MULTI-SCALE ANOMALY DETECTION IN HYPERSPECTRAL IMAGES BASED ON SPARSE AND LOW RANK REPRESENTATIONS

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ABSTRACT

Anomaly detection is a hot topic in hyperspectral data processing since no prior information about the target is required. Meanwhile, multi-scale information can improve the detection performance. This paper proposes a multi-scale anomaly detection algorithm in hyperspectral images based on the sparse and low rank representation. Some pixels are randomly selected to construct the dictionary, and the pixels belonging to large abnormal targets are selected with high probability. Therefore, the low rank matrix and dictionary constitute the pure background component and large abnormal targets, and the sparse matrix contains noise and smaller abnormal targets. Using recursive sliding array RX detection algorithm, large abnormal targets can be detected in the reconstructed image, and small abnormal targets can be detected in the residual between sparse matrix and the reconstructed image. The final detection result is the combination of the two results. Experimental results d[1]emonstrate that the algorithm achieves very promising performance.

Index Terms—Anomaly detection, hyperspectral image, sparse and low rank representation

1. INTRODUCTION

Hyperspectral remote sensing image generally contains more than 200 spectral segments, covering a wide spectral range from visible light to near infrared. The "data cube" formed by spectral information and spatial dimension information achieves the data advantage that other earth observations can't match. Anomaly detection of hyperspectral images is essentially a binary hypothesis testing problem. By measuring the difference between the monitored point and the selected background spectral sample, it can determine whether it belongs to the target or the background [1]. RX (Reed Xiaoli) algorithm is a classic anomaly detection method [2], and various improved algorithms based on it are proposed. Aiming at the problem of pixel mixing in hyperspectral images, the spectral decomposition algorithm has obtained advantages [3]. Kernel RX (KRX) uses nonlinear features, but the algorithm has high computational complexity [4].

The application of sparse low rank representation theory is based on the sparsity of hyperspectral image, and the hyperspectral data can be reconstructed by the linear combination of some spectra in the spectral set of all ground objects. Chen first applied sparse and low rank decomposition in hyperspectral target detection [5]. Then Yuan et al. calculated the sparse representation coefficients of the detected pixels in the background pixel set [6], and judged whether the detected pixels were abnormal by the differences between the coefficients. Zhao [7] proposed a sparse score estimation algorithm. When the utilization rate of the detected pixels in the dictionary set is low, the probability that the pixel is abnormal is relatively high.

In this paper, we propose a multi-scale anomaly detection algorithm for hyperspectral images based on sparse low rank representation. Some pixels are randomly selected to construct a dictionary, and the sparse and low rank decomposition models are solved by the alternating direction method (ADM) [8]. The pixels in the dictionary are selected randomly, which often contain the pixels of large abnormal targets. Therefore, there are large abnormal targets and pure background component in the reconstructed image composed by low rank matrix and dictionary; the sparse matrix contains small abnormal targets and noise. Through the recursive sliding array RX algorithm, large abnormal targets can be detected in the reconstructed image, and small abnormal targets can be detected in the residual between sparse matrix and reconstructed image. The combination of the two becomes the final detection result. Experimental results show that the algorithm has high detection accuracy for multi-scale abnormal targets in hyperspectral images.

2. PROPOSED APPROACH

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2.1. Sparse and low rank decomposition model and algorithm

Background pixels in hyperspectral images are not only different from abnormal pixels, but also have strong correlation. So the global background has the feature of low rank. In the past, when sparse and low rank decomposition was used for hyperspectral images, it was often necessary to establish a background dictionary without abnormal pixels, and the sparse matrix is directly used to detect abnormal objects. It is time-consuming to build the dictionary, and when sparse matrix is used to get the abnormal information directly, the noise will affect the detection accuracy of small targets.

