# A NEW SUBSPACE METHOD FOR ANOMALY DETECTION IN HYPERSPECTRAL IMAGERY

*Yanfeng Gu, Jinglong Han, Chen Wang*

School of Electronics and Information Engineering, Harbin Institute of Technology, Harbin China

## 1. INTRODUCTION

Recently, anomaly detection has been one of the most interesting researches in hyperspectral images (HSIs) applications. Generally, anomalies in HSIs are rare pixels. The Reed–Xiaoli (RX) algorithm is a benchmark anomaly detector for HSIs, which uses the local Gaussian model generally [1]. But for RX algorithm there are two issues to be considered. First it requires the estimation of model parameters, which the estimation accuracy will decrease because the high dimensionality of HSIs. The second is the computational load for the need to estimate the inverse of large covariance matrices. Hence, dimensionality reduction plays an important role as a preprocessing step to improve the detection performance [2].

As anomaly detection is concerned, the key of the dimensionality reduction for HSIs is how to take a good estimation of the anomalous signal subspace which implies anomalous information and suitable for anomalies detection has been a fundamental issue for the hyperspectral processing. So in this paper, we focus on dimensionality reduction through estimating the anomalous signal subspace with the preservation of rare vectors.

A number of methods have proposed for dimensionality reduction such as principal component analysis (PCA) the discrete Karhunen–Loève transform (DKLT)[3][4]. These methods are both based on second-order statistics, because the data variance is mainly influenced by the background but the rare signals which are not suitable for detection application for HSIs. Gu *et al.* proposed a SKPCA method which is nonlinear based on KPCA and high-order statistics to select the anomalous signal component for detection [5]. Oleg *et al.* proposed maximum orthogonal complement algorithm (MOCA) which take into account the preservation of rare vectors [6]. Recently N. Acito *et al.* have improved the MOCA by simplifying the iterative procedure to lighten the computational load and proposed a new method to estimate the rank of the rare signal subspace. But they both not take much attention to look for the subspace that suitable for anomaly detection using HSIs [7].

## 2. RARE SIGNAL SUBSPACE ESTIMATOIN

Hyperspectral vector always lies in a low-dimensional manifold or subspace of high-dimensional feature space because the high-order correlation between spectral bands. The identification of this subspace should adequately reflect needs of application. In this paper we focus on anomaly detection that refers to rare signal subspace estimation. We have the consideration that the signal subspace $\Omega$ is constituted by principal signal subspace $\Omega_A$ and rare signal subspace $\Omega_R$. We can obtain the principal signal subspace $\Omega_A$ by the conventional methods such as PCA/KPCA and *virtual dimensionality* (VD) [8] to determine the rank $K_A$ of the $\Omega_A$. Here suppose that the anomalies as rare vectors that are linearly independent of the background as principal vectors will strongly influence the maximum residual energy on the subspace that is orthogonal to the principal signal subspace. For the well-known linear mixture model

$$x = s + n \tag{1}$$

where $x$ and $n$ are $L$-D vectors standing for signal and additive noise, respectively. And assume that signal vectors are in an unknown $p$-D subspace

$$s = Ma \tag{2}$$

where $M = [M_A, M_R]$ are the basis of principal signal subspace $\Omega_A$ and rare signal subspace $\Omega_R$ respectively.

So the basis of rare signal subspace $\Omega_R$ can be estimate by the following steps. First the data should be noise whitened which is a fundamental step for the rank estimation. Here we adapt the *shift difference* method to estimate diagonal covariance matrix $\Lambda = diag\{\sigma_1^2, \sigma_2^2, \cdots, \sigma_L^2\}$ [9]. Then the whiten data refers to

$$y = \Lambda^{-1/2} x \tag{3}$$

so $V = \Lambda^{-1/2} M = [V_A V_R]$. The basis $V_A$ and its rank $K_A$ can be estimated by second-order statistics or its nonlinear version and VD method. Assuming that we have got the principal signal subspace basis $V_A$, for the rare signal subspace basis $V_R$ , the estimation can be taken as follows:

$$r^k = \arg\left\{\max_{[i,j]\in D} \{R[r]\}\right\}, k \le K_R \tag{4}$$

where $R[r] = \left\| y[r] - P_{V_A}^k y[r] \right\|^2 = \left\| P_{V_A}^{k\perp} y[r] \right\|^2$ , $\hat{v}_R^k = y[r^k], V_A^{k+1} = [V_A^k, \hat{v}_R^k]$ , $P_{V_A}^{\perp} = I_p - V_A \left(V_A^T V_A\right)^{-1} V_A^T$ and $\hat{v}_R$ is the all possible basis for the rare signal subspace $V_R$ that are built by the image pixels. $D$ represents spatial domain and $[i, j]$ is spatial coordinate. $P_{V_A}^{\perp}$ is the projection matrix that orthogonal to subspace spanned by $V_A$. The rank $K_R$ of can be estimated from the iterative procedure based on Neyman-Pearson theory. Finally, $V_R = \left[\hat{v}_R^1, \hat{v}_R^2, \cdots, \hat{v}_R^{K_R}\right]$.

## 3. DETECTION PROCEDURE BASED ON ANOMALOUS SIGNAL SUBSPCE ESTIMATION

The algorithm including the estimation both for principal signal subspace and rare signal subspace summarized as follows:

1) Estimate the noise variance by *shift difference* method and derivate the whitening matrix. Apply the

whitening matrix to hyperspectral data to normalize the variance of noise component.

