Parameter Impacts on Hyperspectral Remote Sensing System Performance[1]

John P. Kerekes
Lincoln Laboratory, Massachusetts Institute of Technology
244 Wood St., Lexington, MA 02173-9185
kerekes@ll.mit.edu

ABSTRACT

The design and use of hyperspectral imaging remote sensing systems involve the selection of a large number of parameters in particular due to the richness of the data. Many of these parameters interrelate in their effect on system performance. The tasks of optimizing parameter values that one has control over and understanding the impact of those that are uncontrollable are important in system design and use.

A computational model of relevant system components and parameter values for a hyperspectral remote sensing system has been developed and used to explore their relative impact on system performance. The hyperspectral remote sensing system is defined by considering the scene and all contributions to the upwelling radiance, the sensor and all effects leading to measured data, and the subsequent processing applied to extract the desired information which is then used as the metric for system performance.

The relative contribution to system performance is studied by defining a nominal configuration for the system and then perturbing individual parameters and examining the impact on system performance that results from these perturbations. By considering the effect of parameter values one at a time, the relative impact can be studied. However, since the entire system is still considered in the analysis, the constraining interrelationships are still present thus providing a more relevant indication of impact.

Results will be presented for a canonical scenario where an airborne hyperspectral sensor observes a scene where an unresolved object is arbitrarily located and the performance metric is detection accuracy. Significant effects in system performance are seen to be attributable to spectral channel selection and the object spectral characteristics and size, while factors such as instrument noise and calibration error play relatively minor roles in system performance.

Keywords: Hyperspectral System Analysis

1. INTRODUCTION

The design of an optical spectroradiometric sensing system for military (or civilian) use requires knowledge of both hardware characteristics and performance requirements, as well as the interrelationships between these two aspects. Conventionally, a set of high level performance specifications are drawn up which define the goals of the system in its ultimate application. For example, an optical imaging system may be required to perform a certain mission from low-earth orbit with a given error rate. These high level requirements are then translated into engineering requirements on the system through, in these cases, a fairly straightforward process since they correspond to well-understood requirements on spatial resolution, signal-to-noise ratio, and dynamic range. The system designers then proceed to configure a design to best meet these engineering requirements given other constraints such as size, weight, power, and cost.

With the advent of multispectral and hyperspectral sensing systems, the information inherent in the measurements is tremendous and the relationship between a high-level performance goal and the engineering specifications may not be so obvious. As an example, consider the goal of detecting man-made material in a natural foliage scene. If the material matches the background well, there will be a nearly exact match in the spectral and spatial characteristics between it and the background and a nominal spatial resolution, SNR and dynamic range will not directly translate into a detectability estimate. Rather, a more sophisticated algorithm using transformations of the spectral data, *a priori* information, and higher order statistics will likely be required to achieve this goal. Indeed, characteristics of the processing algorithm become much more important in characterizing the high-level performance of the system.

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It has become clear that a comprehensive view must be taken to understand the capabilities and complex relationships between spectroradiometric hardware and its performance in the desired application. The requirements on the hardware cannot easily be decoupled from the processing algorithms and the inherent richness of the data demands attention to more than the metric and radiometric characteristics of the sensing system.

In particular, as these increasingly sophisticated sensors are being developed, it has become important to understand what are the ultimate capabilities of the systems, how do they vary with a given situation, and what are the fundamental limitations to performance? For the man-made object detection example above, these questions translate to ones such as how dissimilar must the object and background be to have a detection? how does detectability vary with sun angle or atmospheric haze? is the performance limited by sensor noise, resolution, range, the atmosphere, or by background variability? Understanding the answers to these and other questions is critical to further development of these systems.

Several years ago, similar questions were explored in the context of a proposed hyperspectral satellite sensor for NASA's Earth Observing System called HIRIS (High-resolution Infrared Imaging Spectrometer). This work[1,2,3] developed end-to-end simulation and analytical models that explored the interrelationships between system parameters and performance. Recently, an effort was established to enhance these previous models to work with the HYDICE[4] sensor in a surface object detection application.

