Signal Contamination Model for Adaptive Detection Performance of Local Anomalies in Hyper-spectral Images

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***Abstract**:* This paper presents an analytical model for signal contamination, which considers variability in the extent of contamination that formally introduced in the local AD framework. The impact of signal contamination on local adaptive AD performance is extensively analyzed by employing the RX algorithm.

Keywords: Covariance corruption, Hyper-spectral imaging, Signal contamination, Local anomaly detection

I. INTRODUCTION

The electromagnetic spectrums are used to collect and process information of spectral imaging. To get the range for all pixel in the picture of a scene by means of the idea of finding substance, identify equipment, or detect process is the aim of hyper-spectral imaging. Noticeable glow in three bands are red, green, and blue in color. It is divided by the spectrum into many more bands. This method of separating images into bands can be comprehensive away from the observable. In hyper-spectral imaging, the recorded spectra have fine wavelength resolution and cover a wide range of wavelengths. Engineers construct hyper-spectral sensors and dispensation system for application in astronomy cultivation, bio-medical imaging, mineralogy, physics, and surveillance (observations). Hyper-spectral sensors appear by the side of substance by means of a huge part of the electromagnetic range.

II. EXISTING SYSTEM

In existing, kernel-based nonparametric regression method is proposed for background prediction and clutter removal, furthermore applied in target detection.

Small-target detection is one of the majority significant applications of thermal infrared imagery. Infrared small target detection technology has urbanized swiftly in these existence, and plenty of effectual procedures were planned. In an infrared image with composite setting (background), i.e., low signal-to-clutter ratio, the dissimilarity among targets and background is extremely low, and targets have no tangible form and texture, because of extended imaging remoteness, so target detection in single-frame infrared image with low signal-to-clutter ratio (SCR) has been measured as a complicated and tough dilemma [1, 8]. In general, the high gray area of background clutters can blur the small targets, and a strong background fluctuation may lead to a high rate of false alarm in detection. Moreover, background constitutes a large proportion of an infrared image. Therefore, the detection method based on background prediction and suppression is available.

Existing background suppression methods for single-frame infrared image are mainly classified into the following two categories. One is the filtering methods and the other one is statistical regression. The filtering methods include processing in space domain, which uses filter templates, morphological operators, etc., and processing in frequency domain, which relies on eliminating the low-frequency component. The filtering methods can suppress most part of the correlative background but may be easily interfered because of strong fluctuation of complex background clutters. Regression methods are classified as parametric and nonparametric methods. Classical parametric regression methods rely on a specific model of background clutters and seek to estimate the parameters of this assumed model [2, 3-6]. In comparison with the parametric methods, nonparametric methods rely on the data itself to estimate the regression function. In practice, nonparametric methods are more suitable and adaptive for complex background because of lack of a priori knowledge about background clutters. As a result of the recent development of machine learning theory, kernel methods have been used widely in pattern analysis and statistical regression problems [4 7]. In this letter, a small-target detection algorithm in infrared image is proposed, which predicts and eliminates the complex background clutter by a kernel-based nonparametric regression model and obtains residual “pure” target-like image which only consists of noise and possible targets on local regions in infrared images. Then, a two-parameter constant false alarm rate (CFAR) detecting algorithm is performed to extract the small target from the “pure” target-like image [8-11].

