truck (bottom). The target spectra were implanted into the RIT imagery.

As seen in Figures 6.12, 6.13, and 6.14 the 4-fold random assignment method is best suited for a larger ELR target subspace than the 2-fold AM-PM assignment method. This was also seen in the nadir reflectance spectra suggesting that the ELR BRDF model dimensionality preference is independent of the BRDF sample distribution and more dependant on the similarity between the testing set and training set. When the similarity between these sets is large, the target subspace can be fit with a higher degree of precision and when the similarity is low, the target subspace needs to avoid over fitting.

The superior performance of the ELR algorithm variants could be due in part to the fact...
that they are all one-sided detectors, therefore, a negative target spectrum abundance MLE will result in a poor detection score. The subspace detectors, however, use principal components which do not enforce a positivity constraint on the abundance MLE. In contrast, the subspace detectors are two-sided detectors, therefore, a test pixel with a spectrum equal and opposite to one of the target spectra can have a negative pixel abundance MLE that produces a high detection score (a false alarm). One potential way of correcting this behavior in the subspace detectors is to force the abundance MLE for the first eigenvector to be positive. Another way of correcting this two-sided behavior is to utilize end-members as the target space basis vectors rather than eigenvectors of the covariance matrix. End-members, by definition, strictly enforce a positivity constraint on their loadings.

![Figure 6.13](image.png)

**Figure 6.13:** Shown are the ACE-ELR detector results for the off-nadir reflectance spectra of the blue car (top) and white truck (bottom). The target spectra were implanted into the RIT imagery.
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Figure 6.14: Shown are the AGLRT-ELR detector results for the off-nadir reflectance spectra of the blue car (top) and white truck (bottom). The target spectra were implanted into the RIT imagery.

Figure 6.15: Shown are the best detector results for the off-nadir reflectance spectra of the blue car (top) and white truck (bottom). The target spectra were implanted into the RIT imagery.
6.5 Summary

A target pixel scene implantation testing environment was used to test the relative performance of sub-pixel target detection algorithms. This scene implantation methodology took the hyperspectral vehicle reflectance spectra from the BRDF sampling experiment and linearly mixed them with background pixels from hyperspectral imagery taken of RIT and UC Davis. The target spectra were spectrally resampled using the spectral response functions of the sensors that acquired the background imagery. The spectra were then linearly mixed with the background pixels using a 50% pixel fill factor. These pixels were then split into a training and test set according to two detection schemes: 4-fold random and 2-fold AM-PM.

A data driven BRDF learning algorithm was introduced that learns the eigenvector loadings of the vehicle reflectance spectra as a function of time. This parametrized function was then used to estimate the spectrum of a test pixel, and a hyperspectral target detection algorithm was employed to search for the estimated spectrum. This data driven BRDF learning algorithm favored higher dimensional target subspaces in cases where there was greater similarity between the target training set and testing set populations. Similarly, the algorithm favored lower dimensional target subspaces in cases where their was less similarity between the target and training sets. The BRDF learning technique was compared to subspace detectors and a graph-based SVM detector and shown to be optimal in situations of high vehicle reflectance variability. These cases of high reflectance variability correspond to situations of high vehicle reflectance variability. These cases of high reflectance variability correspond to the off-nadir viewing scenario in which the interplay between the vehicle shape and sun created significant BRDF variation, and the dark vehicle nadir viewing scenario in which the specularity of the darker vehicle paint generated the larger reflectance distribution. Finally, the most successful detectors tested where the A-GLRT detector variants that include both the AGLRT-ELR and SS-AGLRT detectors.
Chapter 7

