WHITENING SPACIAL CORRELATION FILTERING FOR HYPERSPECTRAL ANOMALY DETECTION

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ABSTRACT

Matched and adaptive subspace detectors apply to a wide range of problems in radar, sonar, and data communication, where the signal is constrained to lie in a multidimensional linear subspace. These detectors generalize known results in matched and adaptive detection theory. In this paper we propose an original approach to anomaly detection based on Whitening and Spatial Correlation Filtering (WSCF). The performance is investigated in terms of the detection probability, and the false alarm ratio. A comparison permits us to show how this new method can outperform the well-known Reed and Xiaoli Yu (RX) algorithm.

1. INTRODUCTION

Hyperspectral sensors collect the spectral signature of a number of contiguous spatial locations (pixel) to form a hyperspectral data cube [1]. The basic task underlining many hyperspectral sensor imagery applications is to identify different materials based on their reflectance spectrum. In this respect, the concept of a spectral signature, which uniquely characterizes any given material, is highly attractive and widely used [2]. However, spectra observed from samples of the same material are never identical due to variations in the material surface, even in laboratory experiments. The amount of variability is more important in remote sensing applications due to the variations in atmospheric conditions, sensor noise, material composition, location, surrounding materials, and other factors. To make matters worse, totally different material types can have very similar spectra. Additional sources of spectral variability are calibration and illumination variations which are not currently handled by atmospheric correction codes. Under these conditions, it is sometimes preferable not to introduce target information when the application allows it [3, 4].

If we have no *prior* information about the target or if we wish to work with radiance, the most reasonable approach is to look for pixels whose spectral content is "significantly" different from those of the local background. This process is known in hyperspectral literature as anomaly detection [5, 6, 7]. Hyperspectral and multispectral imagery shows a great potential for this task because it provides both spectral and spatial features about the targets and backgrounds in the imagery.

In a first part, we present an overview of Anomaly Detector algorithms, and in particular Reed and Xiaoli Yu (RX) algorithm [5, 6], which is extensively used in multispectral and hyperspectral imagery. In a second part, we show that RX model fails when target overlays many pixels, and we develop Whitening Spatial Correlation Filtering (WSCF), a new method which allows to solve this problem. Then, in a third part we present a detailed comparison between the two algorithms RX and WSCF on simulated data. In particular, we make a study on the performances of algorithms with respect to the target size. Finally, we conclude on the performance of this new model.

2. ANOMALY DETECTOR

In several applications, we do not have any *a priori* information about the desired target. In such cases, it is possible to design algorithms searching for spectra which deviate from the local background (anomaly detection). This problem is typically formulated as a binary hypothesis test with two competing hypotheses: background only (H_0) or target and background (H_1). Since the two hypotheses depend on unknown parameters (for example background covariance matrix) which have to be estimated from the data, the detector has to be adaptive and is usually designed using the generalized likelihood ratio test (GLRT) approach. The type of statistical model used for the background leads to different anomaly detection algorithms.

2.1. RX algorithm

The use of a multivariate normal distribution model leads to the RX algorithm, which is extensively used for anomaly detection.

$$D_{RX}(\mathbf{x}) = (\mathbf{x}-\mu)^t \hat{\mathbf{\Gamma}}^{-1}(\mathbf{x}-\mu) \quad \underset{H_0}{\overset{H_1}{\gtrless}} \quad \eta, \tag{1}$$

where $\mathbf{x}$ is the spectral pixel vector, μ the mean spectral vector for the region of interest (the mean of each spectral band), $\hat{\mathbf{\Gamma}}$ the estimated spectral covariance matrix, and η a threshold set according to the desired false alarm probability. The quantity D is a spatial map emphasizing the most anomalous pixels. Basically, $D_{RX}(\mathbf{x})$ estimates the Mahalanobis distance of the test pixel from the mean of the background, which is zero for demeaned data [2]. That algorithm is a locally adaptive Constant False Alarm Rate (CFAR) detector [2], which assumes spatially uncorrelated Gaussian clutter and known target spatial signature with unknown spectral distribution and covariance matrix. An estimate of the target amplitude is made at each position within the image.

