A SUBPIXEL TARGET DETECTION TECHNIQUE BASED ON THE INVARIANCE APPROACH.

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1. Introduction and Summary

This paper introduces a method for detection of subpixel targets in image spectrometer data cubes. It is based on the premise that we know what the target is and can characterize it in terms of its reflectance spectrum $r(\lambda)$. Furthermore, we assume the target may exist at spatial scales such that it will present itself as a fraction of a pixel and that it may exist in a significant number of pixels (more specifically we can't assume that we can insure that a significant region of the scene does not contain any targets). We desire a data processing approach that can mitigate atmospheric and illumination effects such that atmospheric correction is not a required prerequisite for the method. The approach presented here involves defining a target spectral subspace that is common across the wide range of atmospheric illumination and viewing conditions that might exist in the scene (i.e., the target subspace is invariant to environmental changes within the scene). The target may be manifest at different locations within the subspace but is not expected to appear outside the subspace. We then introduce a method to characterize a background subspace using the same convex hull geometry used to define the target subspace (i.e., the target subspace and background subspace are defined in a common spectral space but ideally there is little or no overlap between the two subspaces). We then introduce a subpixel target detection algorithm that is based on how well each pixel spectrum can be described by either a set of background basis vectors or a combination of target and background basis vectors. The result is a subpixel target detection algorithm that only requires the target spectrum and a radiance image cube (i.e., an image spectrometer data set calibrated into sensor reaching radiance). The performance of the resulting algorithm is shown for both a HYDICE image and an AVIRIS image. These initial results demonstrate the potential of the approach showing very good background suppression (low false alarms) and a high degree of target detection.

2. Approach

This section presents an overview of the background theory on which this algorithm is based, as well as the advances needed to implement a subpixel version of the invariant algorithm.

2.1 The Invariant Approach

The subpixel algorithm developed here is built on the invariant method for fully resolved target detection described by Healey and Slater (1999). The invariant method is based on the assumption that an individual target may be manifest over a wide range of spectral values in an image due to illumination and atmospheric variation within a scene. However, even though a target may take on many spectral values the total range of those values is small compared to the entire scene spectral space. The goal of the invariant method is to define the subspace of the entire scene space that the target may occupy in terms of a relatively small set of basis vectors that span the target subspace. The range of possible target vectors can be generated by using the MODTRAN radiation propagation model (c.f. Berk et al., 1989) to predict the sensor reaching spectral radiance for the target reflectance vector. By changing the inputs to MODTRAN over a range of variables representing the range of atmospheric, illumination and viewing conditions that might occur under imaging conditions, a wide range of potential target spectral vectors can be generated. We can define a set of basis vectors that will predict these target vectors (i.e., span the spectral space they occupy) according to:

$$\mathbf{x}_i = \mathbf{T}\mathbf{a}_i + \boldsymbol{\varepsilon}_i = \sum_{j=1}^{N} \mathbf{t}_j a_{ij} + \boldsymbol{\varepsilon}_i \qquad (1)$$

where $\mathbf{x}_i$ is the i^{th} MODTRAN generated target vector for the sensor under study, produced by convolving the MODTRAN spectral radiance with the spectral response function of each of the k bands, $\mathbf{T}$ is a matrix made up of N target basis vectors $\mathbf{t}_j$, $\mathbf{t}_j$ is the j^{th} basis vector, $\mathbf{a}_i$ is a vector of N weights particular to the i^{th} target vector and $\boldsymbol{\varepsilon}_i$ is the residual error. Healey and Slater (1999) used Singular Value Decomposition (SVD) to solve for the set of basis vectors that minimize the sum-squared error expressed as:

$$\mathrm{SSE} = \sum_{i=1}^{C}\left(\mathbf{x}_i - \mathbf{T}\mathbf{a}_i\right)^2 \tag{2}$$

where C is the number of MODTRAN runs (17,920 for the Healey and Slater (1999) studies). Slater and Healey (1998) demonstrated that for a wide range of targets imaged by a 200+ band sensor (e.g. HYDICE or AVIRIS), the subspace spanned by variation in atmospheric and illumination variation could be spanned by a small number of basis vectors (typically 9 or less).

