Two Dimensional Decision Spaces Generated from Physics Based Target Detection as Applied to Hyperspectral Imagery

Emmett J. lentilucci

Digital Imaging and Remote Sensing Laboratory, Chester F. Carlson Center for Imaging Science Rochester Institute of Technology, Rochester, NY USA

Abstract

Traditional target detection algorithms are applied to hyperspectral imagery where per-pixel test static scores are generated. These univariate scores are then ranked followed by an applied threshold, which attempts to isolate targets from false alarms. This paper generates two dimensional decision spaces that can further separate targets from false alarms, especially those from saturated pixels. These spaces are generated using the Physics-Based Structured InFeasibility Target-detection (PB-SIFT) algorithm which includes input from structured backgrounds and target spaces. Our approach to target detection involves the generation of target spaces through use of a physical model that predicts what the target will look like to the sensor in uncompensated imagery. That is, rather than atmospherically compensate the imagery, we take the opposite approach by estimating what the sensor-reaching target signature will be in radiance space. Two dimensional decision spaces are generated using HYDICE desert imagery. A one dimensional linear threshold is developed that can further separate pixels that moderately look like targets of interest.

Introduction

This paper investigates a geometric hybrid technique for the detection of subpixel targets in uncompensated image spectrometer data. Physical models are used to predict what the sensor-reaching radiance looks like based on direct solar illumination, upwelled and downwelled radiances as well as reflectivity of the target. This approach uses an atmospheric propagation model to produce an illumination invariant (radiance) target space that can be used in the detection scheme outlined in this paper.

The approach we take throughout this research is geometric or structured in nature. Therefore, in developing our hybrid algorithm, we describe the background data using a linear subspace approach characterized by endmembers. We then present a detector that tells us how much influence the background space has on an image pixel. The output of such a detector is an abundance-like term where large values are synonymous with targets. In general, however, the output of the detector may produce large values, not only for actual targets, but for any other spectral anomaly that has a significant projection (e.g., a bright or saturated pixel) thus producing false alarms. Geometrically, we recognize where these cases can occur. We note that there exists many different image pixels that can have the same background influence or abundance. These pixels may manifest themselves as false positives. We separate such pixels through incorporation of an operator called the Structured Infeasibility Projector (SIP) which incorporates a physically derived target space. Together, the detector and SIP form a hybrid algorithm called the Physics Based-Structured InFeasibility Target-detector (PB-SIFT). When applied to real data, the algorithm produces a two dimensional decision space. Decision boundaries can then be drawn in this space so as to separate target from non-target-like pixels. Additionally, this two dimensional decision space can be reduced to a single dimension through image (test statistic) division. The algorithms are applied to to HY-DICE desert imagery where analysis is made through use of 2D scatter and 1D histogram plots.

Background and Theory Physics Based Modeling(PBM) and Target Spaces

In target detection, we often seek to atmospherically compensate hyperspectral imagery so as to convert sensor reaching radiance to ground leaving spectral reflectance. Once the imagery has been compensated, detection algorithms are used to compare image reflectances to library or measured reflectances in search of a desired target. Rather than compensate the imagery, an alternative is to estimate what the ground leaving spectral reflectance would look like as seen by the sensor in radiance space [1]. This approach entails modeling the propagation of a target reflectance spectrum through the atmosphere up to the sensor. The advantage this technique has over that of compensated imagery is that target illumination variations can be integrated into the process through use of a physical model thus making the approach invariant to illumination effects. Schott [2] derives such a physical model for the spectral radiance reaching an airborne or satellite sensor which incorporates direct illumination variation as well as downwelling and upwelling (or path) radiance. This can be expressed in simplified form as

$$L_{p}(\lambda) = \int_{\lambda} \beta_{p}(\lambda) \left[\left(E_{s}'(\lambda)\tau_{1}(\lambda)\cos\theta + FE_{d}(\lambda) \right) \tau_{2}(\lambda) \frac{r(\lambda)}{\pi} + L_{u}(\lambda) \right] d\lambda$$
(1)