2.2. Other approaches

In [7] Schweizer and Moura developed a CFAR algorithm based an a first-order Gauss-Markov random field model for the clutter. In that algorithm a maximum likelihood technique was used to estimate the clutter parameters, which were then used in a GLRT detector. Several authors have attempted to exploit target spectral characteristics. Ashton used clustering algorithm to find sub-pixel anomalies in multispectral IR terrain imagery. In [8], Ashton and Schaum used RX algorithm to search for anomalies in background-suppressed spectral signatures. A very different approach was exploited by Banerji and Goutsias in [9], who used mathematical morphology to detect mines in individual bands followed by a fusion of the band information. Correlation among the bands was addressed by the use of a maximum noise fraction transformation to generate independent bands.

3. WHITENING SPATIAL CORRELATION FILTERING

3.1. Failure of the model

The purpose of anomaly detection is to search for and locate targets which are generally unknown, but relatively small with low probabilities of occurrence in the image scene. The size of the anomaly target depends on the application. It goes from a size inferior to the spatial resolution of the image, to several tens of pixels. However, even when its size is smaller than the spatial resolution of the image, nothing indicates *a priori* that it is located on a single pixel of the image. That's why the assumption of spatially uncorrelated clutter is generally not valid and the performance of RX algorithm decreases in such cases.

In [3], Liao and al. have noted this problem and propose an efficient pre-filtering to reduce spatial overlap between the target and the clutter and to improve detection of surface mines in multispectral IR and visible imagery. The objective of the Whitening Spatial Correlation Filtering method is the contrary; it is to take this remark into account to improve the detection performances of the RX algorithm.

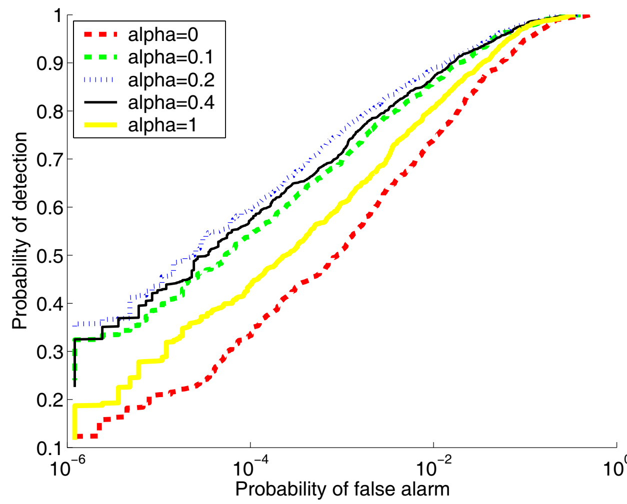

Fig. 1. ROC curves with Abundance=0.6, SNR=14, and Radius=1.

3.2. Proposed WSCF algorithm

The whitening transformation is expressed by (2):

$$\tilde{\mathbf{x}} = \mathbf{\Lambda}^{-1/2}\mathbf{U}^t\mathbf{x}, \tag{2}$$

where $\mathbf{\Lambda}$ is the eigenvalue matrix, and $\mathbf{U}$ an orthogonal linear transformation composed of the eigenvectors of $\hat{\mathbf{\Gamma}}$. Using the whitening transformation, the RX anomaly detector can be expressed as $D_{RX}(\mathbf{x}) = \tilde{\mathbf{x}}^t\tilde{\mathbf{x}}$ which is the Euclidian distance of the test pixel from the background mean in the whitened space. The RX anomaly map is represented by the Euclidian norms of the whitened vectors.

$$\mathbf{I}(i) = \|\tilde{\mathbf{x}}_i\|, \tag{3}$$

where $\|\ \|$ is the Euclidian norm.