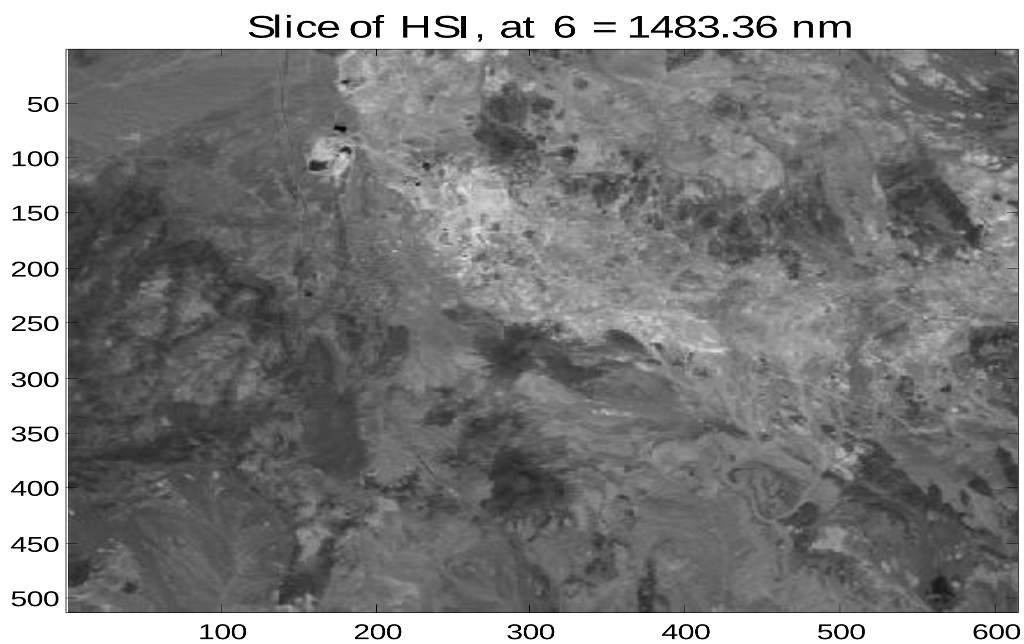

Figure 1: Hyper-spectral Image

III. PROPOSED SYSTEM

Contamination-free Signal Model and RX Detector

The RX algorithm was developed on the basis of a local multivariate Gaussian model, generally assumed after a local mean-removal procedure, for the null (H0, background only) and alternative (H1, target plus background) hypotheses

$X|H0 = V \in N(0, C0 = R_0)$

$X|H1 = \alpha s + V \in N(\alpha s, C_0)$

X is the L-dimensional random vector associated with the generic test pixel x (subtracted of the corresponding local mean vector), s is the unknown spectral signature of the target with amplitude α, V is the background-plus-noise spectral vector, and C_0 is the unknown background covariance matrix (equal to the background correlation matrix R_0) that is shared by the H1 hypothesis. L denotes the number of sensor spectral channels or, more commonly, the number of spectral features if a dimensionality reduction procedure is applied. The asymptotic expression for the RX decision rule is given by the following:

RX (x) = xT • Rˆ_0^ (-1) • x η

Where, η is the detection threshold and $\hat{R}_0 = (1/N)\sum_{i=1}^{N} y_i . y_i^T$ is the maximum-likelihood estimate (MLE) of the correlation matrix obtained over N secondary data {y_i} (i=1)^N which are assumed to be samples of independent and identically distributed (IID) random vectors {y_i} (i=1)^N having the same distribution as the background.

$$\{Y_i \in N(\mathbf{0}, \quad C_0 = R_0)\}_{i=1}^{N}$$

In practical applications, the secondary data are generally taken as N > L pixels surrounding the test pixel thus, well representing the statistical behavior of the local background. The N > L condition is often achieved through spectral dimensionality reduction methodologies. The ratio between the RX test statistic without contamination and the scalar value β = N • ν1/ν2 follows a central F probability density function (pdf) with ν1 = L and ν2 = N − L + 1 degrees of freedom (DF) under H0. The F distribution becomes non-central under H1, with the non-centrality parameter equal to ρ = α2sTR_0^ (-1) s. Asymptotically (when either the sample-size-to-spectral-features ratio f = N/L is very large or R0 is known), the RX test statistic is chi-square distributed with L DF with the non-centrality Parameter under H1 given by ρ. The non-centrality parameter ρ is the theoretical Signal-to-Interference-plus-Noise Ratio, denoted by $SINR_0$.

