EXPLORING LIMITS IN HYPERSPECTRAL UNRESOLVED OBJECT DETECTION

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ABSTRACT

Hyperspectral imaging systems have been shown to enable unresolved object detection through enhanced spectral characteristics of the data. Robust detection performance prediction tools are desirable for many reasons including optimal system design and operation. The research described in this paper explores the general understanding of system factors that limit detection performance. Examples are shown for detectability limits due to target subpixel fill fraction, sensor noise, and scene complexity.

***Index Terms*—** hyperspectral, target detection, system modeling, performance prediction

1. INTRODUCTION

Hyperspectral imaging systems have been shown to enable unresolved, or subpixel, object detection through the enhanced spectral characteristics of the image data [1]. However, the ability of a particular system to detect a given object (or target) in an arbitrary scene can vary widely depending on numerous factors. Robust detection performance prediction tools are desirable for many reasons including optimal system design and operation. While a completely general prediction capability is not likely to be feasible due to the overwhelming complexity of natural scenes (as well as sensor operation and algorithm characteristics), progress has been made in understanding aspects of the performance limits under reasonable constraints on the system complexity.

One empirical approach for the prediction of target detection performance is the target implant method [2], [3]. This method uses laboratory or field measured spectra of a target of interest and "implants" it in a real hyperspectral image. Target detection algorithms can then be applied to the image and empirical performance estimated. This method has the advantage of using real imagery with all its non-ideal characteristics, but this advantage is also a limitation in that the results are specific to that image and not generally extendable.

The research described in this paper explores the general understanding of system factors that limit detection performance in hyperspectral unresolved object detection. While the approach generally applies to systems working throughout the optical regime, we focus the discussion in this paper on systems operating in the reflective solar spectrum (0.4 to 2.5 μm). We begin by identifying many of the factors in the full end-to-end imaging and detection system and discussing qualitative aspects of their impact on detection. We then briefly describe approaches to the analytical modeling of detection performance as a tool for exploring detection limits. Example results are then presented which demonstrate the prediction capability and show sensitivity to selected system parameters. Finally we conclude with a discussion of what has been learned and directions for future research.

2. FACTORS AFFECTING DETECTABILITY

A useful framework for understanding factors that affect unresolved object detection is to consider the end-to-end remote sensing process as a system. Previous work developed a taxonomy of "noise" factors in the context of land cover classification with spectral imagery [4]. That work divided the remote sensing process into three components: the scene, the sensor, and the processing algorithms. This structure helps isolate factors affecting detection to better identify them, while understanding that their impact can still depend very much on interactions of factors across the system. While limited by space in this paper, the following provides a useful overview of these factors in the context of unresolved object detection.

2.1. Scene Factors

The most obvious factor in the scene affecting object detection is the nature of the object itself. That is, what are its spectral and spatial characteristics as sensed by the hyperspectral imaging sensor? While the notion of a "spectral signature" is convenient and useful, it is clear most objects (man-made or natural) express variability in their spectral reflectance. Clearly the size of the object will also affect detection together with aspects such as whether it is in the open and fully visible, or partially occluded by adjacent objects, and how it is oriented.

The other most significant factor is the nature of the rest of the scene, or the background. This factor has many aspects including the spectral contrast with the object as well as its spectral diversity and complexity. The presence of rare, similar, non-target materials may be a source of significant false alarms. Alternatively, a relatively homogenous and benign background may lead to the easy detection of even small low contrast objects.

Other aspects of the scene worth mentioning include effects of the atmosphere (e.g., haze, presence of clouds), shadowing of the object of interest by adjacent objects, and the goniometric configuration of the imaging system (solar and sensor view zenith angles). These are just a few of possible scene factors affecting detection.

2.2. Sensor Factors

Descriptive parameters of the imaging sensor are usually the first thing that comes to mind when people think of factors that affect remote sensing system performance. These include the physical design factors such as aperture size, focal length, and detector size, as well as derived parameters such as spatial and spectral resolution, and noise levels. System accuracies and sensor artifacts can also strongly affect performance.

2.3. Processing Factors

While not normally thought of as part of a remote sensing system, the application of processing algorithms including calibration procedures, feature extraction and actual detection algorithms can, and usually do, significantly affect the detection of objects. A given hyperspectral image can be processed by different analysts with vastly different results, thus bringing in a human component through choices made by analysts.

The above abbreviated discussion of factors affecting detection is already overwhelming in scope and complexity, yet is not even complete. While this is truly a challenging research topic, the complexity is not a reason to not pursue the research. On the contrary, the richness of the challenge offers much room for exploration, and new insights gained through its pursuit can be very beneficial to the remote sensing community.

