Adaptive Subspace Target Detection in Hyperspectral Imagery

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Abstract –Adaptive subspace detectors are widely used for low probability and anomaly detection. The complex remote sensing conditions in which hyperspectral imagery is obtained make the detector performance evaluation a non-trivial task. Many of the detector design parameters can only be studied empirically for their effects on detection performance. In this paper, hyperspectral images are generated using target and background endmember spectra based on the linear mixing model, where additive Gaussian noise is also added to the mixture model. An adaptive subspace detector is then applied to detect target pixels and the performance of the detector is investigated by varying the target abundance, noise variance, distribution of the target abundance, and target subspace dimension. The results show that the actual performance of the detector is highly dependent upon all of the four design parameters.

Keywords: Adaptive subspace detection, Hyperspectral imagery, Remote sensing, Target detection.

1. INTRODUCTION

Passive remote sensing has witnessed rapid development since the first commercial satellite Landsat-1 was launched in 1972. While the earlier optical sensors (e.g. Thematic Mapper) capture scenes with several discrete, broad bands (referred to as multispectral imagery), current advanced optical sensors onboard the satellites or spacecrafts (e.g. HYDICE, Hyerion) are able to capture scenes at hundreds of contiguous bands with bandwidth as narrow as several nanometers (referred to as hyperspectral imagery or HSI). As opposed to multispectral sensors that produce only a few radiance data points for a ground pixel, hyperspectral imaging sensors construct the near continuous quality radiance spectrum for each pixel in the scene. Thus hyperspectral imagery contains far more information than multispectral imagery does. And this subsequently makes a variety of potential civilian and military remote sensing applications possible, such as global change research, mineral identification and abundance estimation, and crop analysis.

The detection of man-made targets or low probability natural materials is among the most popular applications for hyperspectral remote sensing. Large amount of information contained in hyperspectral imagery in terms of targets of interest and backgrounds can be integrated into a detector design process to greatly increase its detection capability. However, extraneous effects (such as atmosphere propagation, spectral variability, mixed pixels), which are notorious for almost all remote sensing applications, may also greatly decrease the detection power of the detector. This subsequently makes the evaluation of the detector performance a non-trivial task. Though many statistical based detectors are successfully applied for hyperspectral imagery target detection, the performance evaluation of these detectors for different imaging conditions is still lacking.

According to Manolakis et al [1], the majority of algorithms used in hyperspectral applications fall into 4 categories: target / anomaly detection, change detection, classification, and spectral unmixing. In this paper, the focus is on "target detection", where different types of detector in hyperspectral remote sensing for both full pixel and subpixel targets are presented. In-depth analyses are given to the widely used adaptive subspace target detector for its rationale, derivation, and performance evaluation with respective to different detector design parameters. The performance evaluation shows that effects of some factors (e.g., the signal to noise plus interference ratio, dimensions of both target and background subspaces) can be resolved theoretically. Others (e.g., the randomness of the target abundance, the overlap between target and background subspaces) can only be studied empirically.

2. TARGET DETECTION

Target detection can be abstracted as 2 competing hypotheses: H_0 (target absent) vs. H_1 (target present). A target pixel is defined as any pixel that contains object or material of interest in specific applications. Anything else that is not of interest is regarded as background. More specifically, the objective of target detection is to decide whether an observed pixel spectrum $\boldsymbol{x}$ contains only background spectra $\boldsymbol{x_b}$ or both background spectra $\boldsymbol{x_b}$ and the target spectrum $\boldsymbol{x_t}$. Though this is the same as hypothesis testing for conventional digital communication and radar/sonar detection. Conceptually, target detection in remote sensing applications depends mainly on the intrinsic characteristics of HSI data, such as spectral variability and sparseness of the target class.