A. *Signal Contamination Model*

Let us define the set of random vectors associated with the contaminated secondary data $\{\widetilde{y_i}\}_{i=1}^{N}$ as follows:

$$\widetilde{Y}_i = \begin{cases} Y_i \in N(\mathbf{0}, C_0 = R_0), i = 1 \ldots. N - K \\ \Psi_i s + Y_i, \quad i = N - K + 1 \ldots\ldots\ldots\ldots.. N \end{cases}$$

Where, k out of N samples contain the target signal and Ψ_i is a scalar random variable associated with the amplitude of the contaminating target signal in the i^{th} sample. Specifically, $\{\Psi_i\}_{i=N-K+1}^{N}$ are assumed to be IID variables. Hereinafter, $\{\Psi_i\}_{i=N-K+1}^{N}$ denotes the set of realizations of the random amplitudes associated with $\{\Psi_i\}_{i=N-K+1}^{N}$. Although the additive contamination model may not provide a comprehensive explanation of the effects of all types of contamination, a study of more complex models (such as replacement models) is beyond the scope of this paper and will be addressed in future research. With the contaminated secondary dataset, the actual decision rule executed when the conventional RX is applied differs from the rule expressed, because the correlation matrix is no longer estimated over a set of target-free pixels $\{y_i\}_{i=1}^{N}$ but, rather, over the set of contaminated pixels $\{\widetilde{y_i}\}_{i=1}^{N}$ (the subscript c means contamination).

B. *RX Detection Statistic in the Presence of Contamination*

The actual decision rule applied by the RX algorithm, when the local background correlation matrix is estimated over the set of contaminated pixels $\{\widetilde{y_i}\}_{i=1}^{N}$, becomes

$$RX_c(x) = x^T \cdot \hat{R}_c^{-1} \cdot x \; H_1 >< H_0 \; \eta$$

To derive an expression for $RX_c(x)$, we follow the signal model by Reed and Yu and-recalling that $\{Y_i\}_{i=1}^{N}$ are IID and zero-mean-reasonably assume that $r_{\Psi Y} = 0$ (i.e., the contaminating signal amplitude is uncorrelated from the underlying residual background, because the latter is zero mean). Such an assumption is similar to the assumption originally hypothesized and it is adopted throughout this paper. Replacing $r\Psi_Y = 0$ leads to the following simplified expression for the contaminated correlation matrix estimate:

$$\widetilde{R_c} \approx \widetilde{R_0} + (k/N)\widetilde{r_\Psi}\,\mathbf{s}\,\mathbf{s}^t$$

To derive the corresponding expression for the contaminated RX $\tilde{R}_c^{-1}$ should be computed. Hence, the contaminated RX test statistic is computed as the contamination-free RX test statistic minus a term that is a quadratic form of the test pixel vector involving the matrix M. Hence, for the same value of x, $\mathrm{RXc}(x) \leq \mathrm{RX}(x)$.

C. Impact of Secondary Data Contamination on RX Detection Performance

The random variables associated with the contaminated RX test statistics under the two hypotheses can be concisely expressed as follows:

$$\mathrm{RX}_c\ (\mathrm{X})\ |H_0 = \mathrm{RX}\ (\mathrm{X})\ |H_0 - Q$$

$$\mathrm{RX}_c\ (\mathrm{X})\ |H_1 = \mathrm{RX}\ (\mathrm{X})\ |H_1 - P$$

Where, $Q \equiv \mathrm{V}^T \cdot \mathrm{M} \cdot \mathrm{V}$ and $P \equiv (\alpha\, \mathrm{s} + \mathrm{V})^T \cdot \mathrm{M} \cdot (\alpha\, \mathrm{s} + \mathrm{V}) = \alpha^2\, \mathrm{s}^T \cdot \mathrm{M} \cdot \mathrm{s} + 2\alpha\, \mathrm{s}^T \cdot \mathrm{M} \cdot \mathrm{V} + Q$ are nonnegative random variables. This indicates that $\mathrm{RX}_c\ (\mathrm{X})\ |H0 \leq \mathrm{RX}\ (\mathrm{X})\ |H_0$ and $\mathrm{RX}_c\ (\mathrm{X})\ |H_1 \leq \mathrm{RX}\ (\mathrm{X})\ |H_1$, i.e., contamination determines a shift in both RX test statistics toward lower values. In addition, it is possible to show that, on average, P is higher than Q or, alternatively, the reduction of $\mathrm{RX}_c\ (\mathrm{X})\ |H_1$ is larger than the reduction of $\mathrm{RX}_c\ (\mathrm{X})\ |H_0$. The expectation of P can be expressed as follows:

