Using a New GUI Tool to Leverage LiDAR Data to Aid in Hyperspectral Image Material Detection in the Radiance Domain on RIT SHARE LiDAR/HSI Data

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ABSTRACT
This paper looks at a data set, called the SHARE 2010 collect, that has been designed to analyze the various impacts of illumination change on materials. Similar fabric materials were placed on different backgrounds where spectral signatures were analyzed to determine impacts of background adjacency. Hyperspectral, multispectral, and LiDAR modalities were used to image the panels in the above mentioned scenarios. Applications such as material detection with results are used to assess difficulties with finding such panels. The incorporation of point LiDAR data sets and physical models will aid in approximating the correct per-pixel signature to be used in the above mentioned detection scheme. This technique can help mitigate issues related to varying illumination across a scene. All of the processing (i.e., LiDAR, MODTRAN, HSI and detection) is performed in a new GUI tool which runs in the ENVI software.

Keywords: Physics based modeling, Material detection, Hyperspectral imaging, Atmospheric Propagation, Radiance, Illumination, Shadows, LiDAR

1. INTRODUCTION

Traditional material detection involves the use of atmospheric compensation routines to provide estimates of ground leaving reflectance retrievals. It is here, in this domain, that measured material reflectances are used in signature matching schemes with the compensated data. In general, compensation approaches work best when illumination conditions are constant across a scene. Dark shadow-like regions will tend to have greater error if not accounted for in the compensation model. This holds true for basic in-scene methods as well such as the empirical line method, where typically two radiance / reflectance pairs are used in the compensation. Piecewise approaches improve upon this in-scene result. Using an alternative forward physics based approach, one models the sensor reaching radiance given a material reflectance. The model, introduced in Section 2.1, has the ability to, not only model a sensor-reaching radiance spectrum for a reflectance signature in the open, but is generic enough to adapt to changes in (colored) illumination (per-pixel) due to shadowing and decreases in indirect illumination sources. Shadowed spectra have been shown to be different, not only in magnitude to fully exposed pixels, but in spectral character as well. This can impact detection results. The model additionally incorporates spectral adjacency contributions, which can additionally impact results (as will be shown in Section 3).

Specifically, this paper demonstrates a method where we obtain geometric scalars from LiDAR data to constrain the forward model, thus leading to an improved material detection of panels in open and shadowed regions. Geometric scene information, which impacts per-pixel illumination loading, is leveraged from facetized, co-registered, point cloud LiDAR data, in a per-pixel manor. This method of incorporating spatial information into the forward model has been demonstrated in the past on co-registered synthetic imagery and has demonstrated significant improvement in the of modeling of material dependant radiance pixels.

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2. BACKGROUND AND THEORY

2.1 Forward Model

The (simplified) forward model or estimate of the sensor-reaching radiance, excluding self-emission and the sensor response, used for this research is based on one used by Schott \(^4\) and is of the form

\[
L(x, y, \lambda) = kE_s(\lambda) \cos(\theta_s) \tau_d(\theta_s, \phi_s, \lambda) \frac{\rho_d(\lambda)}{\pi[sr]} \tau_u(\lambda) \\
+ FE_d(\lambda) \frac{\rho_d(\lambda)}{\pi[sr]} \tau_u(\lambda) \\
+ L_u(\lambda) + E_{adj}(\lambda) \frac{\rho_d(\lambda)}{\pi[sr]} [Wm^{-2}sr^{-1}\mu m^{-1}]
\]

where \(L(x, y, \lambda)\) is the spectral radiance in units of \([Wm^{-2}sr^{-1}\mu m^{-1}]\), \(k\) is a scalar used to modulate the direct illumination source, \(E_s(\lambda)\) is the exoatmospheric spectral irradiance from the Sun in units of \([Wm^{-2}]\) at a zenith angle of \(\theta_s\), \(\tau_d(\theta_s, \phi_s, \lambda)\) is the spectral transmission through the atmosphere along the Sun-target path at position \((\theta_s, \phi_s)\), \(\frac{\rho_d(\lambda)}{\pi[sr]}\) is the Lambertian BRDF in units of \([sr^{-1}]\) analogous to the diffuse hemispherical reflectance (DHR), \(\tau_u(\lambda)\) is the spectral transmission along the target-sensor path, \(F\) is the fraction of the spectral irradiance \(E_d(\lambda)\) from the sky incident on the target (i.e., not blocked by adjacent objects), sometimes called shape factor or sky-view factor, \(L_u(\lambda)\) is the spectral upwelling radiance that does not interact with the target \(\rho_s\), \(E_{adj}(\lambda)\) is the spectral irradiance due to adjacency effects and \(\frac{\rho_d(\lambda)}{\pi[sr]}\) is the Lambertian BRDF of the background in units of \([sr^{-1}]\). The spectral transmission factors \(\tau_u(\lambda)\) and \(\tau_d(\lambda)\) are computed from the optical depths \(\delta\), as