For any radiance vector $\mathbf{x}$ in the image we can solve for the basis vector weights $(\mathbf{a})$ according to:

$$\mathbf{a} = \mathbf{T}^{-1}\mathbf{x} = \mathbf{T}^{T}\mathbf{x} \tag{3}$$

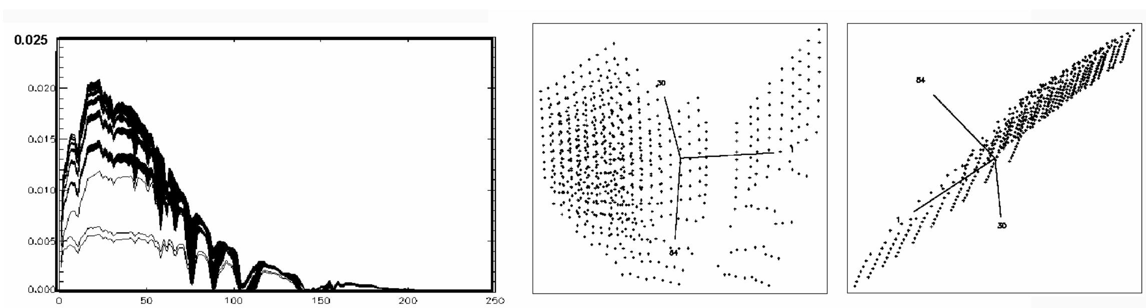
Where we take advantage of the fact that the SVD derived basis vectors form an orthonormal set such that $\mathbf{T}^{-1} = \mathbf{T}^{T}$. Slater and Healey (1999) used the residual error from this process as a target detection metric for fully resolved targets according to:

$$\boldsymbol{\varepsilon} = \mathbf{x} - \mathbf{T}\mathbf{a} = \mathbf{x} - \mathbf{T}\left(\mathbf{T}^{T}\mathbf{x}\right) \tag{4}$$

Pixels with small magnitudes of $\boldsymbol{\varepsilon}$ (i.e., $\left(\boldsymbol{\varepsilon}^{T}\boldsymbol{\varepsilon}\right)^{\frac{1}{2}}$) are well fit by the model (i.e., they look like linear combinations of target basis vectors) and can be identified by thresholding an image expressed as the magnitude of the $\boldsymbol{\varepsilon}$ vectors from Equation 4. This method showed very promising results for fully resolved pixels, significantly out performing simpler approaches (e.g. the Spectral Angle Mapper (SAM) trained on sunlit targets) for targets in partial and full shadow. Regrettably, subpixel targets are not a good match to the model expressed in Equation 4 and an approach involving characterization of the background is required. This subpixel detection approach was the goal of Lee (2003) and is summarized below.

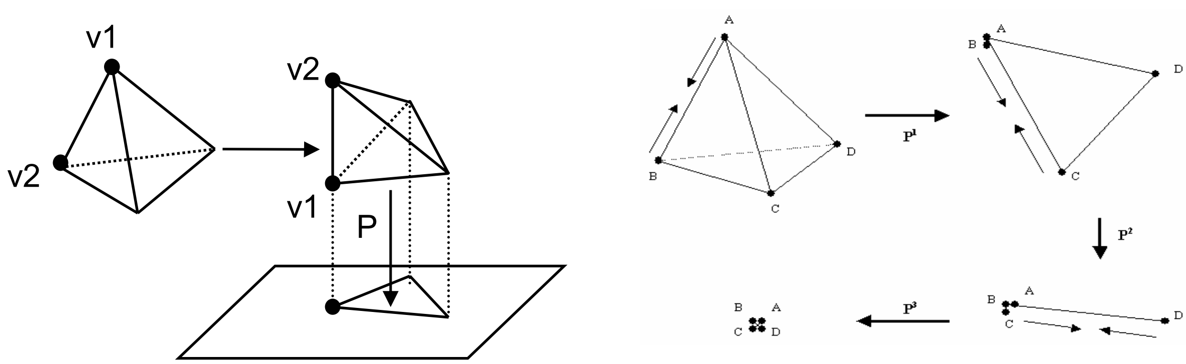
2.2 The Maximum Distance (MaxD) method for Basis Vector Selection