3. ANALYTICAL MODELING

Theoretical modeling of detection performance has been explored by previous researchers [1], [5]. These publications show the detectability of targets from a signal processing perspective where the contrast between the target and background is described by probabilistic models and assumed parameters. This approach has a solid mathematical foundation and is an important contribution to the field, but significantly oversimplifies the complexity of a real imaging situation.

The capture of realism together with the pragmatism of probabilistic modeling and linear systems theory underlies the development of our modeling approach described in previous publications [6], [7]. This model is known as Forecasting and Analysis of Spectroradiometric System Performance (FASSP). It includes realistic target and background variability derived from empirical observations, atmospheric effects through MODTRAN, verified sensor models and commonly used processing algorithms, and is used here to explore detection sensitivities and limits.

4. RESULTS

For this paper we will explore the limits of detectability for a subpixel target as a function of three important system parameters: sub-pixel fraction, signal-to-noise ratio, and background complexity as measured by the number of background classes. Table 1 lists the system parameters for the nominal case and Table 2 provides the list of classes used in the background.

The target and background classes are characterized throughout the model by their spectral mean vectors and spectral covariance matrices. These are input to the model as spectral reflectances derived from empirically compensated HYDICE [9] airborne hyperspectral data collected over well ground-truthed sites.

Table 1. Nominal system parameter setting used in study.

System Parameter	Value
Target	Green cotton fabric
Target fill fraction	varies
Background classes	10
Atmospheric model	Summer mid-latitude
Aerosol model	Rural haze
Meteorological range	10 km
Solar zenith angle	30º
Sensor	HyMap [8]
Relative calibration error	1%
Number of spectral bands	126
Detection algorithm	Spectral matched filter

Table 2. Background classes and their fractions of the scene.

Background Class	Fraction of Scene
1. Grass (type 1 – dark)	25%
2. Trees (type 1 – light)	20%
3. Grass (type 2 – light)	15%
4. Light paved road	15%
5. Trees (type 2 – dark)	10%
6. Building roofs	7%
7. Shadowed trees	5%
8. Light green vehicle	1%
9. Bright blue vehicle	1%
10. Dark green vehicle	1%

The first study is to explore how small of a fraction of a pixel can the object occupy, yet still be detectable. Figure 1 shows the results of the probability of detection at a constant false alarm rate = 10^{-5} versus the subpixel fraction occupied by the target. As can be seen, the object becomes detectable ($P_D > 0.8$) around 20% pixel fill.

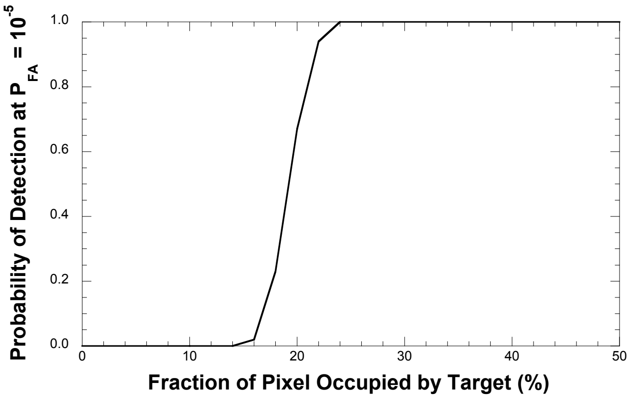

Figure 1. Trade study result showing probability of detection at FAR = 10^{-5} vs. the fraction of a pixel occupied by the subpixel target. Scenario used parameters as defined in Tables 1 and 2.

The next two studies looked at the impact of the other two important system parameters studied for this paper. The first is the sensor signal-to-noise ratio. The system model has a detailed radiometric model for the HyMap sensor including flux-dependent photon noise and fixed noise sources. However, in addition to these noise sources the model includes a "catch-all" noise source defined in Table 1 as "relative calibration error." This noise source adds to the electronics noise (in quadrature) noise with a standard deviation equal to the specified percent of the mean signal radiance level. This has the net effect of providing an upper bound across the spectrum of the combined signal-to-noise ratio and offers a convenient way of varying the system noise with a single parameter. The extra noise can occur due to uncorrected detector non-uniformity or other sources.

Figure 2 shows the detection probability versus maximum (across spectral bands) signal-to-noise ratio. The target subpixel fraction was set to 20% for this study. The results indicate that this particular scenario sits on a fairly steep portion of the detection sensitivity to noise level. Note that the electronics noise (photon and fixed) alone for this scenario with HyMap leads to a maximum SNR around 450.

The third study looked at the complexity of the background as measured by the number of background classes. This was implemented by reducing the number of background classes from the list given in Table 2 one at a time starting from the bottom, and adding the scene fraction for that class to the fraction allocated for the dominant class (grass type 1). As an example, when running the case for 7 background classes, the three vehicle classes were eliminated and the first background class had its scene fraction adjusted to 28%. To obtain detection results that were not all 0 or 1, the target fraction was set to 10%.