\[
\tau = e^{-\delta} = e^{-\beta_{ext}z}
\]

where \(\beta_{ext}\) is the extinction coefficient (accounting for the sum of absorption and scattering) and \(z\) is a particular path length, typically a small segment path length in a layered atmosphere. Specifically, the geometric parameters of interest used to control per-pixel illumination are \(k\), \(\theta\), and \(F\).

2.2 ENVI Plug-in Detection GUI

In this section, we briefly discuss the detection GUI’s three modes of operations (see Figure 1). These modes are atmospheric look-up-table (LUT) creation, LiDAR product map creation, and material detection in imagery. The MODTRAN LUT Creation tab is used to run the atmospheric radiation propagation code MODTRAN. The user provides metadata about the scene and collection geometry in the form of water vapor scaling, atmospheric visibility, sensor elevation, and any background type used to account for adjacency effects. This approach has been successful in the past in modeling the sensor-reaching radiance.\(^5\) Variation in parameters (i.e., a range) is also allowed. This in-turn, creates a stored radiance look-up-table that is used to model a radiance pixel in the image. Other information such as image, map, and reflectance signature absolute directory paths in addition to day of year, time of day, latitude, and longitude are stored in an ASCII configuration file, which is read into the GUI.

2.2.1 LiDAR Processing

The Map Creation tab of Figure 1 is used to to generate the various illumination maps from user provided LiDAR point cloud data (results shown in Section 3.1). These maps are used to estimate per-pixel shadow values, sky illumination values, and terrain angle values relative to the solar disc. Both the shadow and sky-illumination maps are created through a simple projective geometry approach.\(^6\) The shadow map is used to alter the direct loading term of Eq.(1), i.e., \(k\), such that pixels found to be in shade zero out the direct solar illumination term. The sky illumination map is used to generate an estimate of per-pixel sky loading or in-direct loading. This value is then used to appropriately scale the in-direct terms in the forward model of Eq.(1), i.e., \(F\). This computation is very similar to that of the shadow technique except it is not run in a single direction to the sun. Instead, the hemisphere is broken up into N-quads where a computation is executed to determine if the portion of the sky can be seen or not. The end result is a per-pixel scalar estimate of the viewable sky, as seen from the pixels point.
of view. As one might assume, this calculation is a bit more computationally intensive than the single direction shadow approach. The per-pixel values the code generates range from zero to one where $F = 1$ is analogous to the pixel seeing the entire hemispherical sky above. The pixels closest to buildings are dark because the object is essentially blocking the pixels view of the sky.

2.2.2 GUI Material Detection Tab

The detection tab has two distinct detection approaches: global and local. Global simply means no local illumination information is taken into account. In this mode, the user can manually adjust the amount of shadow, sky visibility and surface illumination angle, scene-wide. That is, the values are used for every pixel in the scene. Conversely, a local approach dynamically figures out what the shadow, sky visibility, and surface angles are, on a per-pixel basis. A full material vector space can be used for detection in addition to simply computing the mean vector of the space with or with out sub-space processing. Finally, a variety of common off the shelf detection schemes are available in addition to the GUI writing out some ancillary information files (i.e., check boxes) for additional analysis.

2.3 Test HSI and LiDAR Data

The data used in this research was collected by the Rochester Institute of Technology (RIT) under the SpecTIR Hyperspectral Airborne Rochester Experiment (SHARE) program. This data was collected over the Rochester, New York area on July 26-29, 2010.

2.3.1 ProSpecTIR-VS2

The hyperspectral imaging sensor flown was from SpecTIR, LLC, and was configured to collect from 390 to 2450 nm, for a total of 360 bands (5 nm spectral resolution and a FWHM of 3.8 to 8.5 nm). The data was fully calibrated by SpecTIR. The resulting HSI data from SpecTIR was delivered in the ENvironment for Visualizing Images (ENVI) format. An RGB visualization of the area of interested for this research can be scene in Figure 2(a) along with the corresponding DEM shown in Figure 2(b). Calibrated radiance and ATCOR compensated reflectance imagery was provided.