The goals of this analysis were to identify components that either degrade or enhance performance of the spectroradiometric system and then to quantify the relative level of their contributions. In order to achieve these goals, a model was to be developed that provided a nominal system performance. This model was then to be used to explore the relative contributions of the various components through a perturbation method. The results could then be interpreted to identify the critical components, or "tall poles", in the system.

2. SYSTEM DESCRIPTION

Traditionally, a sensor system is considered to consist of the sensor hardware, software, and possibly the platform. In that context, the "system" engineer designs an instrument that meets certain performance requirements that are testable in a laboratory and satisfies constraints such as weight, power, size and cost.

As argued earlier, multi- and hyperspectral spectroradiometric systems collect prodigious amounts of information and it has become important to expand the idea of the sensor system to include more than just the hardware and software. Thus, in the context of this report, a spectroradiometric system is defined to include all aspects of the flow of information including the source of radiation observed, the scene, the intervening media, the sensor itself, and the subsequent data processing, all the way to the ultimate, high-level interpretation result of the measurement.

This end-to-end system definition is shown graphically in Figure 1. The total system is considered to consist of three subsystems: the scene, the sensor, and the processing. The scene subsystem consists of all sources and effects that contribute to the radiation incident upon the sensor aperture. This includes the sun, the surface characteristics, and the intervening atmosphere. The sensor subsystem includes the traditional connotation of a sensor including descriptions of spectral, spatial, radiometric and calibration errors and effects. It also includes effects due to any communications link errors between the sensor platform and the processing location. Effects or impacts due to platform characteristics are included as well. The processing subsystem includes algorithms and effects of the conversion of the sensor measurements into the high-level information that is defined by the application.

While this system definition is meant to be comprehensive, it is not practical to model every little component and effect in the system. Choices must be made based on priorities established by expected impact and availability of adequate information for their modeling. The section below describes the system components included during this initial development.

Figure 2 presents an overall block diagram to the model showing how the various components are organized in the flow of the two class spectral statistics starting with the scene, proceeding into the sensor, and then into the processing subsystems with the end system performance metric being the probability of error.