Lee 2003 suggests an alternative method to the SVD for basis vector selection that maintains the basis vectors in the native spectral space (i.e., the basis vectors all look like image spectral radiance vectors). This was motivated by the need to separate out target from background basis vectors as discussed in the next section (c.f. Section 2.3). The range of spectral values a target may assume in the image is again generated by using MODTRAN to predict the range of atmospheric, illumination and viewing conditions under which the target might be observed in a particular image. For this study only those conditions relevant to the particular image under analysis were included in the generation of possible target radiance values. The goal was to push the limits of how the target might appear in the particular image but not to exceed those bounds. This should generate a subspace large enough to contain the target but hopefully small enough to reduce false alarms. Typically 840 MODTRAN runs were used (compared to the 17,000 runs used by Slater and Healey (1998) to span the entire possible target subspace (e.g. all seasons, altitudes and water vapor, illumination and view angle ranges). The MODTRAN generated radiance vectors were then converted into discrete radiance vectors corresponding to the imaged radiance vectors for a particular imaging spectrometer by convolving the MODTRAN spectral radiance with the response fractions of the sensors k spectral bands. These target spectral vectors can be thought of as occupying some subspace in the scene spectral radiance domain (c.f. Figure 1). We seek a simplex that encloses these spectral vectors and postulate that such a simplex can be constructed from the extrema of the available data (note this is essentially the same conceptual problem as that of finding extrema or end members in an image cube). The largest magnitude vector (v_1) is one vertex of the simplex and we postulate that the smallest magnitude vector (v_2) is another candidate vertex. Note, that rigorously speaking, the smallest magnitude vector may not be a vertex of the simplex, however, empirical evidence suggests that real data form a cone in spectral space with the apex near the dark point or point of lowest magnitude (c.f. Ifarraguerri and Chang, 1999). Thus, we will tentatively use the darkest pixel (v_2) as a vertex of the simplex. If we assume the target subspace spans ℓ dimensions, a minimum of $\ell+1$ vertices are required to encompass the subspace. Lee (2003) shows that the vertices of the $\ell+1$ element simplex will also be vertices of the ℓ element simplex formed by projecting all the data onto the subspace orthogonal to the difference vector between v_1 and v_2 (i.e., the projection that places v_1 on v_2) as shown in Figure 2. Furthermore, the point v_3 most distance from the point v_{12} (i.e., the point in the projected space jointly occupied by v_1 and v_2) in this new space must be a vertex of the simplex. By projecting the transformed data onto the subspace perpendicular to the difference vector between v_3 and v_{12}, the vertices of the simplex in ℓ dimensions will be vertices of an ℓ-1 element simplex in the new subspace. This process can continue until all the vertices of the subspace are located i.e., projected to a common point. This begs the question of determining how large (i.e., what is the dimension ℓ) is the target subspace. One way to determine the dimension is to use the SVD to estimate the dimension ℓ and then find $\ell+1$ vertices. Another approach is to find more than enough vertices and then use a method that eliminates any vertex that is a linear combination of earlier vertices (Lee, 2003 suggests using a stepwise linear regression (described by Gross and Schott, 1996) on the vector made from the mean of the target vectors to separate out excess vertices). It is important to remember that even though we select the latter vertices of the simplex in the projected spaces they are merely samples from the MODTRAN generated target set and once selected we can express the spectral vector in the image space units for use as the basis vector. At this point we have simply solved for a set of N target basis vectors in the native space and could solve the fully resolved target detection problem described in Equations 3 and 4. Note that in Equation 3 we would need to use the pseudo inverse of $\mathbf{T}$ (i.e., $\mathbf{T}\#$) not $\mathbf{T}^T$ since our native basis vectors do not form an orthonormal set. To solve the subpixel problem we still need to solve for a set of basis vectors to span the background subspace.



(a) (b) (c)

Figure 1. Illustration of potential target spectral radiance values: (a) plots of spectral radiance for the same reflectance spectrum viewed through different atmospheres, (b) a Plot of three bands of the data from figure a showing how the target radiance data is spread over the radiance space, (c) a plot of the same data as a and b illustrating that the subspace occupied by the target radiance values is actually a small subset of the entire spectral space.



(a) (b)

Figure 2. Illustration of (a) The preservation of vertices of a simplex through projection of a data set onto the difference in two vertices of a simplex and (b) the concept of maximum distance determination and sequential projection to find the vertices of a simplex spanning the data space.