2.1 Spectral Variability

Many remote sensing algorithms assume that for each pixel, the laboratory spectroscopic measurement of the material occupying that pixel is representative of the remote sensing measurements [2]. However the fact is that the spectral radiance for a specific material output from the sensor shows great variability from image to image, or even in the different geographic regions of the same image. The sources of variability include atmospheric propagation, sensor noises, particle size and roughness of the substance surface, illumination and viewing angles, and mixed pixels etc. The spectral variability and multi-sources of interference make the formulation of the target signals and the noise model not as simple. The ambiguity of the target signal means that people don't know exactly what the signal is before the detector design and that's why a composite hypothesis testing is always involved. These factors complicate the optimal detector

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design (in many cases, optimal detectors don't exist). And the effects of these factors on detector performance can't be solved theoretically.

2.2 Sparseness of the Target Class

Target detection is, more often than not, carried out in the following 2 scenarios: 1) the detection of man-made objects that are spectrally different from naturally occurred surroundings; and 2) the detection of sparsely distributed minerals among heavy interfering background. So the targets of interest constitute a very small part of the whole hyperspectral image, which makes the target class sparsely populated. This means the probability of H_0 (target absent) is always near 1 and the probability of H_1 (target present) is always near *0*. There are many important implications for this. First of all, the sparseness of the target class means there is not enough calibration data to train a statistical classifier for target and background classification. This is why a detection procedure is proposed rather than a conventional classification procedure. Secondly, many criteria used for optimal detector design are not valid. Bayesian criterion is not applicable because the probability of each hypotheses and the cost assignment are not known a *priori*. The minimum probability of error criterion is also not applicable. Generally under the condition of the sparseness of the target class, the probability of error can be minimized by always accepting the null hypothesis (target absent). A Neyman-Pearson criterion is the only one valid for target detection.

3. ADAPTIVE SUBSPACE DETECTOR

An adaptive subspace detector is one of the most popular detectors designed for subpixel target detection. It combines the linear unmixing model and the subspace model to realize subpixel target detection. The theoretical derivation of an adaptive subspace detector is described as follows: Assume there are $P + Q$ endmembers in HSI data. P of them are targets of interest and Q of them are undesired background. The binary hypotheses can then be formulated as:

$$\begin{aligned} &H_0 \textit{ (Target absent):} \quad \mathbf{x} = \mathbf{S_b a_b} + \mathbf{w}\,,\ \mathbf{w} \sim N(0, \sigma_w^2 I) \\ &H_1 \textit{ (Target present):} \quad \mathbf{x} = \mathbf{S_t a_t} + \mathbf{S_b a_b} + \mathbf{w} = \mathbf{Sa} + \mathbf{w}\,, \end{aligned}$$

where $\mathbf{S}_t$ is an $L \times P$ matrix representing P dimensional target subspace in $\Re^L$, $\mathbf{S}_b$ is an $L \times Q$ matrix representing Q dimensional background subspace in $\Re^L$, L is the number of spectral bands, $\mathbf{S} = \left[S_\mathbf{t}, S_\mathbf{b}\right]$, $\mathbf{a}_t$ is a $P \times 1$ target abundance vector, $\mathbf{a}_b$ is a $Q \times 1$ background abundance vector, i.e., $\mathbf{a} = \left[\mathbf{a}_\mathbf{t}^\mathbf{T}, \mathbf{a}_\mathbf{b}^\mathbf{T}\right]^T$, and the noise $\mathbf{w}$ is modeled as multivariate normal with uncorrelated components, that is, the noise in each band is i.i.d. with a zero mean and known variance of σ_w^2.

The generalized logarithm likelihood ratio can be written as:

$$T(x) = \frac{SSE(\hat{a}_b) - SSE(\hat{a})}{\sigma_w^2}\,, \tag{1}$$

where $SSE(\hat{a}_b)$ and $SSE(\hat{a})$ are the lack of fit when fitting the spectrum of $\mathbf{x}$ by using the full subspace S and the background subspace $\mathbf{S_b}$ in an unconstrained least square sense [1, 3-5].