where $L_p(\lambda)$ is the effective spectral radiance in the p^{th} band in units of $[Wcm^{-2}sr^{-1}\mu m^{-1}]$, $E'_s(\lambda)$ is the exoatmospheric spectral irradiance from the Sun in units of $[Wcm^{-2}\mu m^{-1}]$, $\tau_1(\lambda)$ is the transmission through the atmosphere along the Sun-target path, θ is the angle from the surface normal to the Sun, F is the fraction of the spectral irradiance from the sky $(E_d(\lambda))$, incident on the target (*i.e.*, not blocked by adjacent objects), sometimes called shape factor, $\tau_2(\lambda)$ is the transmission along the target-sensor path, $r(\lambda)$ is the spectral reflectance factor for the target of interest (*i.e.*, $r(\lambda)/\pi$ is the bidirectional reflectance $[sr^{-1}]$), $L_u(\lambda)$ is the spectral path radiance $[Wcm^{-2}sr^{-1}\mu m^{-1}]$, and $\beta_p(\lambda)$ is the normalized spectral response of the p^{th} spectral channel of the sensor under study where

$$\beta_p(\lambda) = \frac{\beta'_p(\lambda)}{\int \beta'_p(\lambda) d\lambda}$$
(2)

with $\beta'_p(\lambda)$ being the peak normalized spectral response of the p^{th} channel. Schott [2] also describes how the MODTRAN radiative transfer code [3] can be used to solve for each of the radiometric terms in Eq. (1) (*i.e.*, $E'_s(\lambda)$, $\tau_1(\lambda)$, $\tau_2(\lambda)$, $E_d(\lambda)$, and $L_u(\lambda)$) given a set of atmospheric and illumination descriptors. Once the terms are solved for, the spectral radiance target vector **x** observed by a *p*-channel sensor can be expressed as

$$\mathbf{x} = [L_1(\lambda), L_2(\lambda), \dots, L_p(\lambda)]^T.$$
(3)

In practice a *family* of radiance vectors is usually generated to account for lack of knowledge about the atmospheric, illumination and viewing conditions. This is accomplished by varying the inputs to MODTRAN to span a range of variables. In doing so, a wide range of potential target spectral vectors spanning a target space can be generated from a single target reflectance spectrum. In general, many of the input parameters to MODTRAN are usually known at the time of image acquisition or can be reasonably estimated (e.g., atmospheric and aerosol model, day of year, location, time of day, sensor height, etc.). For this research, emphasis is placed on varying unknown MODTRAN parameters such as visibility, total column integrated water vapor (or water vapor scale factor in MODTRAN) and ground topography. In the case of water vapor scale factor, a physics based atmospheric compensation algorithm can be used to estimate per pixel total column water vapor which can then be converted to an appropriate range of scale factors. In addition to MOD-TRAN input parameters, target orientation, or more precisely illumination, can be varied to account for projected area effects. This is implemented as a target rotation angle, relative to the zenith angle computed in MODTRAN, for a given time of day. The new irradiance expression for this modulation of the direct term is given by

$$E_{s_new}(\lambda) = \frac{E_s(\lambda)}{\cos \sigma'} \cos \sigma_{new}$$
(4)

where $E_s(\lambda) = E'_s(\lambda) \cos \sigma'$, σ' is the zenith angle, $\sigma_{new} = \sigma' - \sigma_{rot}$ and σ_{rot} is the user specified angle of rotation. In addition to target orientation, the amount of scattering in the atmosphere onto the target (downwelled radiance) is also modulated. This modulation is accounted for by using the shape factor term of Eq. (1). Details on the importance these parameters have on derived target spaces and detection can be found in the literature [4].