To highlight the problem, let us suppose an anomaly map with a zone gathering a high density of anomalies. This map does not allow to determine if this strong density of anomalies is due to the same target distributed on several adjacent pixels, or to a coincidence between disturbed pixels. However, the direction of the spectral pixel vectors in the anomaly $zone$ contains this information. If the spectral pixel vectors have close orientations, we can suppose that

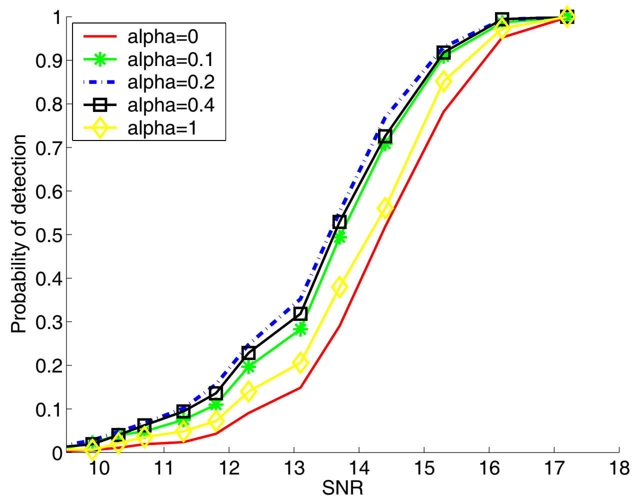

Fig. 2. Pd with respect to the SNR, with Pfa=10^{-4}, Radius=1, and Abundance=0.6.

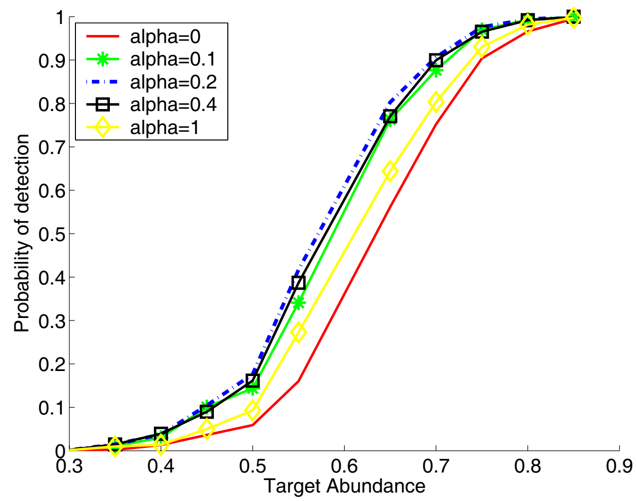

Fig. 3. Pd with respect to the Abundance, with Pfa=10^{-4}, Radius=1, and SNR=14.

it is extremely probable that they are due to the same target. On the contrary if the orientations are distant, we can suppose that they are due to disturbed pixel vectors or different targets. The idea of Space Correlation Filtering is to introduce a methodology as well as a criterion to take this information into account. We have seen that RX anomaly map is represented by the Euclidian norms of the whitened vectors. We propose the following anomaly map for the WSCF approach:

$$\mathbf{I}_{WSCF}(i) = \|\tilde{\mathbf{x}}_i\| + \alpha \sum_{j \in v(i)} \rho_{i,j} \, \|\tilde{\mathbf{x}}_j\|, \tag{4}$$

where α is a parameter discussed thereafter, $v(i)$ is composed of the 8-neighbors of the pixel vector i, and $\rho_{i,j}$ indicates the coefficient of correlation between the whitened pixel vector i and the whitened pixel vector j.

We express $\mathbf{I}_{WSCF}$ as:

$$\mathbf{I}_{WSCF}(i) = \|\tilde{\mathbf{x}}_i\| \left(\frac{\tilde{\mathbf{x}}_i^t \tilde{\mathbf{x}}_i}{\tilde{\mathbf{x}}_i^t \tilde{\mathbf{x}}_i} + \alpha \sum_{j \in v(i)} \frac{\tilde{\mathbf{x}}_i^t \tilde{\mathbf{x}}_j}{\tilde{\mathbf{x}}_i^t \tilde{\mathbf{x}}_i} \right). \tag{5}$$

Let notice that the filter known as minimum variance beamformer, or constrained energy minimization (CEM) algorithm [10] for the interested target signature $\mathbf{x_i}$, applied to the pixel vector $\mathbf{x_j}$ is given by (6):

$$D_{CEM}(\mathbf{x_j}) = \frac{\tilde{\mathbf{x}}_i^t \tilde{\mathbf{x}}_j}{\tilde{\mathbf{x}}_i^t \tilde{\mathbf{x}}_i}. \tag{6}$$

Then $D_{CEM}(\mathbf{x_j})$ can be viewed as the estimated abundance of $\mathbf{x_i}$ contained in the pixel $\mathbf{x_j}$. So, (4) and (5) express $\mathbf{I}_{WSCF}(i)$ like a sum of estimated abundance of $\mathbf{x_i}$ contained in $v(i)$.