Summary

Hyperspectral vehicle tracking and reacquisition algorithms utilize measures of similarities between previously established vehicle spectral signatures and collections of test pixels in order to successfully perform the tracking or reacquisition task. When these algorithms operate in GSD domains in which a vehicle is equal to or smaller than the IFOV, a vehicle is imaged by a single pixel resulting in a single spatially integrated spectrum. This spectrum includes contributions from all visible vehicle surfaces, a majority of which exhibit non-Lambertian BRDFs. The spectrum also includes contributions from multiple materials, such as glass and car paint. In addition, some of the observed surfaces can experience self-shadowing effects while other surfaces can experience illumination contribution from the road surface and surrounding environment. All of these factors contribute to the observed spectrum and the effective vehicle BRDF. The vehicle level reflectance spectrum is therefore a temporally varying function of sun-vehicle-sensor geometry, road surface reflectance, surrounding environmental reflectance and proximity, and changing weather conditions. The sun-vehicle-sensor geometry changes as a function of the sensor and sun position and relative vehicle orientation, while the road surface reflectance and background contributions change as the vehicle moves about the scene. Characterizing and modeling the vehicle BRDF will help tracking and reacquisition algorithms compensate for these temporal variations in the vehicle reflectance spectrum in order to provide more robust measures of spectral similarity. In addition, understanding the phenomenology of vehicle level BRDF provides insight into the relative importance of its contributing factors and aids in the transferring of characterized BRDFs between different vehicles and road surfaces.

In order to study vehicle BRDF and its contributing factors, a hyperspectral BRDF sampling experiment was executed at the Rochester Institute of Technology (RIT) in which four vehicles were rotated and imaged consistently through a six hour span of time in illumination conditions dominated by direct solar radiation. In order to ensure accurate reflectance spectra throughout the day, several instruments were used to characterize in-scene illumination and measure the reflectance and BRDF of in-scene materials. The vehicles were strategically chosen in order to isolate BRDF effects due to vehicle shape and vehicle color while maximizing overall vehicle diversity. In addition to the BRDF sampling conducted throughout the day, a specific experiment was also conducted to isolate and measure the background adjacency effects caused by the illumination of vehicles from the road and nearby environment. These experiments provided a time series of reflectance spectra for each vehicle in addition to a time series of spectrally
characterized direct and downwelled irradiance. An additional data product of the collect was
the real world positions of each vehicle in 3D space, extracted from the time-lapse imagery using
photogrammetric techniques.

Following the experiments, the hyperspectral images were calibrated using the measured
in-scene irradiance spectra. First, the digital count images were dark frame subtracted, median
filtered, and normalized by the integration time. Next, the VNIR and SWIR images were manu-
ally registered. Following registration, a line dependant VNIR gain correction was calculated by
leveraging overlapping VNIR and SWIR bands. Next, target spectral ROIs were cropped and
used in a novel reflectance factor regression technique in order to adjust for the non-Lambertian
BRDF behavior of the calibration targets. Target leaving radiance was then calculated using
the measured irradiance and measured target panel reflectance and calculated reflectance factor
adjustments. Next, radiance predictions were utilized to calculate the camera response functions
in order to convert the digital count images into measures of radiance. Finally, the VNIR and
SWIR images were fused into single hyperspectral data cubes.

In order to understand the characteristics of a distribution of non-Lambertian reflectance
spectra imaged at a diverse array of sun-target-sensor geometries, simulated spectra were gener-
ated. These spectra were created by varying the direct solar illumination component of the inci-
dent illumination using both MODTRAN generated and real-world measured irradiance spectra.
This analysis revealed two characteristics seen in the BRDF reflectance spectra measured in the
BRDF vehicle sampling experiment: a node point seen in the normalized reflectance spectra and
a water absorption feature caused by differences in the relative water absorption between the
director solar and downwelled irradiance. Both features could be used by a vehicle reacquisition
and tracking algorithm to remotely probe a spectrum or series of spectra to determine whether
on not they exhibit non-Lambertian behavior.

The in-scene measurement of irradiance was only conducted for a subset of the total im-
age acquisitions. Therefore, a procedure for extracting estimates for the total irradiance using
the imaged calibration targets was utilized in order to generate reflectance imagery. The re-
fectance imagery of the vehicles was then cropped according to either a nadir or an off-nadir
imaging scenario, and the spectra of each ROI were averaged into a single spectrum. Analysis
of these spectra revealed fundamental differences between the two imaging scenarios. The nadir
reflectance spectra demonstrated a strong dependence on the paint BRDF and a weak depen-
dence on vehicle orientation, whereas the off-nadir spectra demonstrated a weak dependence on
the paint BRDF and a strong dependence on vehicle orientation and vehicle color. These results
agreed with the hypothesis that in a nadir imaging scenario concentrated on the upper vehi-
icle surfaces, orientation is less important given that the vehicle can be approximately modeled
as a flat static target, while in an off-nadir imaging scenario, self-shadowing and background
adjacency effects play a greater role in the vehicle BRDF.