2.3 Selection of Background Basis Vectors

The method for selection of background basis vectors is very similar to the method used to solve for target basis vectors. However, because the data set to be processed is so large (i.e., the entire image) the analysis is often more manageable if we first reduce the dimensionality of the data. First any bands that don't carry information of interest are removed (e.g., high noise or high atmospheric absorption). Second a transformation into a more information rich set of fewer bands is performed using an approach like the Minimum Noise Fraction (MNF) transform with higher order bands truncated (c.f. Green et al., 1998). This might reduce our data dimensionalities for an AVIRIS scene from 224 bands to 180 bands, by band rejection, and to 32 transformed bands using the MNF transform. If we run the MaxD algorithm described in Section 2.2 on the transformed image we could define a set of basis vectors that span the image space. However, there is a good chance that one or more of the basis vectors could be contaminated by the target signature. Since our goal will be to use these basis vectors to effectively suppress the background, having background basis vectors that include target characteristics would be counter productive. To overcome this limitation, we augment the image data set with the native target vectors generated in Section 2.2 after transforming them into the MNF space (in practice, it is often easier to also perform the target space MaxD calculations on data that has been transformed into the image MNF space to reduce data dimensionality). The output of this second MaxD process is a set of basis vectors that span the combined target-background space. As illustrated in Figure 3 any mixed target-background pixels should fall inside the convex hull described by these basis vectors and will not be identified by MaxD as a vertex. We then remove any target vertices from the vertices found by the MaxD of the combined image-target data set. This leaves us with a set of vertices that should only include background pixels and which should span the background subspace.

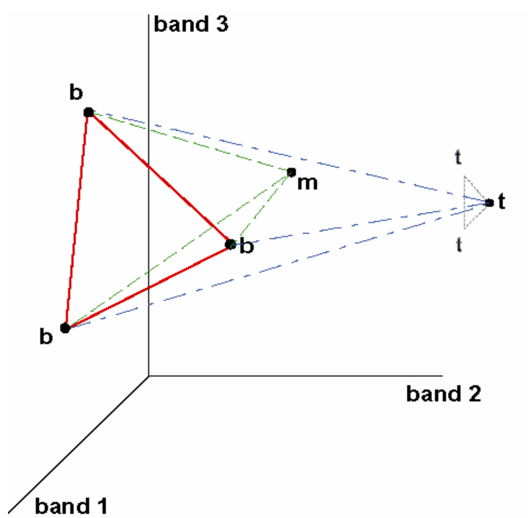


Figure 3. Simplex shapes before and after adding target basis vectors b illustrates a background vector, t a target vector, and m a mixed target-background vector.

2.4 Subpixel Target Detection Algorithm

The final detection algorithm uses a generalized likelihood ratio to compare how well a spectral vector (pixel) can be modeled as a linear combination of background basis vector to how well the spectral vector (pixel) can be modeled as a linear combination of target and background basis vectors. A simplified form of this can be express as:

$$L = \left(\frac{n_b^2}{n_T^2}\right)^{\frac{1}{2}} = \left(\frac{[\hat{\mathbf{x}} - \mathbf{Bb}]^2}{[\hat{\mathbf{x}} - \mathbf{Mc}]^2}\right) = \left[\frac{\left[\hat{\mathbf{x}} - \mathbf{B}\left[\mathbf{B}^{\#}\hat{\mathbf{x}}\right]\right]^2}{\left[\hat{\mathbf{x}} - \mathbf{M}\left[\mathbf{M}^{\#}\hat{\mathbf{x}}\right]\right]^2}\right]^{\frac{1}{2}} \tag{5}$$

where $\hat{\mathbf{x}}$ is the MNF transformed version of the pixel under test, $\mathbf{B}$ is the matrix made up of background basis vectors as columns, $\mathbf{b}$ is the vector of best fit weights obtained by modeling $\hat{\mathbf{x}}$ as a background, $\mathbf{B}^{\#}$ is the pseudo inverse of **B** (i.e., $\mathbf{B}^{\#} = \left(\mathbf{B}^{\mathrm{T}}\mathbf{B}\right)^{-1}\mathbf{B}^{\mathrm{T}}$), **M** is the matrix made up of combining the target and background basis vectors as columns (i.e., the concatenation of **B** and **T**) and **c** is the vector of best fit weights obtained by modeling $\hat{\mathbf{x}}$ as a mixture of target and backgrounds. The numerator of Equation 5 will be small and the dominator large when the background model is a good fit and vice versa when the target-background model is a good fit. Thus a threshold on L that isolates large values can be used as a target detection mask.