4. COMPUTER SIMULATION

This section conducts a comparative analysis between RX algorithm and WSCF algorithm experiments to demonstrate their relative performance using a series of computer simulations. We extract from hyperspectral images of HYDICE sensor imagery (16 bit BIL) four field reflectance spectra from one image and one from another. Low signal/high noises bands and water vapor absorption bands are removed. In our simulation, the first four spectra represent the background, and the last one represents the target. We construct a simulated background with random abundance. Then, we choose circular target repartition with two parameters: the abundance (between 0 and 1) and the radius (expressed in pixel). For each estimation of the Probability of detection (Pd), we perform 1000 processes in which the Probability of false alarm (Pfa), the Signal Noise Ratio (SNR), the radius and the abundance of the target are constant. In each process, the following values are modified: the distribution of the background abundance, the realization of the noise, and the position of the target center (so the target/background ratio repartition).

In Fig. 1, we show a receiving operator characteristic (ROC) curve. Clearly, the WSCF model performs RX model ($\alpha = 0$) for target with radius equal to 1. A good choice of α seems to be 0.2 in this case.

In Fig. 2 let us show the evolution of the probability of detection with respect to the SNR, with constant abundance and target radius. Firstly we can bear out the good choice of $\alpha = 0.2$. Then we can notice that for various values of α the curves do not intersect. Moreover, in Fig. 3 the same phenomenon for the evolution of the probability of detection with respect to the abundance can be observed. So

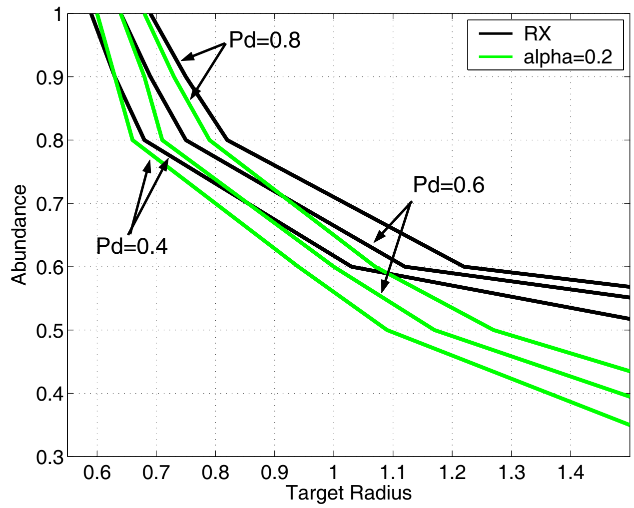

Fig. 4. Abundance with respect to the Radius, with Pfa=10^{-4}, SNR=14 and many Pd.

we can conclude that the best choice of α depends neither on the target abundance nor on the SNR. On the other hand it depends on the target size. It seems to be obvious that the smaller the target size is, the smaller the best α is, and conversely. The limit is defined by $\alpha = 0$ (RX model) for a target radius equal to 0.

In Fig 4 we show the evolution of the target abundance with respect to the target radius, with false alarm probability equal to 10^{-4} and for many probability of detection. Firstly, the larger the target size is, the larger the difference between the two methods is. Then, we notice for a target radius superior to 0.65, the WSCF model with $\alpha = 0.2$ performs the RX model.

5. CONCLUSION

In this paper we have presented a new approach of anomaly detection for multi band imagery named Whitening Spatial Correlation Filtering (WSCF). It is based on a whitening filtering followed by Spatial Correlation Filtering. We have justified the interest of this original method to overcome a failure in the well known RX anomaly detector, due to the fact that the anomalies can cover several pixels. Then we have shown the superiority of this model under the RX algorithm for anomaly target whose radius is superior to 0.65 time the spatial resolution of the image. After this theoretical study, it will be necessary to test the WSCF method on real applications. Several applications seem adapted: for example the detection of surfaces mines or the detection of soil mineralogy.

6. REFERENCES

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