In this paper, a multi-scale anomaly detection algorithm for hyperspectral images based on sparse and low rank representation is proposed. Assume a specific hyperspectral image as a matrix $\mathrm{X} \in \mathbb{R}^{B*N}$. Some pixels are randomly selected to construct a dictionary $D = [d_1, d_2, \ldots, d_m]$, and the number of atoms in the dictionary is m. The coefficient matrix of all pixels is the low rank matrix $\mathrm{S} = [s_1, s_2, \ldots, s_N]$, the sparse residual matrix is $\mathrm{E} = [e_1, e_2, \ldots, e_N]$. The model can be described as equation (1):

$$\begin{aligned} &\min_{S,E} \quad rank(S) + \lambda \|E\|_{2,1} \\ &s.t \quad X = DS + E \end{aligned} \tag{1}$$

The random selection of pixels makes the dictionary contain pixels with large abnormal targets. The low rank matrix and dictionary constitute the pure background component and large abnormal targets, while the sparse matrix E contains small abnormal targets besides noise.

For the solution of model (1), due to the discrete property of rank(s) function, we replace it with matrix kernel norm for convex optimization:

$$\begin{aligned} &\min_{S,E} \quad \|S\|_* + \lambda \|E\|_{2,1} \\ &s.t \quad X = DS + E \end{aligned} \tag{2}$$

The model (2) will be converted into Lagrange equation, which is solved by linearized alternating direction method with adaptive penalty (LADMAP) [9], and the final decomposition result can be obtained.

2.2. Recursive sliding array RX

The essence of the classical RX anomaly detection algorithm is to calculate the Mahalanobis distance between the detected pixels and the mean value of the background. In the reconstructed image composed by low rank matrix and dictionary, there is a big Mahalanobis distance between the large abnormal targets and the surrounding pure background component. The sparse matrix contains small abnormal targets and noise, but the corresponding part of the reconstructed image does not, so there is a big Mahalanobis distance between the two. To sum up, RX algorithm is suitable for anomaly detection of various sizes of abnormal targets. Abnormal targets have the characteristics of low probability of occurrence and small proportion. However, local features are easily ignored in global RX, it is more appropriate to use RX in local areas.

In anomaly detection, the detection decision operator of RX algorithm can be denoted as follows:

$$\begin{aligned} &RX(\mathrm{r}) = (\mathrm{r} - \mu)^T C^{-1} (\mathrm{r} - \mu) \\ &C = \frac{1}{N} \sum_{i=1}^{N} (\mathrm{x}_i - \mu)(\mathrm{x}_i - \mu)^T \end{aligned} \tag{3}$$

Where r is the current pixel being detected, μ is the mean of background, and C is the covariance matrix of the background pixels. The calculated $RX(r)$ value of the current pixel is compared with the set threshold λ to determine whether the pixel is abnormal.

In the traditional local RX algorithm, different sizes of windows need to be set for different sizes of abnormal targets. However, anomaly detection is a detection method without prior information. When the size of the abnormal objects in the image varies greatly, it is difficult to achieve good detection results for multi-scale abnormal targets in the same window size. Therefore, this paper uses the sliding array RX detection algorithm. Each pixel of hyperspectral image is arranged in a row with its own spectral vector as a column to form a matrix of size $B \times N$. Where B is the number of spectra and N is the number of pixels. Every t pixels form an array, which is used as the background to calculate the RX value of the middle pixel (refer to Fig. 1 for details).

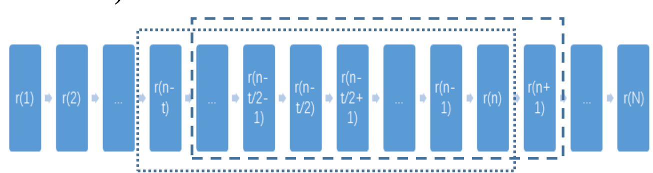
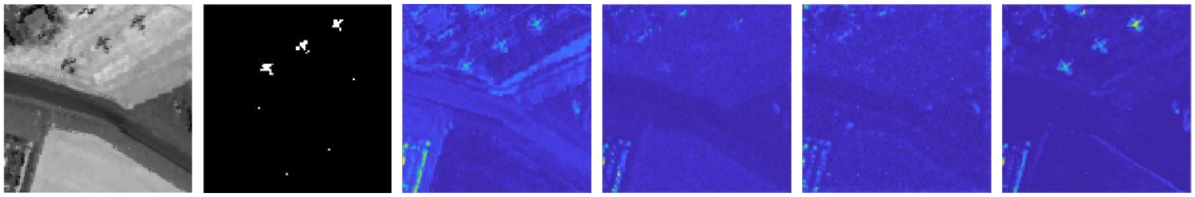