3. Results

The MaxD method of selecting vertices to span the data subspace is essentially the same as the end member selection process. To test the method 50 SWIR bands of a reflectance corrected AVIRIS cuprite scene distributed with ENVI were analyzed with the ENVI PPI routine (c.f. Boardman et al., 1995) to select candidate end members, followed by a matched filter with a reflectance library to find final end members. These results were compared to the MaxD results. The results are shown in Figure 4. The slight differences are due to the fact that MaxD was totally scene derived and PPI was used with a matched filter applied to the reflectance library with the best-fit library value used as the final end member. The two methods show comparable performance, however, the MaxD processing is fully automated (PPI could be) and faster. One potential limitation of the MaxD approach is that some vertices may be extremes because of anomalies or noise in the data set. Meaningful extrema will generally have other points in close proximity. To avoid selecting isolated points the entire first set of vertices can be removed from the analysis and the MaxD repeated to generate a second set of vertices. For data with many anomalies this process could be repeated until sequential vertices are essentially the same. For the data sets we have studied we have never needed to go beyond a second pass. Figure 5 shows an example of how closely several first and second pass vertices compare (for non anomalous vertices). Note that slight changes in magnitude are not critical to this process and that the spectral shapes are very well reproduced (i.e., the correlation between the first and second pass spectra is very high).

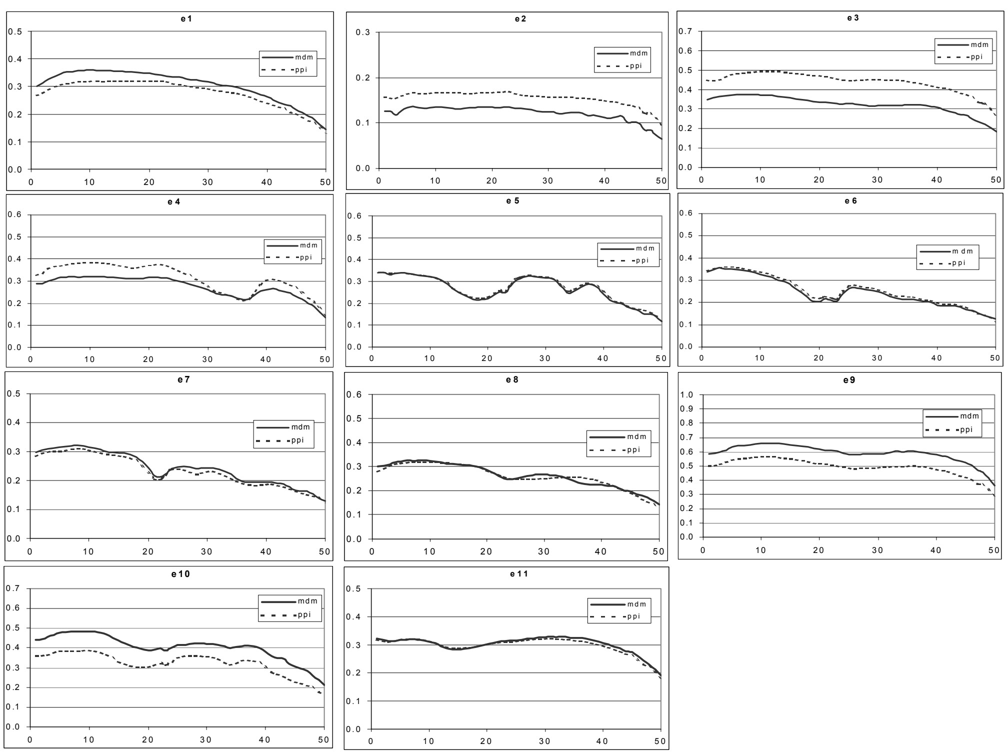


Figure 4. Comparison of vertices selected by MaxD of PPI and a matched filter on library spectra. The original data were 50 bands of an AVIRIS image of Cuprite, Nevada corrected for atmospheric effects.