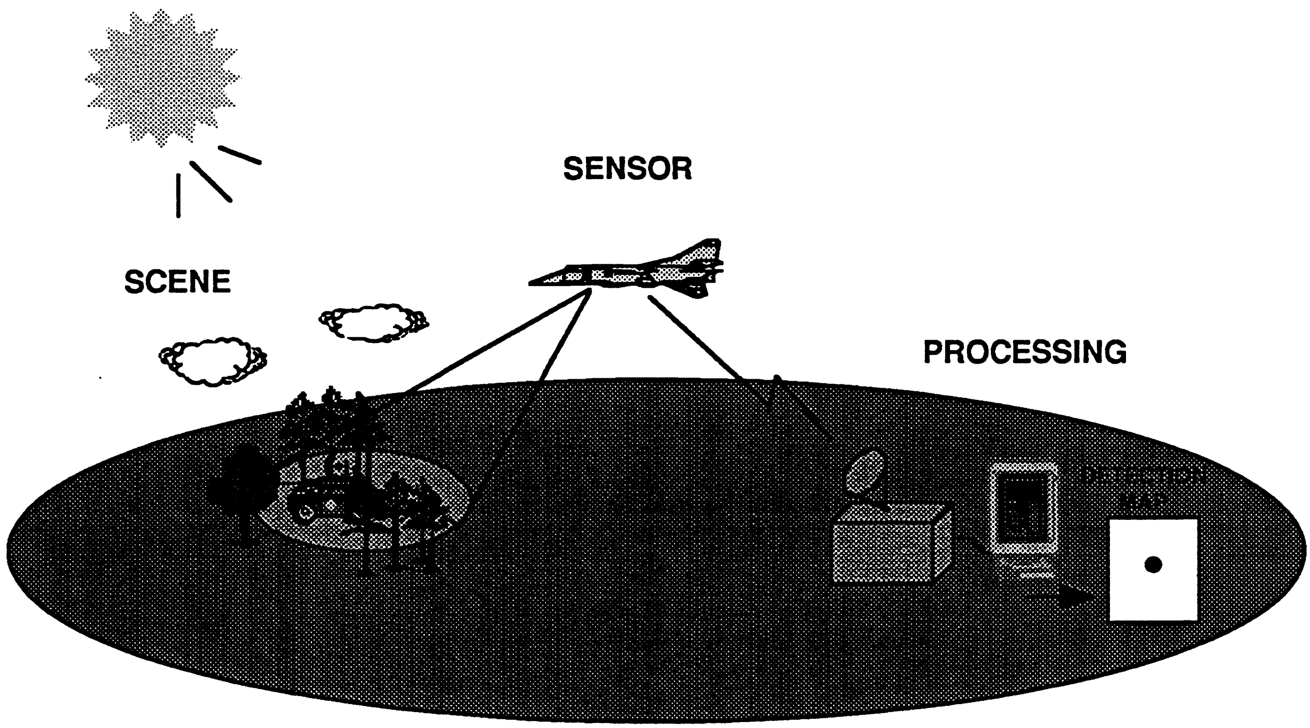

Figure 1. End-to-end spectroradiometric system.