2.3.2 Leica ALS60 LiDAR System

During the collection campaign, Kucera International flew and operated a Leica ALS60 (Airborne Laser Scanner 60) Light Detection and Ranging (LiDAR) system. The Leica ALS60 is a scanning mirror LiDAR mapping system, which operates with a 1064 nm laser. It has built a in inertial navigation system (INS) to provide fully registered 3-D LiDAR data once processed and delivered in the common LiDAR Data Exchange Format (*.LAS) by Kucera. A facetized version of the LiDAR data used for this research (with and RGB texture map draped on
top) can be seen in Figure 3(a). We can clearly see the locations of various red and blue felt materials. Ground photos illustrate the level of illumination at the time of collect, as can be seen in Figure 3(b).

Figure 2. (a) RGB channels from the SHARE 2010 hyperspectral image cube and (b) the corresponding digital elevation model (DEM).

Figure 3. (a) Facetized LiDAR point cloud with RGB texture map draped on top and (b) ground photos of red and blue felt materials in full illumination and full shade.

2.4 Spectral Reflectance Signatures

The ground spectral reflectance of various materials was measured with an Analytical Spectral Devices FieldSpec Pro Spectroradiometer and a lab based CARY 500 Spectrophotometer. Reflectance and full sky irradiance measurements were taken during and shortly after the campaign by two measurement teams using one of two FieldSpec Pro Full Range (FR) spectroradiometers made by Analytical Spectral Devices (ASD), Incorporated. The VNIR detector was a 512-channel silicon photodiode array covering a wavelength range of 350 - 1050 nm with a full-width half-max spectral resolution of approximately 3 nm. The SWIR component of the field spectrometer utilized two indium gallium arsenide (InGaAs) scanning spectrometers. The first SWIR detector covered 900-1850 nm and the second 1700 - 2500 nm. Both SWIR detectors had a nominal spectral resolution between 10 - 12 nm, which was dependent on the scan angle. Spectral reflectance information was collected from materials both in-field and in the laboratory using the ASD FR FieldSpec Pro and the CARY 500. Example spectral reflectances used in this study can be seen in Figure 4.

2.4.1 Image and Material Information

The data collected over the RIT campus was approximately 1 meter GSD for the LiDAR and HSI sensors. The materials themselves were large fabric tarps made of 100 percent cotton / felt dyed either red or blue and sized either 4m$^2$ or 9m$^2$. The fabrics were placed on grass, roof tops, near buildings, and under trees. Additionally there were sub-pixel fabrics. These were also made of 100 percent cotton or polyester dyed either red or blue, cut to about 15 cm squares. The squares were mounted on plywood painted flat black and positioned such that they would achieve a 0.25m$^2$ pixel fill. Ground photos of the various red and blue materials were shown in Figure 3(b). As can be scene, some of the materials were in the open with full illumination while others were in the shadow along side of a building.
3. RESULTS

The following results section is broken up into three parts. Results of LiDAR point cloud processing, radiance signature model matching, and actual material detection results on the SHARE 2010 data set.

3.1 GUI Generated Maps From LiDAR Point Cloud Data

The GUI reads in the LiDAR point cloud data as a standard .las file. The point cloud data is then facetized or rasterized so as to be used as input to the forward projective geometry algorithm. The algorithm simply maps the data from a three-dimensional object space to a two-dimensional view plane where a horizon-based visible surface test is performed. In one version, which looks in the direction of the solar disk, pixels are either labeled shadow or not shadow, as can be seen in the shadow map result of Figure 5. This image correlates very well with the shadows found in the RGB image of Figure 2(a) and is used to modulate \( k \) in Eq.(1). In addition to shadow, the terrain angle, relative to the solar pointing unit vector, is computed, as can be seen in Figure 5(b). This image is used to account for any per-pixel illumination project area effects by modifying \( \theta \) in Eq.(1).

Finally, the forward projective geometry approach is modified slightly and used again to account for sky illumination loading, as described in Section 2.2.1. Figure 6(a) shows the results of breaking the hemisphere up into 8 quads while Figure 6(b) illustrates the result of dividing up the hemisphere into 64 quadrants. We can clearly see the vast improvement in Figure 6(b) by noticing the smoothness across the image.