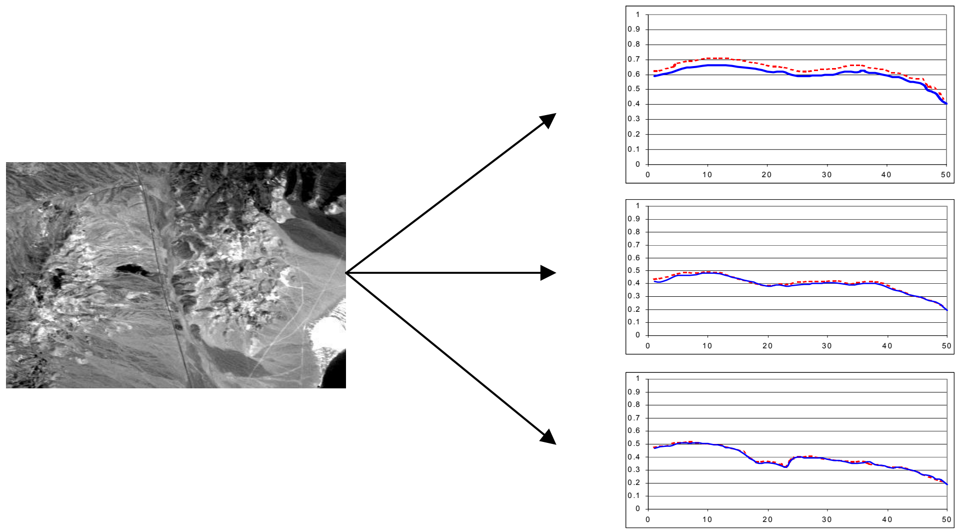


Figure 5: Comparison of first and second pass MaxD for non-noise pixels

The overall subpixel target detection was tested against three data sets of increasing complexity. The first test used synthetic data. Seven background spectra and one target spectrum from the USGS library were sampled into 224 AVIRIS like bands and 992 background and eight target background mixtures were produced using a uniform random number generator to produce fraction weights. The 8-target pixels had two pixels each of 25, 10, 5 and 1 % abundance. The reflectance spectra were converted to sensor reaching radiance using MODTRAN with one pixel at each target abundance propagated through a significantly different highly turbid atmosphere. Finally, noise was added to each radiance vector to simulate noise observed in an AVIRIS dark field image. The target and background subspaces were then generated using the methods described above and the GLR detection algorithm applied. The results shown in Figure 6 should show target pixels at locations 100, 150, 350, 400, 600, 650, 850 and 900. The second 5% pixel is missed due to the very turbid atmosphere and neither of the 1% pixels are detected. Note, there were no false alarms.

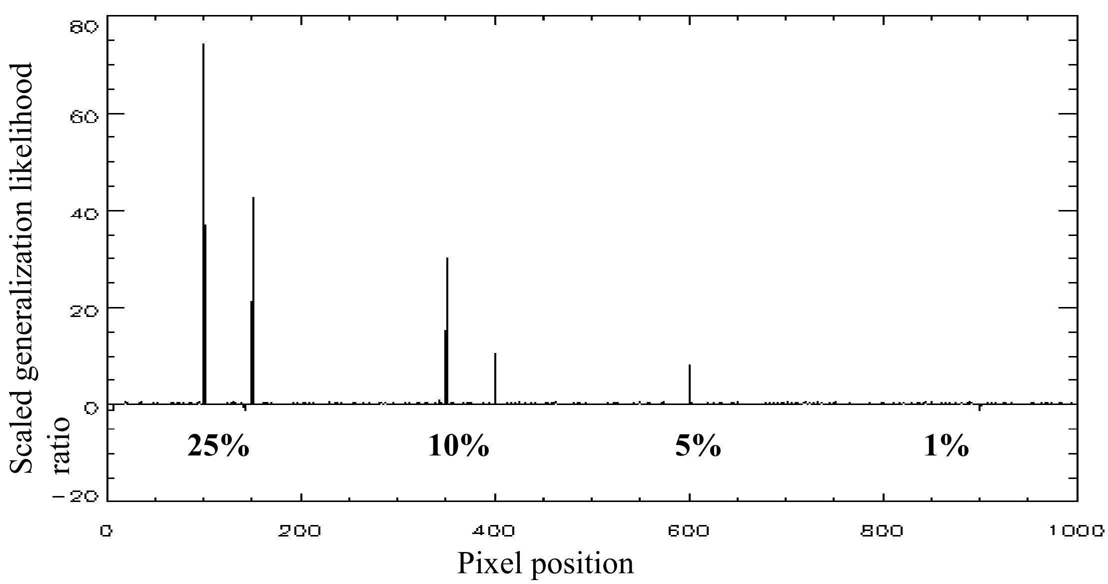


Figure 6: Detection result for the synthesized mixed pixel data set. Note the high level of background rejection.