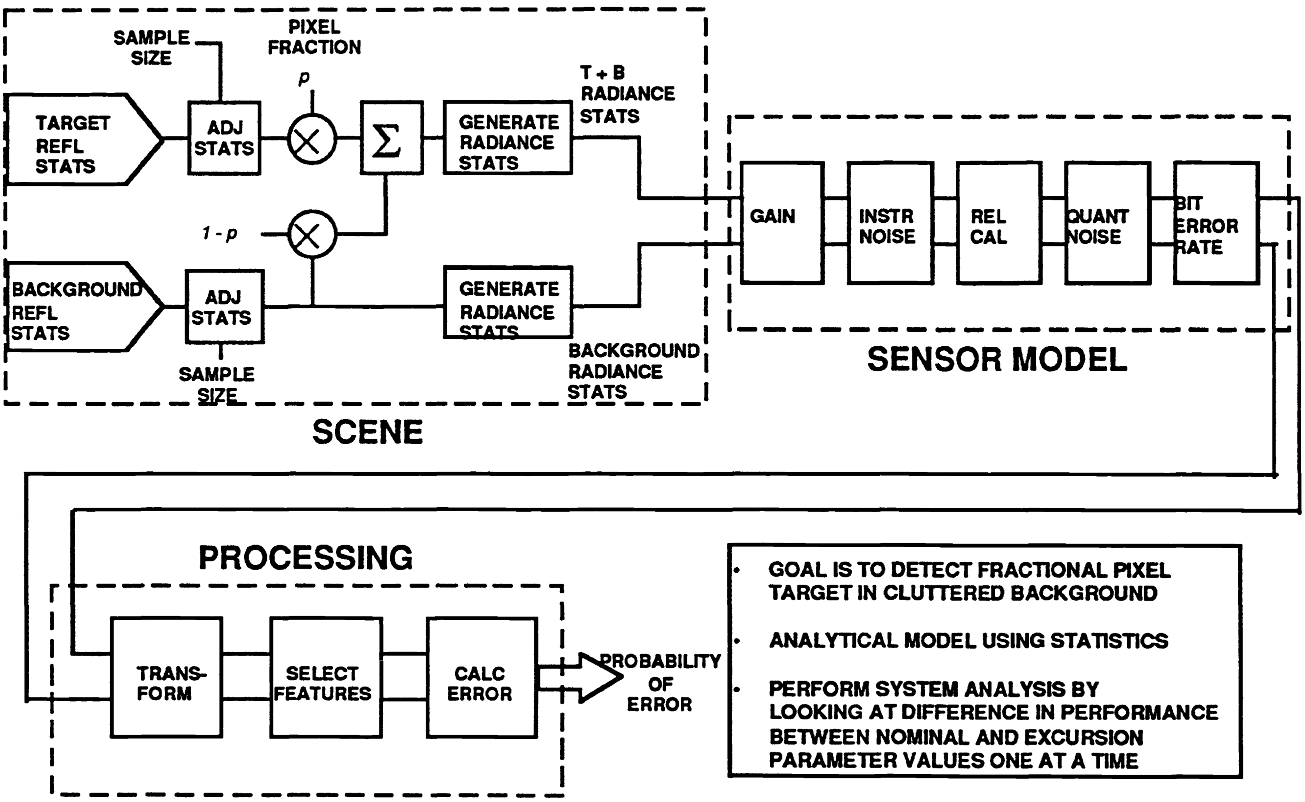

Figure 2 System component block diagram.

Note that the goal of this model is to analyze a HYDICE-like sensor system in an application of detecting a sub-pixel object. Thus, the model has been constructed to work in the solar reflective portion of the optical spectrum with high-dimensional spectral reflectance data describing the object and background classes. However, there are no fundamental limitations preventing the model from being extended to cover the thermal infrared.

The equations used in the model were adapted from the earlier work[2] for the HYDICE instrument. Since that work, an adjustment to the reflectance statistics based on sample size has been added. This model component has become necessary to study the impact of having insufficient spectral reflectance samples by which to adequately describe the statistics for an object class.

The theory of confidence intervals provides a theoretical range for the true value of an estimated parameter. Using well-known results[5], the following equations proscribe the confidence interval for the spectral reflectance means, variances, and correlations.

For the spectral means, μ_p,

$$\left[\bar{\rho}-\frac{\hat{\sigma}_\rho t_{n,\alpha/2}}{\sqrt{N}} \le \mu_\rho < \bar{\rho}+\frac{\hat{\sigma}_\rho t_{n,\alpha/2}}{\sqrt{N}}\right]$$

where,

$\bar{\rho}$	= sample mean
$\hat{\sigma}_\rho$	= sample standard deviation
N	= sample size, $n = N$-1
$\alpha/2$	= 0.025 for 95% confidence interval
t_n	= student t variable with n degrees of freedom

For the spectral variance, σ_ρ^2,

$$\left[\frac{n\hat{\sigma}_\rho^2}{\chi^2_{n;\alpha/2}} \le \sigma_\rho^2 < \frac{n\hat{\sigma}_\rho^2}{\chi^2_{n;1-\alpha/2}}\right]$$

where,

χ_n^2	= Chi-squared variable with n degrees of freedom

For the correlation between spectral channels, μ_w, let $\hat{w}_{ij} = \frac{1}{2}\ln\left[\frac{1+\hat{r}_{ij}}{1-\hat{r}_{ij}}\right]$

then,

$$\left[\hat{w}_{ij}-\frac{z_{\alpha/2}}{\sqrt{N-3}} \le \mu_w < \hat{w}_{ij}+\frac{z_{\alpha/2}}{\sqrt{N-3}}\right]$$

where,

$\hat{r}_{ij}$	= sample correlation between *ith* and *jth* spectral channels
$z_{\alpha/2}$	= standardized normal variable

These equations describe a confidence interval. For use in the model some value within that interval must be chosen. A decision was made to use the end of the interval that results in the most pessimistic impact on probability of error. That is, the estimates of the background and object reflectance data were adjusted to result in greater overlap between the two classes. This was considered a conservative approach. The net result is that the mean vectors are brought closer together, the variances are increased, and the correlations are decreased.

The adjustment to the mean vectors works well when the spectral means are offset from each other and do not cross over. In that case it is obvious how to adjust them so they are closer. If the curves do cross, then the adjustment is made in the more dominant direction. In either case, the Euclidean distance is computed before and after the adjustment. If the adjustment results in greater separation, the adjustment is rejected and the reflectance statistics are not modified.

3. DEMONSTRATION SYSTEM SCENARIO

3.1 Scenario: surface object detection

As a demonstration of the system performance analysis methodology, a surface object detection system scenario was implemented. The scenario was built around data collected over the Yuma Proving Grounds in Arizona. In particular, this scenario examines the system issues involved in HYDICE detecting a subpixel object against a desert background.

