MITIGATION OF CORRELATION AND HETEROGENEITY EFFECTS IN HYPERSPECTRAL DATA

JASON P. WILLIAMS
Dept of Operations Research
Air Force Institute of Technology
Wright-Patterson AFB, Ohio

TREVOR J. BIHL
Dept of Operations Research
Air Force Institute of Technology
Wright-Patterson AFB, Ohio

KENNETH W. BAUER
Dept of Operations Research
Air Force Institute of Technology
Wright-Patterson AFB, Ohio

Abstract
The RX anomaly detector is well known for its unsupervised ability to detect anomalies in hyperspectral images (HSI). However, the RX method assumes the data is uncorrelated and homogeneous, both of which are not inherent in HSI data. To defeat the correlation and homogeneity, a new method dubbed Iterative Linear RX is proposed. Rather than the test pixel being inside a window used by RX, Iterative Linear RX employs a line of pixels above and below the test pixel. Through the use of Receiver Operating Characteristic (ROC) curves, this paper presents Iterative Linear RX alongside the standard RX algorithm, the newly introduced Iterative RX, a successful advancement to the benchmark RX HSI detector, and the global Support Vector Data Description (SVDD) algorithm, a promising new HSI detector, to show the results of the newly proposed method.

INTRODUCTION

The RX anomaly detector is well known for its unsupervised ability to detect anomalies in hyperspectral images (HSI). However, the RX method assumes the data is uncorrelated and homogeneous, both of which are not inherent in HSI data. The purpose of this paper is to present a modification to the newly successful Iterative RX introduced by Taitano (2007). The new method, dubbed Iterative Linear RX, has the ability to defeat some of the correlation and homogeneity problems hindering Iterative RX. Rather than the test pixel being inside a window used by RX, Linear RX employs a line of pixels above and below the test pixel. Through the use of Receiver Operating Characteristic (ROC) curves, this paper presents Iterative Linear RX alongside the standard RX algorithm, the Iterative RX algorithm, a successful advancement to the benchmark RX HSI detector, and the global Support Vector Data Description (SVDD) algorithm, a promising new HSI detector, to show the results of the newly proposed method.

SUPPORT VECTOR DATA DESCRIPTION

Banerjee, Burlina, and Dieh (2006) took the original SVDD algorithm by Tax and Duin (1999) and applied it as a HSI anomaly detector. Linear SVDD attempts to determine the minimum hypersphere that explains the region of the corresponding data. When applied to HSI data, a set of *M* background pixels are randomly selected from the image as the training data. The goal is to find the minimum inclosing hypersphere of the *M* pixels, described by equation 1.

$$\min(R) \text{ subject to } x_i \in S,\ i = 1,\dots,M \tag{1}$$

The radius R and center a of the hypersphere are determined by optimizing the Lagrangian in equation 2.

$$L(R,a,\alpha_i) = R^2 - \sum_i \alpha_i \left\{ R^2 - \left(\langle x_i, x_i \rangle - 2\langle a, x_i \rangle + \langle a, a \rangle \right) \right\} \tag{2}$$

After optimizing L with respect to α_i, the kernel trick can be applied which leads to the SVDD statistic in equation 3.

$$\begin{gathered} SVDD(y) = R^2 - K(y,y) + 2\sum_i \alpha_i K(y, x_i) \\ \text{where } K(x,y) = \exp\left(-\|x-y\|^2 / \sigma^2 \right) \end{gathered} \tag{3}$$

The variable σ^2 is a radial basis function parameter used as a scaling factor to direct the size of the boundaries, hence adjusting how well the SVDD algorithm generalizes the incoming data. The algorithm is processed in the following steps:

1. Randomly select M pixels from the image.
2. Estimate an optimal value for σ^2 using a cross-validation or minimax method.
3. Estimate the parameter (R, a, α_i) needed to model the hypersphere.
4. Determine whether or not every pixel in the images lies within the hypersphere. If the pixel is not in the hypersphere it is declared an anomaly.

RX

The RX detector was introduced by Reed and Yu (1990). It detects anomalies using a moving window approach where the pixel in the center is scored by comparing it to the additional pixels in the window. The window is then shifted one row or column of pixels, and the new center pixel is scored. This process is continued until all possible pixels have been analyzed. Each test pixel is scored using a generalized likelihood ratio test which is simplified to equation 4 if the pixels are assumed to be normal with mean μ and covariance Σ. It should also be noted that as N goes to infinity the RX score becomes the squared Mahalanobis distance between the test pixel and the mean of the background pixels.

$$RX(x) = (x-\mu)^T \left[\left(\frac{N}{N+1} \right) \Sigma + \left(\frac{1}{N+1} \right) (x-\mu)(x-\mu)^T \right]^{-1} (x-\mu) \tag{4}$$

The pixels are determined to be anomalies if their corresponding RX score is greater than $\chi_{\alpha,\rho}$ where α and ρ are the corresponding quantile and degrees of freedom of the Chi-squared distribution.