Fig. 1 Sliding array RX detection algorithm

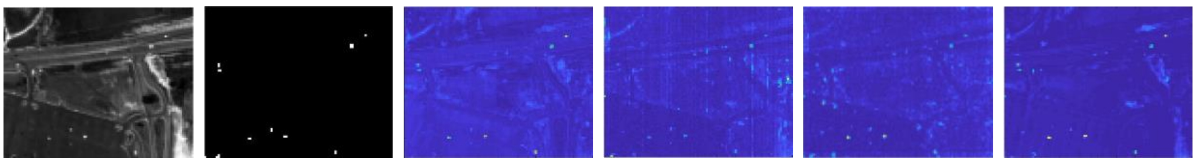
When calculating the detection result of $r_{n-t/2}$, r_{n-t} to r_n (pixels in the dot and wire frame) are used as the background. The detection result of the next pixel $r_{n-t/2+1}$ can be calculated by taking r_{n-t+1} to r_{n+1} (pixels in the dotted box) as the background.

The sliding array RX algorithm takes local pixels as background and has the process of continuously finding the inverse of covariance matrix, which leads to its poor timeliness. Zhao [10] uses Woodbury lemma to transform the inversion of covariance matrix into the addition, subtraction, multiplication and division of matrix or vector.



(a) (b) (c) (d) (e) (f)

Fig. 2 (a) Single band original image of simulated data (b) ground-truth map for the simulated data (c) LRSM (d) GRX (e) CRD (f) SL-RSARX



(a) (b) (c) (d) (e) (f)

Fig. 3 (a) Single band original image of real data (b) ground-truth map for the real data (c) LRSM (d) GRX (e) CRD (f) SL-RSARX

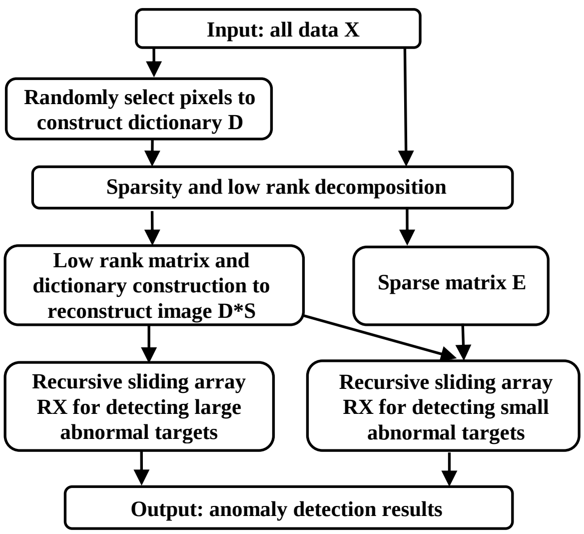


Fig. 4 The process of multi-scale anomaly detection in hyperspectral image based on sparse and low rank decomposition

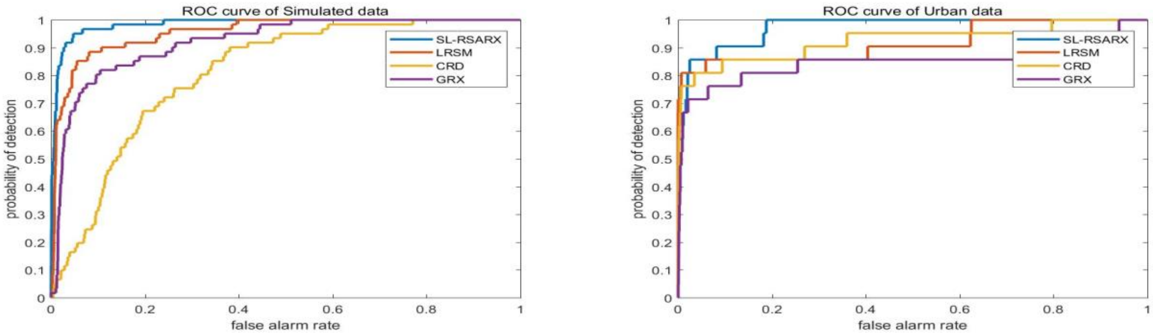
The inverse of the covariance matrix at the current time can be derived from the inverse of the autocorrelation matrix and the background mean value calculated at the previous time, which greatly reduces the amount of calculation.