The spectral reflectance data used for the object and background classes were obtained by applying gains and offsets to HYDICE data. (Originally, field spectrometer "ground truth" data were to be the reflectance data source but all object/background pairs examined were too separable.) The HYDICE data used was collected during on June 26, 1995 at 1625Z from an altitude of 10,000 ft. (approximately 1.5 meter ground pixel size). Thirty pixels over an object and thirty pixels from the nearby desert background which looked very similar (both in mean and variation) in the visible were selected.

Figure 3 shows the resulting mean spectral reflectances obtained for the surface object and desert background classes. It also shows the spectral regions from which the channel sets were selected for the analysis. The nominal system used 17 channels from the visible where the most overlap in the mean vectors occurs. The additional channels in the near infrared (NIR) and shortwave infrared (SWIR) were selected for the excursion values of the processing features to show the added benefits of these spectral regions. No transformations were done in this case, only the spectral subsetting.

The rest of the system parameters were defined to be typical for desert early-morning, off-nadir viewing, and hazy conditions. A sub-pixel fraction of 25% for the surface object was chosen. No adjustments for spectral reflectance sample size were made since the mean vectors were so close together the adjustment would have made the classes more separable. Also, a performance metric of probability of detection was approximated as just one minus the total probability of error.

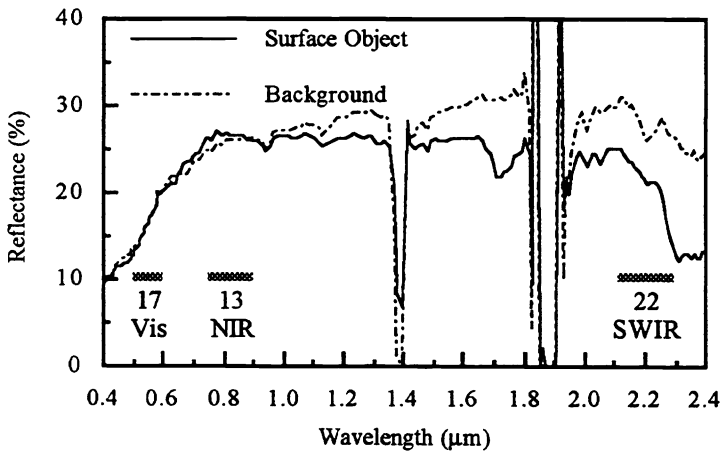

Figure 3. Mean spectral reflectance for the surface object and desert background areas. The number of channels and spectral regions covered in the channel sets are also shown.

3.2 Results and interpretation

Table 1 summarizes the results of the system performance analysis for the set of system parameters shown. The "Nominal Value" column shows the values assigned to each of the parameters for the nominal system definition. This nominal set resulted in a system probability of detection of 0.62 as shown in the title of the table. The "Excursion Value" column shows the values that are assigned one at a time to the parameters (minimizing their effect) and that result in the probability of detection shown in the fourth column. The final column shows the normalized relative contribution to system performance for each of the parameters. This number is calculated for each of the parameters by taking the difference between the nominal system probability of detection and that calculated using the excursion value, and then dividing by the sum of these differences for all parameters considered.

TABLE 1

System performance analysis for detecting a surface object against a natural background. The nominal probability of detection is 0.62.

System Parameter	Nominal Value	Excursion Value	Excursion Prob. of Det.	Relative Contribution
Degrading Parameters (decreasing contribution)				
Spectral Channels	Vis	Vis/NIR/SWIR	0.95	22.8%
Background Covariance Scale	1	0	0.90	19.3%
Object Covariance Scale	1	0	0.89	18.6%
Object Fraction	25%	100%	0.81	13.1%
Relative Calibration Error	1%	0%	0.75	9.0%
Meteorological Range	8 km	32 km	0.73	6.2%
Solar Zenith Angle	60°	0°	0.70	5.5%
View Nadir Angle	60°	0°	0.69	4.8%
Instrument Noise Factor	1	0	0.63	0.7%
Bit Error Rate	10^{-6}	0	0.62	0.0%
Contributing Parameters (decreasing contribution)				
Mean Difference	Present	Absent	0.58	57.1%
Covariance Difference	Present	Absent	0.59	42.9%

In Table 1, the set of parameters under the heading "Degrading Parameters" are parameters whose impact is to lower detection probability. The purpose of the excursion values are to eliminate, or at least reduce, the impact of these parameters. The set under the heading "Contributing Parameters" are those whose impact is to increase the detection probability. Modifying their values to the excursion values results in a lower probability of detection.