3.2 Radiance Signature Model Matching

In this section, we analyze the spectroscopic result of the model in Eq.(1) at the various locations of the materials in the image. Figure 7 compares the blue felt panels in both the open (i.e., full illumination) and shade to the radiance model estimate at the pixel location incorporating local illumination information from the LiDAR processed maps. We can see that the shadowed pixel has a better model fit than that of the open pixel. The lack of fit could be due to calibration errors, but that would impact both signatures, thus that is probably not the source of error. The fit for the pixel in the open is very good in the VIS / NIR and is slightly larger than
the actual pixel in the SWIR. The fit for the blue shadowed pixel is good at all wavelengths. It is clear that the blue panel in the open is different both in magnitude (an order of magnitude) and in spectral character to that of the blue panel in the shade.

Interestingly enough, we see the opposite trend when model matching the pixels containing the red fabric, as seen in Figure 8. Here, the open pixel model fits very well to the actual pixel while the shadowed pixel model is slightly larger in the VIS and NIR regions. Overall, however, it is encouraging to note that updating the forward radiance model of Eq.(1) with the per-pixel map information provides us with a better estimate of how the signature should appear to the sensor, whether it be in full illumination or full shade.

### 3.3 GUI Material Detection

In the following section, we analyze the results of running an off-the-shelf detection scheme, such as the spectral angle mapper (SAM), on various methods of preparing data. We initially use the spectral angle between vectors to see if our dynamic forward model is creating more accurate estimates of radiance pixels containing blue and red fabrics. In all cases, we start by using an in-scene approach on reflectance data (compensated with ATCOR), followed by standard matching with a lab measured reflectance spectrum to compensated data, and end with
the local detection approach on radiance data. Analysis is in the form of a visual detection image and histogram of scores. The image and image histograms have been inverted such that “large” values are analogous to likely found materials. The histograms have been coded with delta function “spikes” at the exact locations of the open (large spikes) and shadowed (shorter black spikes) fabric panel scores. Ideally, we would want all spikes to be as far from the background as possible.

3.3.1 Blue Panel

Using the ATCOR compensated data, which was provided by the company that collected the imagery, an in-scene open blue panel pixel was used as input to the standard SAM algorithm found in the ENVI® software. This result can be seen in Figure 9. We can see that, not surprisingly, most of the open blue pixels are far from the background though not all the shadowed pixels have been separated. This is mainly due to the fact that the open and shaded signatures are spectrally different, as was shown in Figure 7.

![Figure 9. Output detection map and histogram of scores (highlighting open and shadowed materials) using an in-scene blue reflectance signature as training to the SAM algorithm on reflectance compensated data.](image)

This was then followed by using a lab measured reflectance spectrum (as seen in Figure 4) with the ATCOR reflectance data, as input to the standard SAM algorithm found in ENVI®. The results can be seen in Figure 10. As expected, the results are slightly worse than using an in-scene pixel, for the tail of the distribution to the right is not as long. This approach is the accepted / standard approach to material detection using reflectance imagery.

![Figure 10. Output detection map and histogram of scores (highlighting open and shadowed materials) using the blue spectral reflectance, shown in Figure 4, used as input to the SAM algorithm on reflectance compensated data.](image)

For an additional comparison, the spectral information divergence (SID) algorithm was also implemented. This result can be seen in Figure 11, which looks very similar in nature to that of Figure 10, using the SAM algorithm.

The result of using the SAM algorithm on calibrated radiance data in local mode can be seen in Figure 12. We can clearly see that the shadowed targets have distanced themselves from the background. This is because, at these locations in the image, the model has accounted for shadowing of the material. If we take this result one step further and factor in grass adjacent photons (since the panels are surrounded by grass) we get the result
Figure 11. (a) Output detection map and (b) histogram of scores (highlighting open and shadowed materials) using the blue spectral reflectance, shown in Figure 4, used as input to the SID algorithm on reflectance compensated data.

seen in Figure 13. Here, we see additional improvement as the shadowed pixels in the histogram have moved further to the right (or away from the background) then the results shown in Figure 12 (or any other previous results for that matter).

Figure 12. (a) Output detection map and (b) histogram of scores (highlighting open and shadowed materials) using the blue spectral reflectance, shown in Figure 4, as input to the GUI in local mode, on radiance data.

Figure 13. (a) Output detection map and (b) histogram of scores (highlighting open and shadowed materials) using the blue spectral reflectance, shown in Figure 4, as input to the GUI in local mode, on radiance data with a grass signature used to account for adjacent photons.