It was also shown that the BRDF of the white vehicles in the nadir imaging scenario exhibited
similar, more diffuse behavior than the darker vehicles. This observation lead to a study of
commercial vehicle paint in which a weak functional relationship between the relative diffuseness
of commercial vehicle paint and total DHR was observed using real-world measured vehicle paint
BRDF coefficients (measured by Gunther et. al.[55]). Even though the paint surfaces of the white
and dark vehicles appear glossy and specular, the study validated the nadir BRDF observations
that showed that white vehicle paint has a very small sharp specular lobe due to the clear
coat Fresnel reflection, but otherwise behaves like a Lambertian reflector. This type of linear relationship between vehicle specularity and total DHR has useful implications for a vehicle tracking and reacquisition algorithm. Indeed, if an algorithm tries to fit a series of reflectance signatures to a set of previously characterized vehicle BRDFs, it could use the total DHR of the vehicle to probabilistically weight the BRDFs based on their relative diffuseness.

Despite the fact that they were different colors, the BRDF analysis also showed a significant similarity in the relative ordering of the reflectance spectra between the two Chevy Sparks in the off-nadir imaging scenario. This observation gives further standing to the conclusion that vehicle shape is a dominating factor in off-nadir imaging scenarios in which self-shadowing and background adjacency effects appear to dominate the BRDF. The two vehicles appeared to share the same off-nadir BRDF model separated by a simple linear transformation. This striking similarity between the two cars, despite their differences in paint BRDF seen in the nadir imaging scenario, suggests the possibility of transfer learning between the same car models of different colors. This implication is important for vehicle tracking and reacquisition algorithms because it would mean that a small, diverse subset of differently shaped vehicles of a single color could be used to model the BRDF of a larger vehicle population. This is an important characteristic of a realistic tracking system given that characterizing every make, model, and color every year is an intractable solution to characterizing real world vehicle BRDF.

The results of the background adjacency experiment showed a strong vehicle illumination contribution from the adjacent horizontal surfaces. The experiment was conducted on both grass and asphalt surfaces. This adjacency effect was measured by taking the per pixel difference of two radiance images of a white truck with and without a small 1m x 1m black panel placed on the ground in front of the front-door panel. The radiance difference imagery, therefore, characterized the target leaving radiance resulting from a small 1m x 1m patch of grass or asphalt. The results showed a percent difference in vehicle reflectance of 24% and 5% for the asphalt and grass surfaces and a 240% difference in vehicle reflectance between the asphalt and grass surfaces. Thus, if a vehicle reacquisition and tracking algorithm did not account for such a dramatic change in spectral shape and magnitude, it would lose track of a white vehicle after it pulls into a parking space.

A scene implantation test environment was constructed in order to test the relative effectiveness of several target detection algorithms. In this test environment the nadir and off-nadir vehicle reflectance spectra were divided into a testing set and a training set according to two possible assignment methods: a random method that randomly assigned the reflectance spectra and an AM-PM method that divided the spectra into two groups according to image acquisition time stamp. Hyperspectral background imagery of RIT and UC Davis was also divided into a training and testing set. The test spectra were then implanted into the test background using a 50/50 linear mixture model a cross-validation was used to make up for the small target sample sizes. The background imagery was selected to have a large number of vehicles in the field of view in order to generate false alarms in the detectors.

Several algorithms were compared in the scene implantation test environment. These tested algorithms included subspace detection algorithms, the ELR data driven BRDF learning algorithms, and graph-based SVM algorithms. The results showed that the AGLRT-ELR and the SS-AGLRT were to most successful algorithms tested. Furthermore, the results showed that the ELR algorithm was best suited for applications of higher reflectance variability due to a
CHAPTER 7. SUMMARY

non-Lambertian vehicle BRDF. These cases of high reflectance variability correspond to the off-nadir viewing scenario in which the reflectance changed significantly due to self shadowing effects and the dark vehicle nadir viewing scenario in which the less diffuse vehicle paint caused the strong variations in reflectance.