Structured Detection and Infeasibility Metric

If the target and background spaces are described using geometric techniques then the application of a detector based on vector geometry is most appropriate. One such algorithm that relies on (orthogonal) projections is the Orthogonal Subspace Projection (OSP) detector [5]. This can be expressed to include input from *target spaces* such that we have

$$T_{PBosp}(\mathbf{x}) = \frac{\|\mathbf{P}_{\mathbf{T}}\mathbf{P}_{\mathbf{B}}^{\perp}\mathbf{x}\|}{\|\mathbf{P}_{\mathbf{T}}\mathbf{P}_{\mathbf{B}}^{\perp}\mathbf{t}_{avg}\|}$$
(5)

where $\mathbf{P_T} = \mathbf{TT}^{\dagger}$ where \mathbf{T}^{\dagger} is the pseudo-inverse of **T** defined as $\mathbf{T}^{\dagger} = (\mathbf{T}^T \mathbf{T})^{-1} \mathbf{T}^T$ and $\mathbf{P}_{\mathbf{B}}^{\perp} = \mathbf{I} - \mathbf{BB}^{\dagger}$. Matrices **T** and **B** are matrices comprised of endmembers (in columns) that span the target and



Figure 1. HYDICE hyperspectral desert image. Shown is a 250×300 pixel \times 170 band subset extracted from a larger HYDICE flight line.

background subspaces, respectively. The vector \mathbf{t}_{avg} is the average target space spectrum.

The structured infeasibility projector (SIP) provides for a measure of un-target-like behavior by projecting the test pixel onto the subspace orthogonal to the target space and is expressed as

$$T_{SIP}(\mathbf{x}) = ||\mathbf{P}_{\mathbf{T}}^{\perp}\mathbf{x}|| \tag{6}$$

where $\mathbf{P}_{\mathbf{T}}^{\perp} = \mathbf{I} - \mathbf{T}\mathbf{T}^{\dagger}$. The detector of Eq. (5) and SIP metric of Eq. (6) form the Physics Based-Structured InFeasibility Target-detector (PB-SIFT) which produces a two dimensional decision space where probable targets have large abundances and low SIP scores. This concept of using an added "infeasibility" metric similar to what the SIP produces was motivated by the original work of Boardman [6]. Here, the developed infeasibility concept was stochastic in nature where in this research we set out to develop a geometric equivalent. This metric can also be extended to include the joint statistics of target and background spaces [4].

Results

The previously mentioned SIFT algorithm was applied to HY-DICE desert imagery collected in Arizona. A subset, derived from a much larger flight line, can be seen in Figure 1. Due to low signal-tonoise and heavy water absorption, only 170 of the original 210 spectral channels (0.4 to 2.5μ m) were used during processing. Overall, this image contains approximately 60 man-made objects positioned against a desert background. Objects are of varying size (full/subpixel) and spectral character. The target of interest was a green panel which we will label Target 3 (T3). This panel represented 16 full and 11 sub pixels. Truth masks identifying target locations were created by a group at MIT's Lincoln Laboratory.

The target space was created using Eq. (1) where the measurement of the targets reflectance, $r(\lambda)$ was obtained using a hand held spectrometer. Known MODTRAN input parameters included atmospheric and aerosol model (desert extinction), sensor altitude, day of year, latitude, longitude, and time of day. Other input parameters, such as visibility, ground elevation, and water vapor scale factor, were varied. For this scene, four visibility values (15 to 40



Figure 2. Illustration of the 180 vector target space. Over plotted (heavy black line) is an image derived (T3) target pixel.

km) were used along with three elevation values (scene elevation \pm 50 feet). The five water vapor scale factors used (0.3 to 0.7) were derived from water vapor maps computed using two different atmospheric compensation algorithms. Since the terrain seemed fairly flat and open, the target illumination (orientation) was only varied by $\pm 10\%$ with the shape factor set to one. This produced a target space containing $4 \cdot 3 \cdot 5 \cdot 3 \cdot 1 = 180$ vectors. Figure 2 illustrates all 180 vectors in the target space along with an overlayed image pixel of the desired T3 target panel. The target and background spaces were then represented using endmembers found by implementing the Maximum Distance method (MaxD) [7]. These endmembers were used in Eq.'s (5) and (6) to formulate the required projection operators.