A more rigorous test was applied to HYDICE imagery of the arm test site containing a number of target panels. The imagery was degraded to make the target panel of interest subpixel (cf. Figure 7). The results show complete success for the four-subpixel target pixels and no false alarms (cf. Figure 8). The ARM site was, however, not very stressing since the scene was not very cluttered and the target had a fairly high contrast.

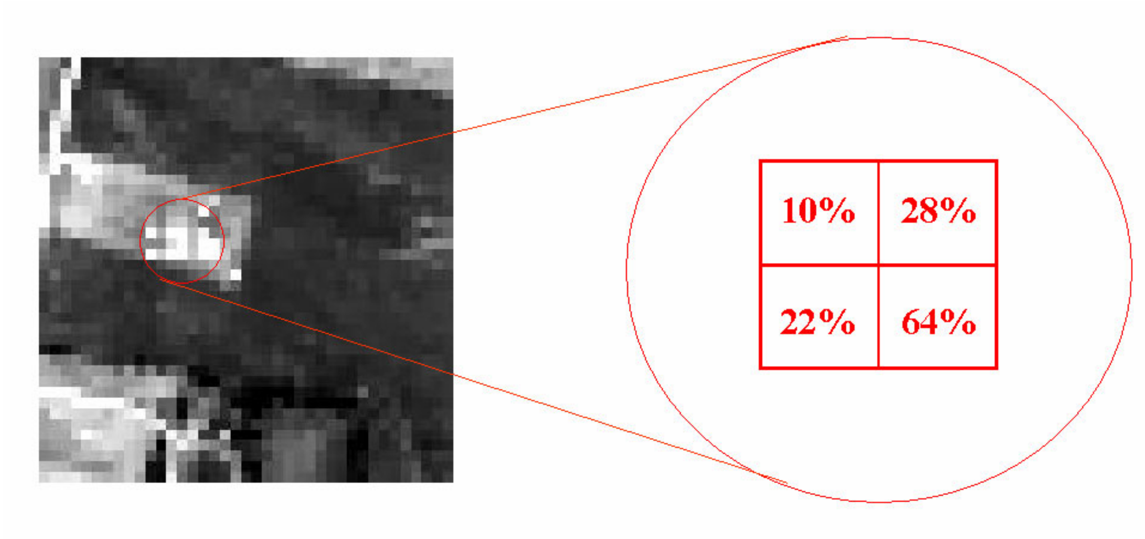


Figure 7: Original HYDICE image and target panel spectrum (top) and degraded image and fill factor estimates for the target panel (bottom).

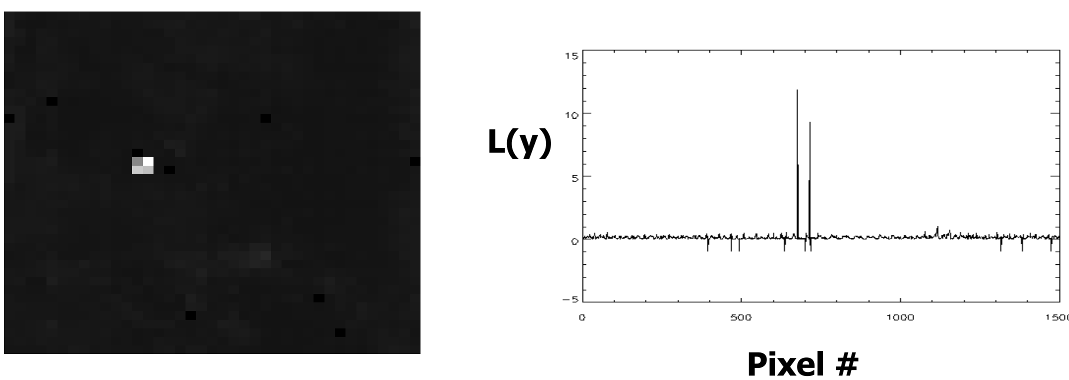


Figure 8: Detection image and scan profile of the detection metric for the HYDICE image in Figure 7.

Finally, an AVIRIS image of a cluttered urban area was used, with the target a reddish brown paint used for basketball courts (cf. Figure 9). The reflectance spectrum used was acquired for the single known target using a field spectrometer. The scene had a wide range of natural and man-made clutter including a mixture of commercial/warehouse and residential neighborhoods to add a wide range of spectral diversity. The results showed two target sites. High-resolution air photos were used to evaluate the detections as shown in Figure 9. The first site was the basketball court where the ground truth data were acquired approximately one year after the AVIRIS overpass. The second detection site was at a tennis court where the perimeter of the court appeared to be painted with the same paint used on the basketball court. Also shown in Figure 9 for reference is the approximate sample size for a nominal 20m AVIRIS pixel.