The detection results of multi-scale abnormal targets can be calculated by the improved sliding array RX algorithm based on Woodbury lemma. The covariance matrix will be calculated by the reconstructed image, and the small abnormal targets can be detected by the Mahalanobis distance between the pixels in the sparse matrix and the corresponding parts of the reconstructed image. At the same time, the Mahalanobis distance between the pixel and the surrounding background in the reconstructed image can be calculated to detect large abnormal targets. The final detection result is the sum of the two normalized detection values. The overall algorithm flow is shown in Figure 4.

3. EXPERIMENTS

In order to verify the effectiveness of the proposed algorithm, we choose simulated and real hyperspectral image data for experiments. The sparse and low rank decomposition recursive sliding array RX anomaly detection (SL-RSARX) algorithm is compared with other methods. It includes low rank and sparse model (LRSM), global RX detection (GRX) and collaborative representation anomaly detector (CRD). LRSM algorithm will use the sparse matrix decomposed by LRR model directly for anomaly detection. GRX algorithm uses RX algorithm for anomaly detection of global data. Based on the feature that the pixels in the background can be approximately represented by their spatial domain, but the abnormal pixels can not. CRD algorithm uses the pixels in the outer window to represent the pixels in the inner window approximately. After many times of experimental comparison, this experiment set the outer window size as 7, the inner window size as 5, sliding double window for anomaly detection.

The simulated data is based on the real hyperspectral image of San Diego, and the real data is from the urban hyperspectral image obtained by hydice sensor in Texas, USA. We have removed the bands polluted by water vapor and noise. In the 100 × 100 area selected by the simulation data, the apron of different materials, various buildings and a small amount of vegetation constitute the background part of the area. The original abnormal targets were three aircraft on the apron, all of which were relatively large. We use the method of target transplantation to mix the spectrum of the abnormal target with the background pixel at the ratio of 0.35 to form four smaller abnormal targets. The original single band image of the final simulation image is shown in Figure 2 (a), and Figure 2 (b) is the ground truth map. The real data is 80 × 100 parts in the upper right corner, including roads, land, grassland, trees, etc. the real abnormal targets are small cars. Figure 3 (a) is the original single band



(a) (b)

Fig. 5 (a) ROC curve of simulated data (b) ROC curve of real data

TABLE 1 AUC of various algorithms in simulated and real data

Algorithm	LRSM	GRX	CRD	SL-RSARX
Simulated data	0.9536	0.9206	0.8089	0.9839
Real data	0.9158	0.8504	0.9246	0.9711

image of this part, and the real distribution of small abnormal targets is shown in Figure 3 (b). In the experiments, the array length is set to 4000, and the detection results of all algorithms are averaged by five independent experiments.

The simulation data contains both large aircraft abnormal targets and small synthetic abnormal targets. The abnormal targets in real data are smaller. Figure 2-3 shows the detection results of the four algorithms. LRSM algorithm only uses sparse matrix, which contains more noise, resulting in higher false alarm rate. GRX algorithm is difficult to detect small abnormal targets. CRD algorithm has a good detection effect for small abnormal targets, but it is difficult to detect large abnormal targets because of the small size of inner and outer windows. The SL-RSARX algorithm has good detection accuracy for multi-scale abnormal targets. Figure 5 shows the ROC curves of four algorithms for two sets of data, and table 1 contains the area under the ROC curve (AUC) of each algorithm. Compared with other algorithms, the ROC curve of SL-RSARX algorithm is closer to the upper left corner and the AUC value is larger in both simulated and real data.

4. CONCLUSION

In this paper, a multi-scale anomaly detection algorithm in hyperspectral images based on sparse and low rank representation is proposed which is named SL-RSARX. Specifically, some pixels are randomly selected to generate a dictionary, and the pixels of large abnormal targets are often selected into the dictionary. Therefore, the reconstructed image constructed by the decomposed low rank matrix and dictionary contains pure background and large abnormal targets, while the sparse matrix contains noise and small abnormal targets. Using recursive sliding array RX algorithm, large abnormal targets can be detected in the reconstructed image, and small abnormal targets can be detected in the comparison between sparse matrix and reconstructed image. The experiment results demonstrate the efficiency of our proposed method comparing with the traditional method.

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