One problem that plagues the vector algebra approach to background characterization is the fact that one runs the risk, depending on target/background contrast, of selecting a desired image target as a background endmember. If this happens, the target signature will be grouped with the background description and will ultimately get suppressed in the detection stage, where we look to suppress the background only. To circumvent this dilemma, we seek background endmembers using an augmentation approach. In this approach, we simply augment the background data vectors with the physics derived target space vectors. The idea is that we are trying to mask or shield the actual target image pixels with the physically derived ones. If the shielding process is successful, then the endmember finding routine will locate the physically derived vectors before it finds the actual target image pixel. Since we know which vectors went into the augmentation, we can check for them and remove them accordingly after the endmember selection process.

The results of applying the PBosp and SIP algorithms to the desert scene can be summarized in the 2D scatter plot of Figure 3. This is a plot of the normalized PBosp detector versus the SIP metric. For visualization purposes, 10 of the more interesting targets, including T3, have been identified and labeled. Here we see that most pixels have low abundances and are associated with the background while the interesting pixels tend to manifest themselves outside this background distribution. We also notice that target T3 has relatively high abundance with a low SIP value, which is desired.

Another way to view the PBosp detector values, relative to the



Figure 3. Two dimensional decision space created using the PBosp detector with the added SIP metric, as applied to the hyperspectral desert imagery. Illustrated are thresholds established using a simple slope technique.

background distribution, is to generate a histogram of all the scores while simultaneously labeling interesting or target-like pixels. That is, we marginalize the PBosp axis. This method of visualization can be seen in Figure 4. For continuity, we have kept the same color coding as that established in Figure 3. We can see, again, that most of the scores have low abundances and are associated with the background. If we simply set a linear threshold in the PBosp axis only, we will incur many false alarms due to targets T2 and T5 (which is also a green cotton/nylon fabric). However, we can mitigate these false alarms and therefore improve performance by setting an additional constraint for the SIP values on the x-axis. One such method is to set a linear threshold on both the PBosp and SIP axes. This approach has been implemented and is currently being further developed [8].

Another simple approach involves image division. That is, we seek those pixels with both large abundances and low infeasibility scores. This desired maximization can be obtained by simply dividing the PBosp scores by the SIP values, on a per-pixel basis. This ratio generates a one dimensional decision space. The histogram of these "new" scores can be seen in Figure 5. We now notice that those pixels with both large abundance and low infeasibility have further separated themselves from the background. From this Figure, we can identify a region in which to establish a reasonable threshold, m = 0.3. This one dimensional threshold manifests itself as a line, with a slope of m, in the two dimensional decision space, as can be seen in Figure 3. Expressed as a binary hypothesis test we have

- H_0 : Target Present
- H_1 : Target Absent

where we accept the null iff $\gamma_i \ge m$ where

$$\gamma_i = \frac{PB_osp_i}{SIP_i} + b_o \quad \text{for} \quad i = 0, 1, \dots, N \tag{7}$$

where N is the total number of pixels and b_o is an abundance offset, usually set to zero. With m = 0 and b_o set to an abundance value, say 0.6, we have the classic linear threshold in the PBosp axis, as can be seen in Figure 3.



Figure 4. Histogram of PBosp scores, normalized. Interesting targets have colored delta functions associated with them and are usually above the back-ground distribution.