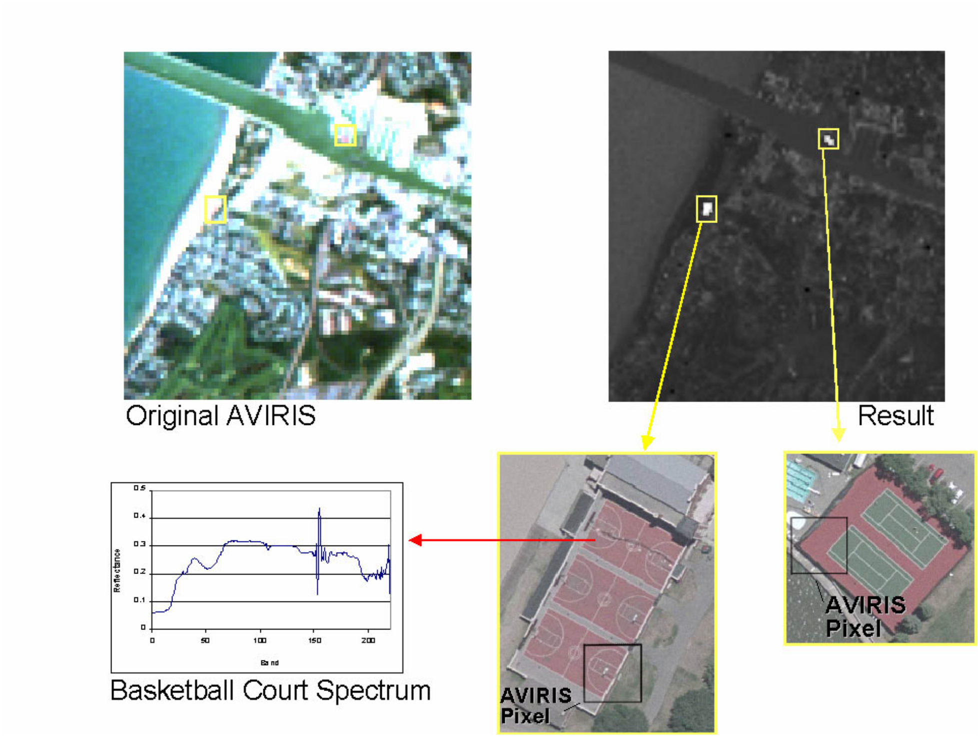


Figure 9: AVIRIS Results

4. Conclusions and Recommendations

The results shown in the previous section are quite encouraging. They indicate that the MaxD method shows potential as a simple, rapid and effective method for selection of native basis vectors. Note this is the same as an end member selection problem so that the MaxD approach could also be used for rapid selection of end members. Furthermore, the subpixel invariant method presented here shows good performance against an initial range of data sets with high detection rates and low false alarms over the range of targets and backgrounds tested. The method is particularly attractive because the only required inputs are a known target reflectance spectrum and an image cube expressed as spectral radiance. The effects of atmosphere and illumination are accounted for by the invariance process. From one perspective, this simplicity of inputs and the high level of automation of the process are significant advantages. On the other hand, the current implementation of this approach is limited to detection of targets whose reflectance spectrum can be defined in advance and to image sets that can be reasonably calibrated into spectral radiance. For the sensors used here (HYDICE and AVIRIS), the nominal sensor calibration data to convert counts to spectral radiance appeared adequate for the targets studied.

Future work in this area needs to address methods to more fully automate the process and to test the approach against a wider range of targets and backgrounds with a particular emphasis on low contrast targets and targets more directly influenced by the surround (e.g., partial shadow and tree shine). Ongoing work on this approach at RIT is concentrating on a more explicit treatment of noise in the algorithm to deal with sensors with significant noise levels. We are also investigating better ways to define the variability in the target space. This effort is focused on trying to define the full range of ways the target is likely to appear in the scene to improve target detection without generating too large a target space, which is likely to lead to false alarms. Finally, we are investigating methods to hybridize the original fully resolved invariant method and the subpixel method presented here to determine if higher performance can be achieved with a hybrid version.

5. References

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