It can be shown that $T(\mathbf{x})$ can be further written as:

$$T(\mathbf{x}) = \frac{\mathbf{x}^\mathbf{T}(\mathbf{P_b}^\perp - \mathbf{P_S}^\perp)\mathbf{x}}{\sigma_w^2}\,, \tag{2}$$

where $\mathbf{P_b}^\perp$ and $\mathbf{P_S}^\perp$ are orthogonal to the full subspace S and the background subspace $\mathbf{S_b}$. And based on this subspace representation, the probability distributions of $T(\mathbf{x})$ under each hypothesis can be represented by a Chi-squared distribution of degree of freedom P, i.e.,

$$T(\mathbf{x}) \sim \begin{cases} \chi_P^2(0) \\ \chi_P^2(SINR_0) \end{cases}\,, \tag{3}$$

where

$$SINR_0 = \frac{\|\mathbf{P_b^\perp}(\mathbf{S_t a_t})\|^2}{\sigma_w^2}$$

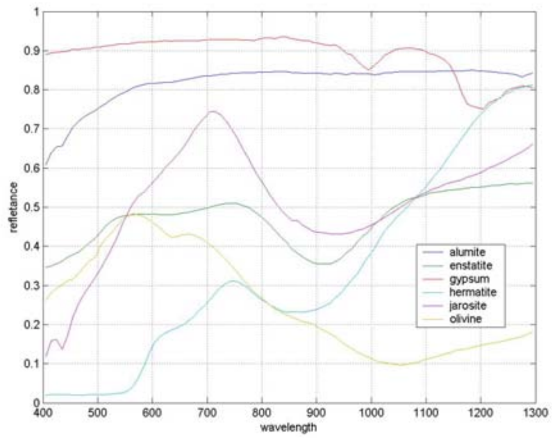
can be interpreted as the signal to interference and noise ratio.

The detector represented by equation (2) is known as an adaptive subspace detector. The performance of the detector is theoretically determined by equation (3) if all of the design parameters are known and deterministic. The real performance of the detector, however, is affected by the variations of σ_w^2 and a_t, the formation of S_t and S_b, and their degree of separation. The main objective of this paper is to investigate the effects of some of the non-deterministic detector design parameters on the actual detection performance of the adaptive subspace detector.

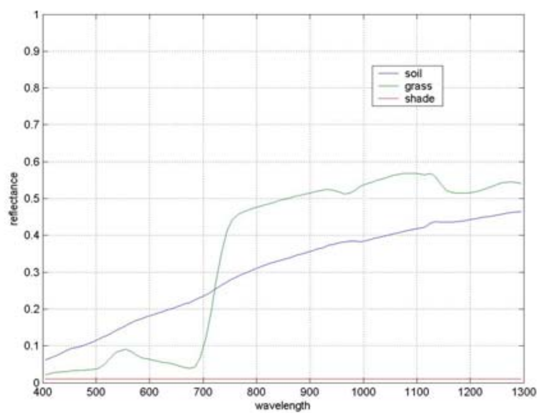
4. EXPERIMENTAL RESULTS

In this experiment, HIS data was used to investigate how the variations of target abundance noise variance**,** target abundance distribution, and dimension of the target subspace might affect the actual performance of an adaptive subspace detector. The background endmembers used included bare soil, grass, and shade endmembers. The background subspace dimension Q was held at a constant value of 3. The dimension of the target subspace P might range from 1 to 6. The target endmembers used were alunite, enstatite, gypsum, hermatite, jarosite, and olivine. The high-resolution endmember reflectance spectra were obtained from [6]. Figure 1 illustrates both the target and background endmember reflectance spectra. The spectral range is from 400 nm to 1300 nm, with a 10 nm bandwidth.