ITERATIVE RX

This standard RX detector has been improved and dubbed Iterative RX by Taitano (2007). The Iterative RX detector works by running the RX detector multiple times, with each iteration calculating better estimates of the true mean and covariance of the background pixels. The Iterative RX algorithm is processed in the following steps:

1. Reduce the dimensionality of the data by running principal component analysis on the whole data set and retaining the *p* largest principal components. This is necessary due to the vast amount of data being processed within each iteration.
2. Run the standard RX algorithm on the data set, but remove any pixels that are in the set of anomalies from the data being used to estimate the mean and covariance of the background. For the first iteration the set of anomalies is empty.
3. Determine the current set of anomalous pixels from the newly calculated RX scores that are greater than $\chi_{\alpha,\, \rho}$. This allows for pixels to enter and exit the set of anomalous pixels each iteration.
4. If the set of pixels identified as anomalies is identical to the previous iteration or the maximum number of iterations has been reached, stop, otherwise return to step 2.

ITERATIVE LINEAR RX

Iterative Linear RX is similar to Iterative RX except instead of a window being moved through the image, it employs a vertical line of pixels above and below the test pixel. If the number of pixels above or below the test pixel exceeds the height of the image, the required pixels are taken from the bottom of the previous column or from the top of the following column. There are two major advantages of the using a line over a window. First, the average distance between the test pixel and the pixels used to estimate the mean and covariance is drastically increased, as depicted in figure 1, thus decreasing the effect of correlation and heterogeneity inherent in the data. Second, the use of the line gives the ability to test every pixel in an image, which the RX method cannot do to the required window.

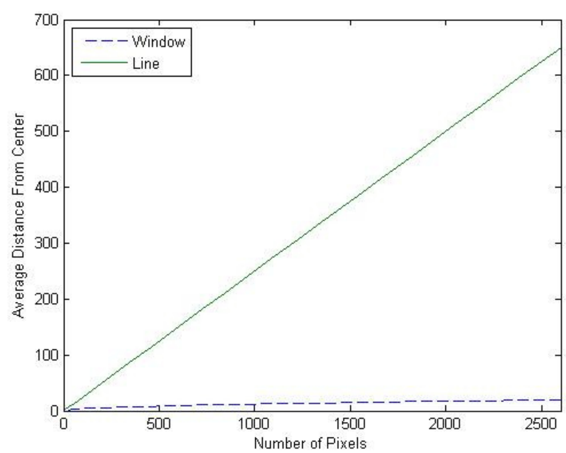

Figure 1: Average Distance from Test Pixel

METHODOLOGY

All four of the anomaly detectors were compared using images from the ARES desert and forest radiance collections. The images consist of 210 wavelength bands, primarily from the visible spectrum, however only 145 are used due to atmospheric distortion. This paper will depict two of the six images tested in the experiments, ARES

1F and ARES 2D, displayed with their corresponding truth masks in figure 2. The pixels surrounding the anomalies, called border pixels, contain background and anomaly data; therefore they are not considered in either class when scoring the detectors. ARES 1F consists of total 30,560 pixels, of which 1,007 are considered anomalies and ARES 2D consists of 22,360 pixels with 523 anomalous pixels.