$$E\ \{P\} = E\ \{\alpha^2\, \mathrm{s}^T \cdot \mathrm{M} \cdot \mathrm{s} + 2\alpha\, \mathrm{s}^T \cdot \mathrm{M} \cdot \mathrm{V} + Q\}$$

$$= E\ \{\quad\} + E\ \{Q\} \geq E\ \{Q\}$$

$$\equiv \alpha^2\, \mathrm{s}^T \cdot \mathrm{M} \cdot \mathrm{s} \geq 0$$

Since, V and M are statistically independent and v is zero mean. The expectation of the nonnegative random variable quantifies how much greater the average reduction of $\mathrm{RX}_c\ (\mathrm{X})\ |H_1$ is than the average reduction of $\mathrm{RX}_c\ (X)\ |H_0$

$$E\ \{\mathrm{RX}_c\ (\mathrm{X})\ |H_0\} = E\ \{\mathrm{RX}\ (\mathrm{X})\ |H_0\} - E\ \{Q\}$$

$$E\ \{\mathrm{RX}_c\ (\mathrm{X})\ |H_1\} = E\ \{\mathrm{RX}\ (\mathrm{X})\ |H_1\} - E\ \{Q\} - E$$

Alternatively, $E\{\quad\}$ can be used to quantify how much smaller the average distance $-\delta_{\mathrm{RX}c} \equiv E\ \{\mathrm{RX}_c\ (\mathrm{X})\ |H_1\} - E\ \{\mathrm{RX}_c\ (\mathrm{X})\ |H_0\}$ between $\mathrm{RX}_c\ (\mathrm{X})\ |H_1$ and $\mathrm{RX}_c(\mathrm{X})|H_0$ is than the average distance $.\delta_{\mathrm{RX}} \equiv E\{\mathrm{RX}\ (\mathrm{X})\ |H_1\} - E\ \{\mathrm{RX}\ (\mathrm{X})\ |H_0\}$) between the corresponding contamination free detection test statistics.

$$\delta_{\mathrm{RX}c} = .\ \delta_{\mathrm{RX}} - E\ \{\Delta\} = \frac{N}{N-L-1} \cdot \rho - E\ \{\Delta\}$$

Where, the theoretical mean values of $\mathrm{RX}(\mathrm{X})\ |H_1$ and $\mathrm{RX}(\mathrm{X})\ |H_0$ are used to compute δ_{RX}. Studying involves performing a first-order analysis, where only average behavior of detection test statistics under contamination can be inferred, while neglecting aspects linked to detection test statistic distribution (e.g., variance) that may be significant from a performance perspective.