This method of creating a one dimensional threshold is best suited for pixels with both moderate to large abundance and reasonably small SIP scores. It does not perform well in further separating pixels that have moderate to low abundances and small SIP scores. This is because of the 1/x type mapping of the PBosp/SIP scores in addition to the fact that the method does not take into account the increased target/background variability seen with decreasing abundance. An approach that considers these variables is currently being investigated [4, 8]. However, it does provide for a fast, simple one dimensional technique that further enhances a likely targets contrast, relative to the background.

Conclusions

The research presented in this paper explored methods of improving target detection using the concept of physics based modeling. The work builds upon an original body of work related to detection using illumination invariant subspaces. In this paper we continue to refined the process of creating target spaces as well as implementing detectors and metrics that could adapt to such spaces. Two such algorithms, the PBosp detector and SIP metric, were applied to HYDICE desert imagery. Physically derived target sub-spaces were created and together, with the detection and infeasibility algorithms, were used to generate two dimensional decision spaces. Visualization of these spaces was explored using 2D scatter plots and 1D histograms. From this, a one dimensional linear threshold criteria was established based on the ratio of the PBosp and SIP algorithms. This method proved to be useful for further separating targets with moderately high abundances and low SIP scores. It does not, however, take into account the joint statistics of the target and background spaces. Future efforts will address linear and non-linear thresholds as well as the inclusion of sensor noise and calibration errors into the target space.

References

 G. Healey and D. Slater. Models and methods for automated material identification in hyperspectral imagery acquired under unknown illumination and atmospheric conditions. *IEEE Transactions on Geoscience*



Figure 5. Histogram of PBosp/SIP scores. We can see that target T3 is further separated from the background due to the 1/x type mapping, which emphasizes pixels with moderate to large abundances and moderate to small SIP value.

and Remote Sensing, 37(6):2706-2717, November 1999.

- [2] J.R. Schott. Remote Sensing: The Imaging Chain Approach. Oxford University Press, New York, 1997.
- [3] A. Berk, L.S. Bernstein, and D.C. Robertson. MODTRAN: A moderate resolution model for LOWTRAN 7. Technical Report GL-TR-89-0122, Air Force Geophysics Laboratory, Hanscom AFB, MA, 1988.
- [4] E.J. Ientilucci and J.R. Schott. Target detection in a structured background environment using an infeasibility metric in an invariant space. In Paul E. Lewis Sylvia S. Shen, editor, *Proc. SPIE, Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XI*, volume 5806, pages 491–502, Orlando, FL, April 2005.
- [5] J.C. Harsanyi and C.I. Chang. Hyperspectral image classification and dimensionality reduction: An orthogonal subspace projection approach. *IEEE Transactions on Geoscience and Remote Sensing*, 32(4):779–785, July 1994.
- [6] J. W. Boardman. Leveraging the high dimensionality of AVIRIS data for improved sub-pixel target unmixing and rejection of false positives: mixture tuned matched filtering. In Robert O. Green, editor, *Summaries* of the Seventh Annual JPL Airborne Geoscience Workshop, volume 1 of JPL Publication 97-21, page 55, Pasadena, California, January 1998.
- [7] K. Lee. A sub-pixel scale target detection algorithm for hyperspectral imagery. PhD dissertation, Rochester Institute of Technology, 54 Lomb Memorial Drive, Rochester, NY, 2003.
- [8] E.J. Ientilucci and J.R. Schott. Physics based target detection usng a hybrid algorithm with an infeasibility metric. In *To be Published in IEEE Internation Conference on Acoustics, Speech, ans Signal Processing*, Toulouse, France, May 2006.

Author Biography

Emmett J. Ientilucci received his A.A.S degree in optical engineering from Monroe Community College (1989) and his B.S., M.S., and Ph.D. degrees in imaging science from the Rochester Institute of Technology (1996, 1999, and 2005, respectively). He is currently a post-doctoral researcher in the Digital Imaging and Remote Sensing Laboratory and member of the technical staff. His interests include physics based target modeling, hyperspectral image analysis, radiometry, and hybrid target detection methods.