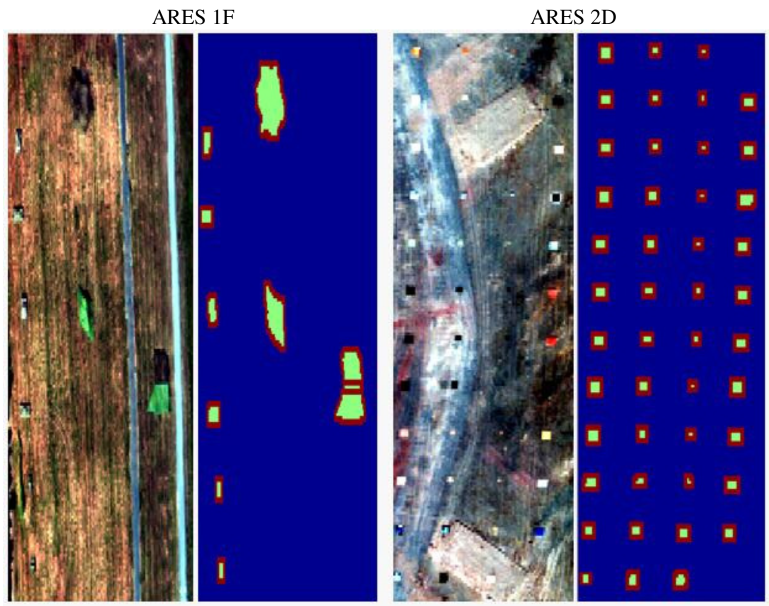

Figure 2: ARES 1F and ARES 2D with corresponding Truth Masks

The SVDD algorithm was run with $\sigma^2 = 905$ based off of the minimax method described by Banerjee, Burlina, and Diehl (2006) and $M = 500$. Standard and Iterative RX was run using a square window of 21 pixels based on the recommendations of Taitano (2007). Iterative Linear RX used a line size equal to the number of pixels in the vertical direction of the image, based on preliminary results, and both were run using a maximum of 30 iterations. Prior to any processing with the RX detectors, principal component analysis was performed and the seven largest principal components were retained based on previous experiments.

The goal of the experiments was to compare the promising SVDD detector, the Standard and Iterative RX detector, and our Iterative Linear RX detector. Each of the detectors were run using various values of alpha for the Chi-squared distribution, and their results were collected and used to generate ROC curves to visually score them.

RESULTS

The majority of the images the Iterative Linear RX tested provided better results than Iterative RX and SVDD. In the few cases where Iterative Linear RX was not the clear winner, due to known issues, methods are being implemented to overcome the problems.

When viewing the ROC curves, which are displayed in figure 3, it is easily seen that Iterative Linear RX is performing with the highest abilities. In both of the images SVDD fairly successful in detecting outliers, however, Iterative Linear RX is showing even better results. In the ARES 1F image, Standard and Iterative RX does a poor job with the large anomalies, because when the window is centered on an anomalous pixel on the target the majority of the window also contains the anomaly. This completely defeats the purpose of the window, which is to give a good estimate of the true background of the image; hence, the pixel being analyzed appears like the other pixels in the window and is not classified as an anomaly. Iterative Linear RX defeats this problem by only containing a small portion of even a large anomaly due to the vertical line used to estimate the background. In the ARES 2D image, the Standard and Iterative RX methods do a poor job due to its inability to classify targets on the border of the image. In the tests, the window size was set to 21 by 21 pixels which generates a border of 10 pixels all the way around the image that it cannot test and in this particular image creates problems. On the other hand Iterative Linear RX can test every pixel in the image, and thereby does a much better job of classifying the anomalous pixels.

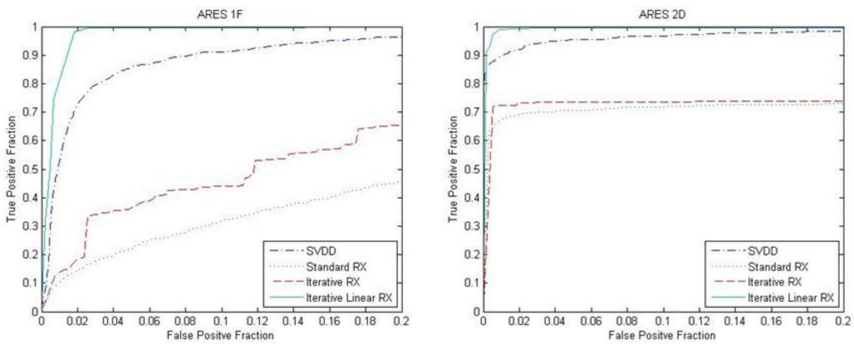

Figure 3: ARES 1F and ARES 2D ROC Curves

DISCUSSION

This paper presented an update to the newly introduced Iterative RX algorithm by altering the method of determining the mean and covariance estimates of background pixels within HSI data. The new method also accounts for a portion of the correlation and heterogeneity that is inherent in this data and assumed to be nonexistent by the Standard and Iterative RX algorithm. It has shown to be successful in classifying anomalies at a higher rate than the Iterative RX method, which is a reasonable competitor to the SVDD algorithm. It is also a fully unsupervised method, whereas SVDD is a supervised method that requires the random selection of background pixels. In low anomaly to background environments that are tested in this image SVDD is likely to get a good estimate for the background, however, due to the random selection process, it is possible to get a bad draw.

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