A data driven BRDF learning algorithm was introduced that learns the eigenvector loadings of the vehicle reflectance spectra as a function of time. This parametrized function was then used to estimate the spectrum of a test pixel, and a hyperspectral target detection algorithm was employed to search for the estimated spectrum. This data driven BRDF learning algorithm favored higher dimensional target subspaces in cases where there was greater similarity between the target training set and testing set populations. Similarly, the algorithm favored lower dimensional target subspaces in cases where their was less similarity between the target and training sets. The BRDF learning technique was compared to subspace detectors and a graph-based SVM detector and shown to be optimal in situations of high vehicle reflectance variability.

The goal of this research was to study the contributing factors and phenomenology of vehicle BRDF. In order to do so, a BRDF sampling experiment was planned and executed at RIT. The HSI radiance data had calibration problems so the data was re-calibrated from digital counts using in-scene methodologies. The sampled BRDF and background adjacency results provided practical insights into the nature of vehicle BRDF, vehicle paint BRDF, and the relationship between nadir and oblique collection scenarios. Finally, a data driven BRDF learning algorithm was proposed and demonstrated to be more effective than the current state-of-the-art subspace detection algorithms and an optimized implementation of a graph-based semi-supervised manifold learning algorithm.
Chapter 8

Future Studies

8.1 Towards a Vehicle Tracking Algorithm

Many possible paths of further exploration exist as a result of this research. A clear application based continuation of this work is the development of a vehicle tracking algorithm that dynamically adjusts its internal BRDF model of the vehicle being tracked according to the ambient illumination conditions caused by clouds, road surfaces, and the nearby environment. Such an algorithm would need to be able to dynamically generate a BRDF model for new vehicles, previously unseen and therefore uncharacterized. The algorithm would therefore need a database of vehicle BRDFs from a diverse sampling of vehicle shapes, sizes, paints, and surface dirt/mud contamination, representative of the vehicle population upon which the algorithm is to be deployed. The BRDF database would also need to contain information about how each BRDF model changes with respect to the different illumination conditions such as road surfaces.

There are two obvious avenues for the creation of a vehicle BRDF database: a modeling based database and a measurement based database. A facet-modeling approach would utilize DIRSIG to generate a large collection of \textit{a priori} vehicle BRDFs that would comprise the database. In addition, modeling could also be used to dynamically adjust the BRDF model based on the changing illumination conditions. Modeling could even be used to sample the BRDF at the necessary geometries, preventing the need to store the entire realization of the vehicle BRDF. If a modeling approach is pursued, however, it would be important to validate the models using real-world collected imagery. The high resolution BRDF sampling experiment conducted as a part of this research with the associated vehicle positions, facet models, cloud cover maps, and spectrally characterized illumination and background BRDF could be used for this type of model validation (see Chapter 3).

A measurement based approach would involve conducting real world measurements of actual vehicles. This could be accomplished in an uncontrolled environment, similar to the BRDF sampling collect described in Chapter 3, or a controlled environment, such as a gymnasium, where the illumination sources can be manipulated. Another example of a controlled measurement environment is outdoors on a moonless night, away from contaminating illumination sources. The speed of these BRDF sampling collects could be increased by placing the vehicles on a car dealership type turntable in order to more quickly sample the BRDF at different orientations. The speed of the collect could also be increased by using a quad-copter style drone equipped...
CHAPTER 8. FUTURE STUDIES

with a gimbaled camera that is programmed to fly a route that samples the angular hemisphere of the vehicle. Another potential solution to speed up the BRDF acquisition rate in a controlled environment would be to image scaled diecast model replicas of vehicles, painted with real automotive paint and imaged in a laboratory. If using diecast models, however, a study would need to be conducted in order to validate the efficacy of such an approach.