2) Estimate the rank $K_R$ of principal signal subspace $\Omega_A$ by VD method and apply KPCA to the whitened data. Take the eigenvectors corresponding to the $K_A$ largest eigenvalues to constitute the basis $V_A$ for the principal signal subspace $\Omega_A$

3) Through the procedure that presented at section 2 to estimate the basis $V_R$ for the rare signal subspace $\Omega_R$ and its rank $K_R$ .

4) Project HSIs onto the basis $V_R$ to get rare signal subspace $\Omega_R$ . Apply RX detector on $\Omega_R$ for the final detection result.

Here RX detector uses local Gaussian model, with this approach, the background pixels in a local neighborhood around the pixel under tested are assumed to be independent identically distributed Gaussian random variable. After estimating the background mean vector and covariance matrix, the Mahalanobis distance between the pixel under test and the background mean vector is compared to a threshold to detect an anomaly.

## 4. EXPERIMENT RESULTS

In this section, the proposed method is compared with other subspace extraction methods based on different rules to evaluate the effectiveness of the proposed method. Real HSIs collected by the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) are used in the experiments. After bands that correspond to the water absorption regions and low SNR, and bad bands are removed, 126 available bands in the wavelength range from 0.4 to 1.8 $\mu m$ remain in our experiments. Fig. 1 shows the 6$^{th}$ band of the data and the anomalies are circled by red which the rare pixels that we want to preserve.

Based the procedure we proposed above, the principal signal subspace is estimated first. Here $K_A = 4$ by the VD Algorithm and $\Omega_A$ is constituted by the first three component transformed by KPCA. $K_R = 3$ estimated from the iterative procedure is used to constitute $\Omega_R$ . To further demonstrate the performance of the rare signal subspace for anomaly detection estimated by the proposed method denoted by RX-RSUB, a comparison is performed between the proposed method and the SKPCA [5] that apply RX detector to our rare signal subspace and subspace driven by KPCA respectively. Fig. 2 shows the detection results for the two kinds of method. From the detection results, it can be found that rare subspace has a better performance as the anomalies have a more separation with the background. We get the conclusion that subspace estimated by our proposed procedure is more effective to have preservation for rare pixel. It’s especially effective for anomaly detection in hyperspectral imagery, where KPCA with singularity rule is much depends on the local complexity of scene.

Fig.1.Real HSI scene with rare pixels to be preserved

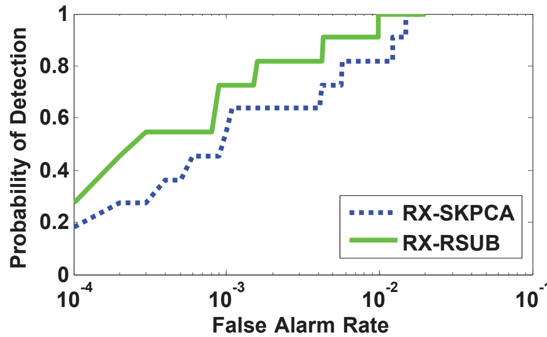


Fig. 2.Comparison of ROCs for RX detector between SKPCA and Rare Subspace

## 5. CONCLUSIONS

In this paper, a new subspace method is proposed for anomaly detection in HSIs. Through accurately estimating and separating the anomalous signal subspace from the principal signal subspace, i.e., background subspace, the proposed subspace method make local Gaussian model assumption ease to be better satisfied. This can improved the detection performance of the conventional RX algorithm. The experimental results just prove that the proposed method outperforms the SKPCA in terms of rarely anomalous target detection in HSIs.

## REFERENCES


[1]S. Reed and X. Yu, "Adaptive multiple-band CFAR detection of an optical pattern with unknown spectral distribution," *IEEE Trans. Acoust., Speech,Signal Process.*, vol. 38, no. 10, pp. 1760–1770, Oct. 1990.

[2]D.Manolakis and G. Shaw, "Detection algorithms for hyperspectral imaging applications," *IEEE Signal Process. Mag.*, vol. 19, no. 1, pp. 29–43, Jan. 2002.

[3]J. A. Richards, Remote Sensing Digital Image Analysis: An Introduction, 2nd ed. New York: Springer-Verlag, 1993.

[4]W. C. Therrien, "Discrete Random Signals and Statistical Signal Processing," ser. Signal Processing Series. Englewood Cliffs, NJ: Prentice-Hall,Apr. 1992.

[5]Y. Gu, Y. Liu, and Y. Zhang, "A selective KPCA algorithm based on highorder statistics for anomaly detection in hyperspectral imagery," *IEEE Geosci. Remote Sens. Lett*, vol. 5, no. 1, pp. 43–47, Jan. 2008.

[6]O. Kuybeda, D. Malah, and M. Barzohar, "Rank estimation and redundancy reduction of high dimensional noisy signals with preservation of rare vectors," *IEEE Trans. Signal Process.*, vol. 55, no. 12, pp. 5579–5592, Dec. 2007.

[7] N. Acito, M. Diani, and G. Corsini, "A New Algorithm for Robust Estimation of the Signal Subspace in Hyperspectral Images in the Presence of Rare Signal Components," *IEEE Geosci. Remote Sens. Lett*, vol. 47, no. 11, Nov. 2009

[8]C.-I Chang and Q. Du, "Estimation of number of spectrally distinct signal sources in hyperspectral imagery," *IEEE Trans. Geosci. Remote Sens.*,vol. 42, no. 3, pp. 608–619, Mar. 2004.

[9]A. Green, M. Berman, P. Switzer, and M. D. Craig, "A transformation for ordering multispectral data in terms of image quality with implications for noise removal," *IEEE Trans. Geosci. Remote Sens.*, vol. 26, no. 1, pp. 65–74, Jan. 1988.