Hyperspectral anomaly detection method based on linear background removal

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Abstract. In view of the fact that the existing hyperspectral image anomaly detection algorithms only pay attention to distinguish between target and background by using spectral differences and ignore the correlation between pixels, and that local RX algorithm is easy to detect global non-anomalies as anomalies when the background is relatively complex, a hyperspectral anomaly detection method based on linear background removal is proposed. In this method, the edge information of hyperspectral image is obtained first, then the line part of edge image is extracted by Hough transform, and finally the local anomaly detection is carried out based on the linear background removal. By comparing the ROC curve and AUC value of this algorithm with RX algorithm and local RX algorithm, it shows that the algorithm of this paper can effectively reduce the false alarm rate of detection and has a better detection effect.

1. Introduction

Hyperspectral remote sensing not only acquires the spatial information of surface features, but also acquires the spectrum curve of surface features with fingerprint effect, so that subtle differences of surface materials can be identified. In general, it is difficult to obtain the prior spectral information of the target. Hyperspectral anomaly detection can detect the target with obvious difference from the background without prior knowledge, which has high practical application value.

According to different application theories, anomaly detection algorithms can be divided into statistical anomaly detection algorithms and geometric anomaly detection algorithms. 1) Anomaly detection algorithm based on statistical model. From the perspective of statistical model and likelihood ratio detection, the anomaly detection algorithm based on statistics considers that background data obey certain statistical distribution, while the abnormal target deviates from such distribution. Based on the assumption that the background obeys Gaussian distribution, the widely used RX (Reed-Xiaoli) anomaly detection algorithm calculates the Mahalanobis distance between the pixel to be measured and the background by estimating the mean value and covariance matrix of the background, so as to determine whether the pixel is an abnormal target [1]. There are also Gauss Markov Random Field algorithm [2] and Adaptive Matching Subspace Detection algorithm [3]. 2) Anomaly detection algorithm based on geometric model. The theoretical basis of the geometric anomaly detection algorithm is the least square principle, which believes that the background can be represented by a set of spectral vectors, while the abnormal target cannot. This algorithm does not involve the problem of statistical distribution, so it is more practical. Typical examples of such algorithms are the Subspace-
based Exception Detection algorithm [4] and the Collaborative Representation Based Exception Detection algorithm [5].

Both statistical anomaly detection methods and geometric anomaly detection methods ignore the spatial correlation between pixels. A hyperspectral anomaly detection method based on linear background removal (LBR-LRX) was proposed in order to effectively combine the spatial and spectral information to improve the anomaly detection effect.

2. Algorithm description

The algorithm of this paper firstly performs Principal Component Analysis (PCA) on the hyperspectral image to be detected, and the extracted first few principal components were respectively tested for edge, and the edge of the hyperspectral image was extracted by comprehensive analysis. Then, the Hough transform is used to extract line information from edge image. Finally, hyperspectral anomaly detection based on linear background removal is realized.

2.1. Edge detection

In hyperspectral images, edge can be defined as a set of pixels with abrupt change in spectral feature vector values. There are many bands of hyperspectral data, and when the edge is extracted with a single image, the edge detection results of each band will not be exactly the same. This gives rise to the concept of edge extraction for hyperspectral images.

This paper firstly conducts PCA on hyperspectral images, selects the first few principal components after PCA, then conducts separate edge detection on selected principal components, and the final hyperspectral edge information was obtained by comprehensively considering the edge extraction results of several principal components.

In order to integrate the edge images of each band into the only edge image \( \text{Edge}_{\text{Total}} \), we can find the gradient value with the strongest performance at each pixel position of the image as the gradient value of the composite edge image. For each position \((i,j)\) in the hyperspectral image, the edge of the hyperspectral image is expressed as:

\[
\text{Edge}_{\text{Total}}(i, j) = \max \{ \text{Edge}_k[i, j] \} = \max \{ \max (\text{Grad}^d_k[i, j]) \}
\]

Where \( k \) is the number of bands and \( d \) is the number of gradient operators.

In this paper, Prewitt operator in 8 directions is used to detect the edge, the exponent of the above formula becomes: \( d=1,2,\ldots,8; \ k=1,2,\ldots,n \).

2.2. Hough transform straight line detection

Hough transform [6] is a line extraction algorithm which is used and studied more. It has good anti-noise performance, fault tolerance and recognition. Its main idea is to make the line in the image form a point in the new parametric coordinate system through a line-to-point transformation, and obtain the equation of the line by detecting the position of the point.