Rather than using point estimates of BRDF from a BRDF database, established BRDFs could be used as basis functions to describe new vehicles. This approach could interpolate between the characterized BRDF models using a lower dimensional vehicle BRDF manifold space, similar to Locally Linear Embedding [75]. This treatment of vehicle BRDFs would be similar to research performed by Matusik who characterized over 100 BRDFs and explored the manifolds in which those BRDFs exist [46]. Knowledge about this manifold space could be increased by better understanding the structural manifold space in which the shape and size of commercial vehicles exist. That assumption is based on this research, which showed a strong functional relationship between vehicle shape/size and vehicle BRDF, especially at off-nadir imaging scenarios (see Section 5.5.2). One potential study that could aid in the understanding of this relationship between vehicle shape/size and vehicle BRDF would be to use structural linear or non-linear PCA on a diverse set of vehicle facet models. By setting common control points of facet models, such as front and rear windshield corners, headlights, side-mirrors, front and rear licence plates, and tires, a distribution of data points could be used to determine the manifold in which vehicles structurally exist. Relating such a structural manifold to a BRDF manifold would assist in the accurate interpolation between BRDF models and improve the matching of a new, previously uncharacterized vehicle BRDF to the database populated BRDFs. An interesting corollary of this study would be the characterization of the transfer functions between the BRDFs of similary shaped vehicles that are different colors, as was observed in this research (see Section 5.5.2).

In order to increase the accuracy of the described BRDF database dependant vehicle tracking algorithm, additional measurements of regionally specific vehicle populations could be made in order to populate the prior probability distributions of the BRDF/structural manifold space. For example, if deploying the vehicle tracking algorithm to Rochester, NY, knowledge about the distribution of vehicles in the city of Rochester would aid in the probabilistic BRDF data association task necessary to compare the observed BRDF signature to the previously characterized BRDF signatures. Examples of regionally specific vehicle population features include the relative amounts of various vehicle colors and classes, the relative type and amount of soil contaminants on those vehicle surfaces, and the population of vehicle colors and associated vehicle paint BRDFs. These populations could be derived from both real world observations as well as regionally specific vehicle sales history.

Finally, a natural extension of using a BRDF database dependant tracking algorithm is the ability to classify the sub-pixel vehicles being tracked. The algorithm could utilize the proximity of the observed BRDF to previously characterized BRDFs of known vehicles in the BRDF/structural manifold space in order to estimate human useable features about the vehicle such as the vehicle class (truck, sedan, pickup, etc.), vehicle color, vehicle make and model, and potentially even the vehicle year.
8.2 A Forward Model Based BRDF Learning Algorithm

In this research, a data driven BRDF model was proposed that learns the leading eigenvector loadings of the spectral distributions as a function of sun-target-sensor geometry. While data driven models are capable of modeling any structural variation in the vehicle BRDF, regardless of any human intuition of what radiative transfer operations are occurring, data driven models fail to generalize to new scenarios previously unseen by the learning algorithm. For example, if a data driven algorithm has not observed a unique reflectance signature, it will be unable to predict that signature. A forward modeling approach, however, uses a physics based model of the vehicle and illumination sources to predict the BRDF and thereby the reflectance signature. A forward model has the benefit of generalizing to sun-target-sensor observation geometries previously unseen.

If a parametric BRDF forward model were used for the BRDF learning process, regression would be used across the observed reflectance spectra in order to determine the underlying parameters. For example, a simple Ward BRDF model could be used to model the nadir scenario reflectance spectra presented in Section 5.4 by learning the underlying Ward BRDF parameters. These parameters could then be utilized to predict the vehicle reflectance at any sun-target-sensor geometry. The nadir scenario is a limiting case in which the vehicle BRDF can be modeled as a flat surface. A parametric forward model for the off-nadir imaging scenario would prove to be more difficult in that it would need to account for self-shadowing effects, multiple materials, and background adjacency effects.

8.3 Improving Sub Pixel Vehicle Target Detection Schemes

Both subspace and single spectrum sup-pixel target detection algorithms were explored in Section 6.3. It is clear that subspace detection algorithms have the advantage of modeling the target reflectance variability inherent in a non-Lambertian target. These algorithms, however, utilize target abundance MLEs to determine the signature basis vector loadings that include both the pixel fill and the basis vector loading. Therefore, knowledge of the basis vector loadings alone will not aid in the determination of this coefficient without also having knowledge of the pixel fill.