The results in Table 1 are listed in decreasing order of contribution. For this example, the nominal choice of using only 17 visible channels as compared to the excursion of adding 35 channels from the NIR and SWIR leads to the spectral channel set being the most significant contributor to degrading the probability of detection. The next most significant parameters are the variability in the object and background reflectances. The "Covariance Scale" parameter indicates whether the covariance is scaled by 1 (present) or 0 (not present). The fourth most significant parameter is the object fraction. Improving the resolution of the sensor so the object completely filled a pixel (while holding all other parameters constant) is seen to increase the probability of detection, but by not as much as that gained by using a more extensive channel set. A random pixel-by-pixel relative calibration error of 1% in the sensor focal plane response was the next most significant parameter, followed by the haze in the atmosphere (meteorological range or visibility), the sun angle, and the view angle. Given the high signal-to-noise ratio of HYDICE, instrument noise plays an insignificant role as does the assumed communications link bit error rate (BER).

Regarding the parameters that contribute to the probability of detection, the difference in the reflectance mean vectors is seen to be more significant than a difference in the reflectance covariance matrices. These parameters were studied by replacing the mean (covariance) of the object class with that of the background class while retaining their nominal covariance (means).

This example shows that for the particular scenario chosen, the selection of spectral channels and the natural variability in the scene are the most important sources of error in detecting the selected object against a natural background. This suggests the use of multispectral or hyperspectral sensors which cover the NIR and SWIR regions are best for this application. Understanding the characteristics of the variability of the scene should be a priority since this variability dominates among the scene parameters that the observer has little control. Also, while instrument noise and communication link BER's have little impact, the random calibration error level of 1% (residual error after nonuniformity corrections have been applied) indicates that this parameter should be well-controlled in an operational system.

While one should recognize that the results of this type of analysis are very dependent upon the particular set of system parameters selected and their nominal/excursion values, this example does demonstrate the ability to quantify in a reasonable manner the impact on end-to-end system performance of a set of diverse quantities in a spectroradiometric remote sensing system.

4. SUMMARY AND CONCLUSIONS

A methodology and demonstration of a spectroradiometric system analysis has been shown. The context has been one of sub-pixel object detection using a hyperspectral sensor working in the reflective solar spectrum. The general approach, methodology, model, validation, and a demonstration example were presented. The results of the analysis have shown the relative importance of such diverse quantities as variations in the scene background, atmospheric haze, and instrument noise on detection performance.

To explore these relative contributions, an approach was adopted which first identified the various system components and parameters and described them as contributing or detracting from the overall system performance. Then, given a nominal system scenario description, the model is used in a forecasting mode to predict the system performance metric. This prediction is then used as a basis with which to compare predictions of performance as the individual system components are eliminated one-by-one. These differences in performance are then used to estimate the relative contributions from the various components and their parameters.

An initial model was developed by building upon the results of previous research in this area. The model uses first and second order statistics to describe object and background classes. Spectral reflectance statistics are input to the model and then modified as appropriate by the various system effects. The output is an estimate of the error probability in detecting the object. This analytical approach has the advantage of being computationally simple.

A demonstration of this analysis was performed for an example scenario of detecting a sub-pixel object against a desert background. The results for this example indicated that the spectral channel set used and the variations in the background as well as the object reflectances were most critical in determining the overall detection probability. In this case, components such as atmospheric haze and instrument noise had relatively minor roles. However, the results of these analyses are very situation specific and broad implications should be drawn carefully.

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