Each point \((x,y)\) in the two-dimensional space corresponds to a straight line in the coordinates with \( b \) as the reference variable and \( k \) as the independent variable. Therefore, the straight line between two points in the two-dimensional coordinate can be represented by the intersection of two lines in the parameter coordinate [7]. The line can be converted to a parametric coordinate to improve the conversion mode. The specific r-q parametric equation is:

\[
\theta = x \cos \theta + y \sin \theta , \quad 0^\circ \leq \theta \leq 180^\circ
\]

In order to conduct linear detection, the range of possible values of \( q \) and \( r \) should be discretized into several intervals at certain quantitative intervals. The entire parameter space is discretized into a two-dimensional grid, and a counter is set for each grid cell. For each feature point \((x,y)\) in the two-dimensional image, all \( q \) values can be traversed to obtain the grid points through the curve, and the counter can be accumulated. When all the feature points are converted, the point with large counter in the parameter space can be found, and the position of the line in the two-dimensional space can be calculated by this method [8].


2.3. **LBR-LRX algorithm anomaly detection**

The local RX (LRX) algorithm [9] assumes that the hyperspectral data conform to the Gaussian model in the local range and replaces the global calculation with local calculation. The statistics of the local RX algorithm are estimated using concentric double sliding windows centered on each pixel to be detected. In this paper, a window of size $3\times 3$ is used for local anomaly detection. The calculation formula is as follows:

\[
D_{LRX}(x) = (x - \mu_k)^T \Sigma_k (x - \mu_k)
\]

Where $\mu_k$ is the mean value of the 8 pixels around the pixel $x$ to be detected; $\Sigma_k$ is the covariance matrix of these 8 pixels.

Local RX algorithm considers both spectral and spatial information for anomaly detection and improves the detection effect. When the local RX algorithm has a complex background, it may detect global non-anomalies as anomalies, resulting in a high false alarm rate. In this paper, the hyperspectral anomaly detection algorithm based on linear background removal is proposed. On the basis of LRX algorithm, the linear background detected by Hough transform is removed, which effectively reduces the false alarm rate of LRX algorithm and has better detection performance. The algorithm flow chart is as follows:

![Algorithm Flowchart](image)

**Figure 1.** LBR-LRX algorithm flowchart

3. **Experimental verification**

3.1. **Experimental data**

In this paper, we use hyperspectral images of two different scenes at the San Diego airport of America, which are collected by the sensors of AVIRIS. The spectral range of the image is 0.4-2.5 $\mu$m. The low signal-to-noise ratio band, sensor fault band and water vapor absorption band are eliminated, and 189 bands are retained. The subgraph with a size of $150\times 150$ is taken from the middle part as experimental data 1, and the subgraph with a size of $100\times 100$ is taken from the upper left corner as experimental data 2. The atmospheric correction of the image has been realized using ENVI. The image spatial resolution is 3.5m. Experimental data 1 and 2 are shown in figure 2 and 3. The image is mainly composed of buildings with different roofs, tarmac of different materials, airport runway and a small amount of vegetation. The aircraft on the airstrip is the target to be detected.

![Experimental Data](image)

**Figure 2.** Experimental data 1 (a) RGB color image (b) Spatial distribution of target
3.2. Parameter setting and evaluation index

In the experiment, PCA was first performed on hyperspectral data, and the first 6 principal components were extracted, whose percentage $R^2=99.78\%$. The extracted principal components are detected by Prewitt operator in 8 directions, and the maximum value of each component is obtained to form the final edge image. The Hough transform was used to extract the line information in the edge image. After debugging, the first 5 peaks in the Hough transformation matrix, which were greater than 0.3 times the maximum value, were selected as the peak positions. When the distance between two detected line segments was less than 5 pixels, they were merged into a line segment, and when the length of the merged line segment was less than 7 pixels, they were discarded. Select 3pixel×3pixel window for local anomaly detection and detection of LBR-LRX algorithm. The experiment was run in the programming environment of Matlab R2019a.

In order to make a more scientific and quantitative analysis, the Receiver Operation Characteristic Curve (ROC) and the Area under ROC Curve (AUC) were used to analyze the experimental results. The x-coordinate of the ROC curve represents the false alarm rate, and the y-coordinate represents the detection rate of the target. If the detected targets and backgrounds are more similar, then the ROC curve is straighter and the AUC value is smaller, indicating that the detection performance of the algorithm is worse. If the detected target differs significantly from the background, the curve bends more to the left and upward and the AUC value is larger, indicating that the detection performance of the algorithm is better. The AUC value range is 0-1.