256 by 256 HSI data were generated using the target spectra and the background spectra based on the linear mixing model. Five percent of the total pixels are randomly selected as target pixels and the rest are background pixels (95%) in each HSI data. AN adaptive subspace detector was then applied on the generated HSI data to detect the target pixels. Figure 2 shows how the generated HSI data looks like, the spatial distribution of the target pixels, amplitude of the test statistic T for each pixel, and the distribution of the detected target pixels.



a. Target endmember spectra



b. Background endmember spectra

Figure 1. Target and background endmember spectra

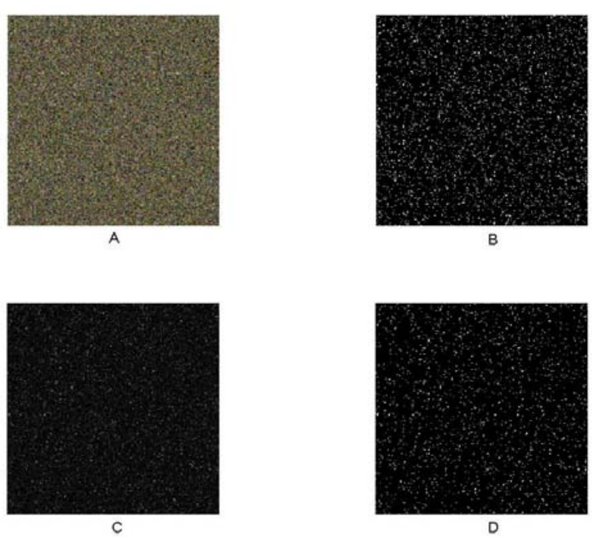


Figure 2. Generated HIS data
A (True color image), B (Spatial distribution of the target pixels), C (Amplitude of the test statistic T), and D (Detected target pixels)

Since four parameters (target abundance $\mathbf{a}_t$, noise variance σ_w^2, distribution of target abundance, and dimension of the target subspace P) were investigated in this study, the experiment was divided into 4 subgroups. The test is performed on each subgroup by varying one parameter while holding all other parameters constant. For the target abundance distribution study, a Gaussian model was used to fit the target abundance distribution. The probability of false alarm was set to 0.001. The results obtained from this study are illustrated in Figures 3-6 for each subgroup.

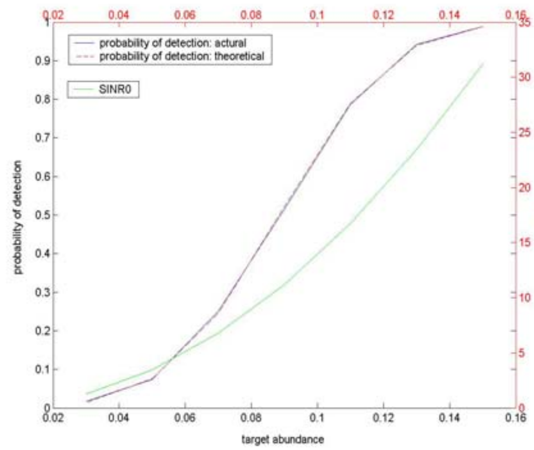


Figure 3. Effect of $\mathbf{a}_t$ on the detector performance
($\sigma_w^2 = 0.0005$, $P = 1$)

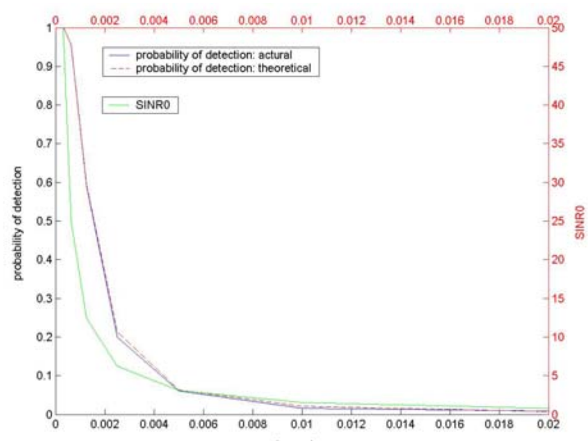


Figure 4. Effect of σ_w^2 on the detector performance
($\mathbf{a}_t = 0.15$, $P = 1$)

It can be seen from Figure 3 that the probability of detection of the adaptive subspace detector increases quickly as the target abundance $\boldsymbol{a}_t$ increases. The probability of detection can reach nearly 100% when the target abundance is as large as 15% and nearly 1% when the target abundance is as small as 3%. This means that an initial guess of the average target abundance is important for the detection evaluation in real applications.