This pixel fill could be estimated from the sensor GSD and the predicted vehicle size. The vehicle size could be predicted using a probabilistic BRDF database association as previously discussed, or by calculating an MLE estimate for the amount of background present in the pixel and calculating the target pixel fill as one minus the background pixel fill. The background spectrum could be obtained from neighboring pixels with no vehicle present. This research only evaluates single pixel representations of the sub-pixel vehicle reflectance. However, no matter what the sensor GSD, there is always a possibility that the vehicle reflectance is divided into to neighboring pixels. Therefore, in a realistic tracking scenario, the spatial relationships between neighboring pixels must also be accounted for when estimating vehicle pixel fill and detection scores. Knowledge of both the target pixel fill and the basis vector loadings could be jointly utilized to increase detector accuracies.

Another weakness of subspace detectors occurs when the basis vector loadings are allowed to be positive and negative, as is the case with a linear PCA decomposition of the target spectra
distribution. When the loadings are allowed to be negative, a two-sided detector is created which will score the negative of the target spectrum the same as the actual target spectrum. To rectify this short coming in subspace detection schemes, the use of end-member basis vectors should be explored, which strictly enforces a positivity constraint on the end-member loadings. In addition, because the first eigenvector of a PCA decomposition is typically associated with the broadband intensity variation of the reflectance spectra, the MLE estimate for the first eigenvector could be checked for positivity, and if the value is negative, the test spectrum would be classified as background.

There exist several possible paths of improving the ELR detection algorithm introduced in Section 6.4. The first potential improvement is to incorporate the vehicle orientations into the regression process for the off-nadir imaging scenario vehicle reflectance spectra. In the implementation described in this research, the vehicle orientation was ignored, which introduced errors into the regression process. Another potential path for improving the ELR detectors is to explore the results of using non-linear methods to determine the vectors that span the target subspace. Similarly, end-member basis vectors could also be explored.
Appendix A

ROC Curves

A.1 Nadir Imaging Scenario
Figure A.1: Shown are the subspace and graph-based detector results of the 4-fold random test for the nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.2: Shown are the subspace and graph-based detector results of the 2-fold AM-PM test for the nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.3: Shown are the SMF-ELR detector results of the 4-fold random test for the nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.4: Shown are the SMF-ELR detector results of the 2-fold AM-PM test for the nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.5: Shown are the ACE-ELR detector results of the 4-fold random test for the nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.6: Shown are the ACE-ELR detector results of the 2-fold AM-PM test for the nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.7: Shown are the AGLRT-ELR detector results of the 4-fold random test for the nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.8: Shown are the AGLRT-ELR detector results of the 2-fold AM-PM test for the nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.9: Shown are the best performing detector results of the 4-fold random test for the nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.10: Shown are the best performing detector results of the 2-fold AM-PM test for the nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
A.2 Off-Nadir Imaging Scenario

Figure A.11: Shown are the subspace and graph-based detector results of the 4-fold random test for the off-nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.12: Shown are the subspace and graph-based detector results of the 2-fold AM-PM test for the off-nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.13: Shown are the SMF-ELR detector results of the 4-fold random test for the off-nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.14: Shown are the SMF-ELR detector results of the 2-fold AM-PM test for the off-nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.15: Shown are the ACE-ELR detector results of the 4-fold random test for the off-nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
APPENDIX A. ROC CURVES

Figure A.16: Shown are the ACE-ELR detector results of the 2-fold AM-PM test for the off-nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
APPENDIX A. ROC CURVES

Figure A.17: Shown are the AGLRT-ELR detector results of the 4-fold random test for the off-nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.18: Shown are the AGLRT-ELR detector results of the 2-fold AM-PM test for the off-nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.19: Shown are the best performing detector results of the 4-fold random test for the off-nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Figure A.20: Shown are the best performing detector results of the 2-fold AM-PM test for the off-nadir reflectance spectra of the blue car, red car, white car, and white truck (top to bottom).
Bibliography