3.3. Analysis of experimental results

The figure 4 and 5 respectively shows the effect of RX, LRX and the LBR-LRX algorithm on anomaly detection of experimental data 1 and 2. As can be seen from figure 4 and 5, when RX algorithm estimates the mean value and covariance matrix of the background, it assumes that it simply obeys a single Gaussian distribution. The background estimation is polluted by abnormal targets. The detection results contain a large number of falsely detected stripe anomalies, and the false alarm rate is high. The detection effect of LRX algorithm is improved compared with that of RX algorithm. However, in the detection results, many linear backgrounds such as airport runway boundary and building boundary are detected as anomalies. In the estimation of pixel anomaly degree, this LBR-LRX algorithm not only considers the difference of adjacent pixel spectrum, but also removes linear background on the basis of LRX algorithm, which is obviously better than the previous two algorithms in suppressing background information.
Figure 4. Comparison of detection results of different anomaly detection algorithms on experimental data 1 (a) RX algorithm (b) LRX algorithm (c) LBR-LRX algorithm

Figure 5. Comparison of detection results of different anomaly detection algorithms on experimental data 2 (a) RX algorithm (b) LRX algorithm (c) LBR-LRX algorithm

Figure 6 shows the ROC curves of each anomaly detection method on different experimental data. Table 1 compares the AUC values of each anomaly detection method. It can be seen from the ROC curve that: at the same detection rate, the LBR-LRX algorithm has a lower false alarm rate, indicating that the LBR-LRX algorithm has a strong background suppression ability. The ROC curve characteristics of LBR-LRX algorithm on experimental data 1 and 2 are obviously better than RX algorithm and LRX algorithm. At the same time, LBR-LRX algorithm has a higher AUC value.

Table 1. AUC values of each anomaly detection algorithm

| Data     | RX   | LRX  | LBR-LRX |
|----------|------|------|---------|
| Data1    | 0.9064 | 0.9139 | 0.9437  |
| Data2    | 0.8356 | 0.9104 | 0.9548  |

Figure 6. ROC curve comparison of each anomaly detection algorithm (a) Experimental data 1 (b) Experimental data 2
4. Conclusion

Considering that most of the current anomaly detection algorithms consider from the perspective of spectral information and ignore the spatial correlation of ground objects, and the existing local RX algorithms tend to identify global non-anomalous targets as anomalies, a hyperspectral anomaly detection algorithm based on linear background removal is proposed. This algorithm makes full use of the space and spectrum information of hyperspectral data, considers the spectral difference of local neighborhood, and uses Hough transform to remove the linear background which is detected as the target by mistake. The results show that the LBR-LRX algorithm can effectively reduce false alarm rate and improve the detection effect.

References

[1] I.S. Reed, X. Yu, Adaptive multiple-band CFAR detection of an optical pattern with unknown spectral distribution, J. Proceedings of the IEEE, 38 (1990) 10: 1760-1770.
[2] G. Rellier, X. Descombes, F. Falzon, et al, Texture feature analysis using a Gauss-Markov model in hyperspectral image classification, J. IEEE Trans on Geoscience and Remote Sensing, 42 (2004) 7: 1543-1551.
[3] C.I. Chang, Hyperspectral imaging: Techniques for Spectral Detection and Classification. Kluwer Academic/Plenum Publishers, New York, 2003.
[4] K.I. Ranney, M. Soumekh, Hyperspectral anomaly detection within the signal subspace, J. Proceedings of the IEEE, 3 (2006) 3: 312-316.
[5] W. Li, Q. Du, Collaborative representation for hyperspectral anomaly detection, J. Proceedings of the IEEE, 53 (2015) 3: 1463-1474.
[6] PRIYANKAM, B.C. BIDYUT, A survey of Hough transform, J. Pattern Recognition, 48 (2015) 3: 993-1010.
[7] M. Zhang, W.B. Yu, F. Shen, et al, Research on the method of hyperspectral data straight line detection based on improved Hough algorithm, J. Shanghai Aerospace, (2017) 3.
[8] R.J. Duan, W. Zhao, S.L. Huang, et al, A fast straight-line detection algorithm based on improved Hough transform, J. Instrumentation and Instrumentation Journal, 31 (2010) 12: 2774-2780.
[9] D. Borghys, I. Kasen, V. Achard, et al, Comparative evaluation of hyperspectral anomaly detectors in different types of background, J. Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery, 8390 (2012) 12: 83902J-83902J-12.