IV. Experimental Results

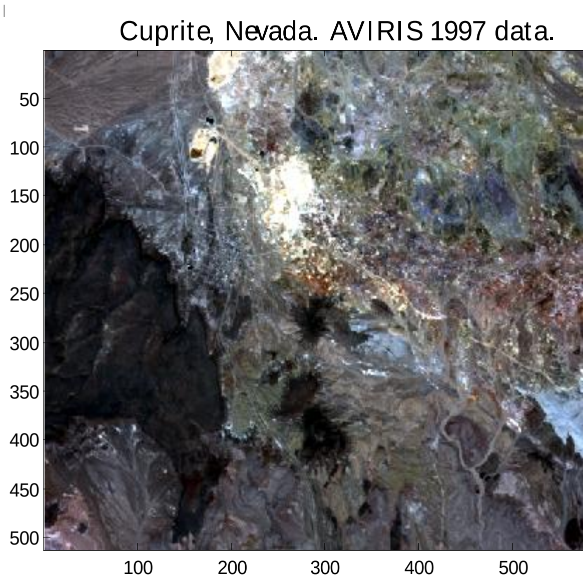

Figure 2: Contamination Hyper-spectral Image

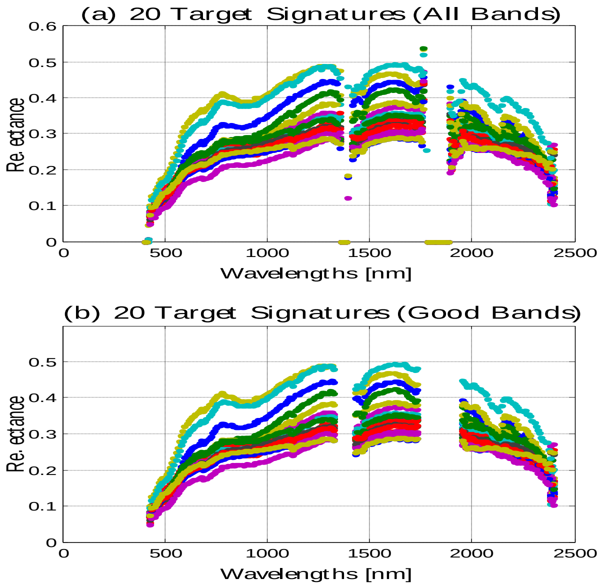

Figure 3: (a) Target Detection Contamination bands (b) Target Detection without Contamination bands

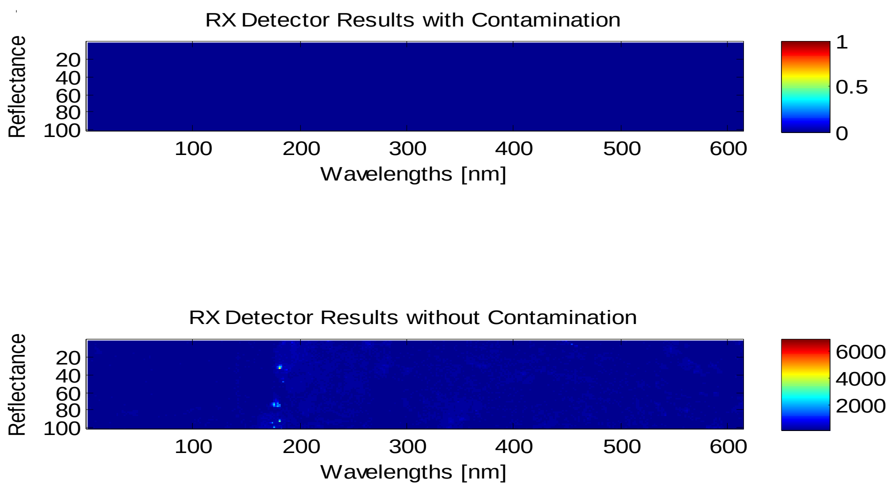

Figure 4: Contamination Signal Model Using RX Detector

V. Conclusion

In this paper, the impact of target signal contamination on the performance of adaptive detection of local anomalies in hyper-spectral images has been examined. Contamination by the target signal is a general circumstances practiced in remote sensing applications such as search-and-rescue operations and landmine detection. An analytical model for signal contamination has been developed that included variability in the extent of contamination. The proposed model has been shown to exhibit flexibility in modeling contamination variability. Specifically, this has been expressed in stipulations of viz., (1) the desired target signal energy with respect to background interference-plus noise level; (2) the contaminating signal amplitude pdf (and, thus, the overall contaminating signal energy with respect to background interference-plus-noise level); and (3) the contamination fraction. The study has shown that contamination involves a shift of the contaminated RX test statistics toward lower values.

VI. REFERENCES

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