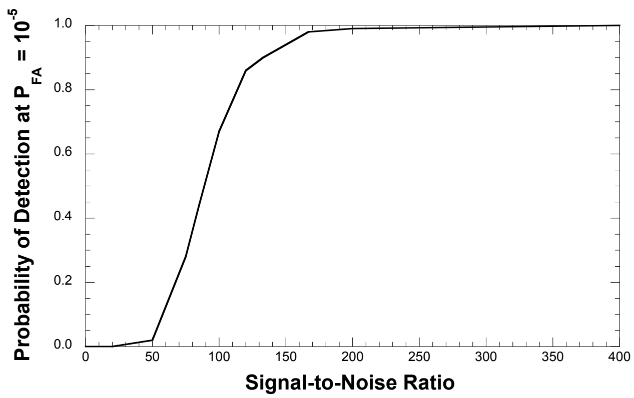

Figure 2. Trade study result showing probability of detection at FAR = 10^{-5} vs. maximum instrument signal-to-noise ratio across spectral bands. Scenario used parameters as defined in Tables 1 and 2 with the target fill fraction set to 20%.

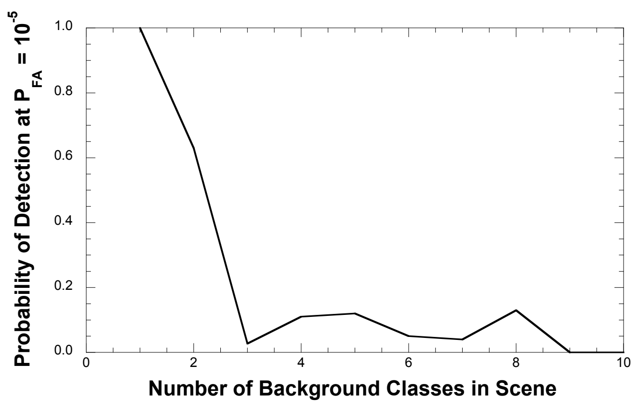

Figure 3. Trade study result showing probability of detection at FAR = 10^{-5} vs. number of background classes. Scenario used parameters as defined in Tables 1 and 2 with the target fill fraction set to 10% and the background classes varied as described in the text.

Figure 3 shows the results for this study on the background classes. It is obvious that the results are not monotonic with number of classes. In particular the addition of the third background class (grass type 2) had a severe impact in lowering the detection probability, yet adding the next two classes (road and dark trees) actually yielded a higher detection probability. Looking at the spectra for these classes we observe the grass type 2 spectra are rather bright with less spectral variation than the type 1 grass, corresponding to yellowing or dying grass. This seems to have led to the class being a bit of an "outlier" and driving the detection probability down for the specified false alarm probability. The addition of the next two classes seems to have reduced the effect of this class allowing a higher detection probability, although the actual number is quite low and the target would still be considered not detectable.

This result of a non-monotonic trend with number of background classes is no surprise to anyone who has worked in hyperspectral target detection. While some general trends can be observed, it is quite common to have cases arise where a given target can be found in one image, but not in another similar, yet slightly different scene [10]. The lesson learned through these types of studies is that there is significant complexity in hyperspectral target detection.

While there is not room in this paper to discuss in detail, it is worth describing two other related aspects of our research into the performance of hyperspectral target detection. One is the development and operation of a blind test for the community [11]. This blind test provides data and an automatic scoring mechanism for researchers to test their algorithms on an independent data set for which the truth is withheld. These data have been actively used and well received by the community [12].

Also, our research has raised an issue that is often ignored in empirical performance studies of hyperspectral target detection. The issue is the fact that most studies use imagery that have relatively few target samples while achieving small numbers of false alarms. We have published and made available as an online tool a technique to estimate confidence regions on receiver operating characteristic (ROC) curves based on the sample sizes [13], [14]. This tool helps researchers understand the limitations of small sample sets on empirical performance estimation and algorithm comparisons.

5. CONCLUSIONS

This paper provides a discussion and example results of ongoing research in exploring the detection limits of hyperspectral imaging systems. We present a viewpoint of modeling the full end-to-end imaging process including the scene, the sensor, and processing algorithms as a coupled system, and identify examples of system factors that affect detection performance. The example shown provides a glimpse into the ability of the modeling approach to explore these limits by showing how little of a pixel may an object occupy while still being detectable in a typical scenario. We also examined the sensitivity of the detectability to sensor system noise and the complexity of the background. While the example results shown here are specific to the studied scenario, they represent typical performance limitations and illustrate the capability of the analytical end-to-end system modeling tool. Future work will continue to develop, validate, and apply the model to expand our understanding of system performance.

6. REFERENCES

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