# NOISE ADJUSTED HYBRID SUBPIXEL DETECTION ALGORITHM

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## 1. INTRODUCTION

A challenging problem in hyperspectral imagery (HSI) is the detection of subpixel materials. Over the years, numerous subpixel detection algorithms have been developed. The method of estimating the parameters needed by the detectors, however, has not received as much attention. For example, two classical statistical-based detectors are the Adaptive Matched Subspace Detector (AMSD) [1] and the Adaptive Coherence Estimator (ACE) [2]. The two algorithms differ in their statistical approach to modeling the background. ACE is an unstructured detector; that is, it models the background as a Gaussian distribution. Although research has consistently shown that ACE is a powerful detector for HSI data [3], it has also been shown that Gaussian distributions are inadequate for modeling the backgrounds typically found in HSI data [4]. Rather than using a purely Gaussian model, the structured background detector, AMSD, uses a linear mixing model to obtain endmembers and abundances to represent the background. The resulting endmembers, however, are not physically meaningful. Since the endmembers are the eigenvectors of the image correlation matrix, the abundances are really the magnitudes along the eigenvector directions. The Hybrid Structured Detector (HSD) [5] was designed to combine the benefits of statistical testing while using physically-meaningful parameters obtained from the linear mixing model. In our previous work on the HSD, the noise estimates were taken from the entire raw image causing some redundancy in the algorithm. Our current method, the Noise Adjusted Hybrid Subpixel Detector (NAHSD), provides improved estimates of the noise statistics by examining the difference between the original image and its linear mixture estimate.

## 2. ALGORITHM DESCRIPTION

The NAHSD algorithm utilizes the same theoretical foundation as the HSD [5]. This foundation is based on a set of hypotheses that differentiate pixels containing a material of interest from pixels containing background spectra. A general model for such a hypothesis test is

$$H_0 : \boldsymbol{x} = \boldsymbol{B}\boldsymbol{a}_b + \boldsymbol{n}, \ \ H_1 : \boldsymbol{x} = \boldsymbol{S}\boldsymbol{a}_s + \boldsymbol{B}\boldsymbol{a}_b + \boldsymbol{n} \tag{1}$$

where $\mathbf{x}$ is the pixel under test, $\mathbf{B}$ is an $L \times Q$ matrix representing background endmembers where $L$ represents the number of spectral bands, $Q$ represents the number of endmembers, $\mathbf{a}_b$ is a vector containing the abundances for the associated endmembers, $\mathbf{S}$ is an $L \times P$ matrix representing desired material endmembers, $P$ represents the number of material endmembers, $\mathbf{a}_s$ is a vector containing their associated abundances, and $\mathbf{n}$ represents the noise in the signal. The desired material signatures, **S,** are given and the background endmembers, **B**, are estimated from the data using a variant of the Iterative Error Analysis (IEA) algorithm [6]. Typically, Gaussian modeling is used for the noise, **n**, as it provides a good balance between enhanced fitting of the data over simpler models while still retaining mathematical tractability. It is in the estimation of these Gaussian parameters that HSD and NAHSD differ. HSD uses the entire image to estimate the Gaussian parameters whereas, in the proposed formulation, the Gaussian parameters only model the noise. NAHSD addresses this mismatch by establishing the noise as the error image between the spectral signature of the original pixels and their physics-based linear mixing model estimates. The resulting error pixels capture sensor noise and other effects that are not well represented by the linear model. The Gaussian parameters are then calculated over the entire error image which minimize these noise artifacts. This leads to our final detector

$$D_{HSD}(\boldsymbol{x}) = \frac{(\boldsymbol{x} - \boldsymbol{B}\widehat{\boldsymbol{a}}_b)^T \boldsymbol{\Gamma}^{-1} (\boldsymbol{x} - \boldsymbol{B}\widehat{\boldsymbol{a}}_b)}{(\boldsymbol{x} - \boldsymbol{E}\widehat{\boldsymbol{a}})^T \boldsymbol{\Gamma}^{-1} (\boldsymbol{x} - \boldsymbol{E}\widehat{\boldsymbol{a}})} \tag{2}$$

where $\boldsymbol{E}\widehat{\boldsymbol{a}} = \boldsymbol{S}\widehat{\boldsymbol{a}}_s + \boldsymbol{B}\widehat{\boldsymbol{a}}_b$, $\widehat{\boldsymbol{a}}$ is the estimate of the abundances obtained using the FCLS algorithm, and $\boldsymbol{\Gamma}$ is the covariance matrix computed from the error image. Note that the estimated mean of the error image is subtracted from **x**, **B**, and **S** before the detection score is computed.

## 3. RESULTS

Results comparing NAHSD to traditional algorithms AMSD, ACE, and HSD have been obtained on real-world data that contain subpixel materials. The images contain various backgrounds that provide challenging opportunities for subpixel material detection. Since reflectance signatures were provided for materials of interest, atmospheric compensation techniques were used to map the signatures to radiance. The MODerate resolution atmospheric TRANsmission (MODTRAN®) model developed by the Air Force Research Laboratory [7] was used to generate desired material radiance signatures for all images under a variety of illumination conditions. It is also worthwhile to note that the ground truth provided was at the object-level meaning that only the centers of the locations of the materials of interest were provided. Since subpixel materials can span multiple pixels depending on where they fall within a pixel, a clustering threshold was used to combine adjacent pixels into an object. Each object was then assigned the maximum detection score from the pixels that made up the object and each object was identified as a material of interest or as clutter based on its location relative to the object-level ground truth. An estimate of the appropriate number of endmembers also needed to be addressed since it affected the performances of the AMSD, HSD, and NAHSD algorithms. The Neyman Pearson Approach [8] was used to obtain an estimate of the number of endmembers for a given probability of false alarm and for each detector / material of interest / image combination. For comparison purposes, separability plots [3] were used to depict algorithm performance given different types of materials of interest in various environments. Results demonstrate the capability of the NAHSD for improved subpixel detection of materials of interest.

## 11. REFERENCES


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