Algorithms such as the matched filter (MF) and the adaptive cosine estimator (ACE) were also run on both reflectance and radiance data sets using the blue felt material reflectance (results of which are not shown here). The output detection images produced (using MF or ACE) consisted of all noise. The only time a result was obtained is when a subspace detection was employed. This can only be attributed to some type of implementation issues with the covariance (since both methods employ a covariance). Obtained results all looked exactly the same, regardless of the algorithm used or domain processed in (i.e., reflectance or radiance). That is, most of the open blue panels were found with the shadowed targets sitting in the middle of the background distribution with a score of approximately zero. It is evident that the covariance transforms the low SNR or dark regions in
some way so as to cluster these pixels in the center of the background distribution. At this time, these results need further investigation.

### 3.3.2 Red Panel

A similar set of experiments were performed using the red panel material (shown in Figure 4). Again, we operate on the ATCOR compensated reflectance data first followed by radiance image processing. Figure 14 illustrates the result of using an in-scene red pixel on reflectance imagery to find itself and others like it. We can see that the tail of the histogram is long (as expected) with all of the open targets found. Again, some of the shadowed targets are still in the background because their spectral signature is different enough from the open spectra to make them spectrally distinct.

![Reflectance, SAM, In-Scene Pixel](image1)

Figure 14. (a) Output detection map and (b) histogram of scores (highlighting open and shadowed materials) using an in-scene red reflectance signature as training to the SAM algorithm on reflectance compensated data.

If we use the standard method of processing, which entails simply using the red reflectance spectrum with reflectance imagery, we get the result seen in Figure 15. These results (in terms of background separation) are actually worse than what we saw using the blue spectrum on reflectance data (i.e., Figure 10). Both the open and shadowed pixels are immersed in the background.

![Reflectance, SAM](image2)

Figure 15. (a) Output detection map and (b) histogram of scores (highlighting open and shadowed materials) using the red spectral reflectance, shown in Figure 4, used as input to the SAM algorithm on reflectance compensated data.

The local approach on radiance data, as seen in Figure 16, performs almost as good as the in-scene result of Figure 14 with the exception that the shadowed pixels are actually further separated from the background than in the in-scene result. If we further introduce adjacency effects due to grass (i.e., the grass reflectance spectrum of Figure 4) we obtain the result show in Figure 17. Not only has the open pixels clustered together but there has been additional improvement in the shadowed pixels. These pixels have almost been pulled out from the background all together. Certainly a better result than using the in-scene method.

![Reflectance, SAM](image3)

Figure 16. Output detection map and histogram of scores (highlighting open and shadowed materials) using the red felt material reflectance (results of which are not shown here). The trends

Again, algorithms such as the matched filter (MF) and the adaptive cosine estimator (ACE) were run on both reflectance and radiance data sets using the red felt material reflectance (results of which are not shown here). And again, the output detection images produced (using MF or ACE) consisted of all noise. The trends
were exactly the same as was found testing with the blue panel material, as previously explained above. This interesting result certainly warrants further investigation.

4. CONCLUSIONS

This paper demonstrated the use of a new ENVI® based detection tool (though not part of an ENVI installation) that implements a dynamic per-pixel modification to the physics-based forward modeling approach to material detection. The approach takes advantage of co-registered LiDAR data to capture any per-pixel illumination changes due to geometry and thus updates the forward model accordingly. Results showed that the dynamic forward model was able to find both blue and red panels in the open and shade (simultaneously), on calibrated radiance data using a vector matching approach (i.e., the spectral angle mapper (SAM)). The issues related to the covariance based detection schemes (i.e., spectral match filter (MF) and adaptive cosine estimator (ACE)) need to be addressed and understood. Perhaps there is a way to combine both the outputs from the vector based approach with the essence of a covariance based approach thus yielding a hybrid detector that takes advantage of the best of both detection schemes. A new shared data set, named the SHARE 2012 data, maybe a good candidate to further examine all detection results (especially the covariance based detectors) in both the reflectance and radiance domains. The SHARE 2012 data spectrally contains the exact same blue and red fabric panels. These panels are again placed in various locations throughout the scene, some in full shadow and some in full sun. In addition, some panels were placed over different background types such as grass and gravel. Results presented either with the SHARE 2010 or 2012 datasets, should be summarized using the more elegant receiver operating characteristic (ROC) curve. The ROC curve has the ability to illustrate the performance of all detection schemes on a single graph, assuming there is a truth mask. Finally, a geometrically enhanced (through use of point cloud LiDAR data) atmospheric compensation version of the code has been under development. This enhanced compensation is simply the result of solving for reflectance in the forward model of Eq.(1). This new compensation reflectance cube could then be used in standard reflectance-type material detection.
REFERENCES