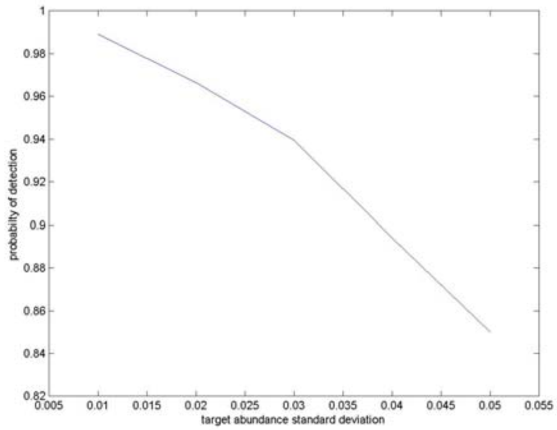


Figure 5. Effect of the distribution of $\mathbf{a}_t$ on the detector performance ($P = 1$, $\sigma_w^2 = 0.0005$, $\mathbf{a}_t = 0.15$)

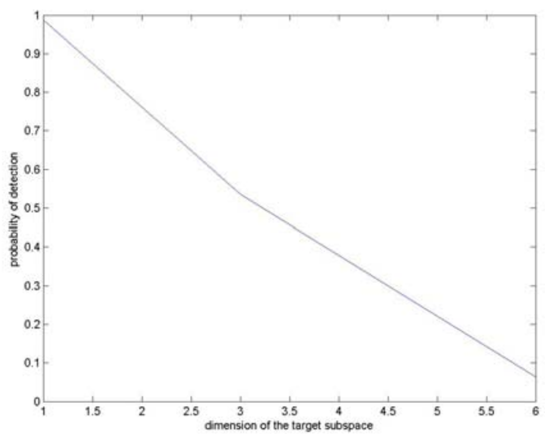


Figure 6. Effect of P on the detection performance ($\mathbf{a}_t = 0.15$, $\sigma_w^2 = 0.0005$)

Figure 4 shows that the probability of detection decreases quickly as the noise variance increases given fixed target abundance. This is of great importance in real applications. As was mentioned before, there are several factors that may contribute to the general SNR of remotely sensed imagery. More often, target detection will be carried out in heavy interference conditions. Multiple passes of denoising procedure are needed not only for a good visual representation, but also for a decent detector performance. In the theoretical derivation, it is assumed that the target abundance is known and deterministic. Accordingly, the detector design is optimal in the Neyman-Pearson sense. In real applications, the target abundance is neither known a *priori* nor uniformly distributed. Figure 5 shows how the randomness of the target abundance affects the probability of detection. A higher variance of the target abundance distribution yields a lower probability of detection. Figure 6 shows how the probability of detection decreases as the dimension of the target subspace increases. As P increases to 6, the probability of detection decreases to less than 10%. In many applications where the target reflectance spectrum is unavailable or people would like to work with raw radiance data, a set of basis vectors calculated from HSI are used to span the variability of the target radiance in remote sensing imagery. Though Healey and Slater's study [7], which concludes generally 9 basis vectors are enough for any material under any imaging conditions, is promising, this experiment indicates that 9 basis vectors for target subspace maybe too large for a good detection performance.

5. SUMMARY AND FUTURE WORK

In this paper, in-depth performance evaluation of the adaptive subspace detector as applied to hyperspectral imagery is presented. The results indicate that the detector performance is directly related to parameters, such as the target abundance, noise variance, distribution of target abundance, and dimension of the target subspace, that are intrinsic to the characteristics of the hyperspectral imagery. The experimental setup can be applied to any form of target detectors and will provide good reference for real remote sensing applications.

Additional factors, such as parameters related to the background spectra (the dimension of the background subspace and the formation of the background subspace), and the separation between the target and background subspaces, are also unique to hyperspectral imagery. Thus, extensive studies are still needed to examine how these factors may affect the detectors' performance to improve the overall detector design.

6. REFERENCES

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