Hyperspectral Anomaly Detection Based on Subspace Low-Rank Decomposition

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Abstract. This paper mainly studies the anomaly detection algorithm on the basis of denoising and reconstruction of hyperspectral image, combined with some basic methods, such as subspace representation, tensor decomposition, spectral global and spatial non-local similar low-rank decomposition, norm constraint and so on. the mixed noise (Gaussian noise, impulse noise and dead line) of hyperspectral images which seriously affect the accuracy of anomaly detection are preprocessed. On this basis, the global RX algorithm is used to detect anomalies in the denoised hyperspectral image, and the simulation data are compared with the original real data. The experimental results show that the subspace low-rank decomposition anomaly detection algorithm is better than other existing algorithms in speed and accuracy, which shows the feasibility and superiority of this algorithm.

Keyword: Hyperspectral Image, Subspace Representation, Low-Rank Decomposition, Anomaly Detection

1. Introduction
Hyperspectral images contain both spatial and spectral information, and their spectral dimensions are composed of hundreds of continuous narrow bands. In practical application, it is difficult to obtain prior spectral information of matter under the influence of various conditions, especially in military applications such as battlefield reconnaissance and camouflage identification. Therefore, anomaly detection based on unsupervised idea has gradually become a hot field of target detection in hyperspectral images. Anomaly detection does not need the spectral information of the target to be measured. Through the discrimination of spectral characteristics, the image is divided into target class and background class.

However, affected by the current technology and environmental conditions, the hyperspectral image data collected by spectral imagers are easily affected by a variety of noises, which cause serious interference to the subsequent image data processing and analysis. such as unmixing, classification and target detection [1]. Before the target detection of the hyperspectral measured data, a relatively pure hyperspectral image can be obtained by denoising and reconstructing the hyperspectral image.

In recent years, people have proposed many hyperspectral image denoising algorithms, using the reconstructed image for anomaly detection, and achieved good results. At present, the existing denoising methods roughly include low-rank learning, sparse representation, tensor decomposition,
deep learning and so on. For example, Du et al. proposed a low-rank matrix decomposition method combined with band-by-band noise model [2]; Xue et al proposed a sparse representation of joint subspace low-rank constraints [3]; Sun et al proposed a subspace low-rank learning and block-matched four-dimensional filtering (BM4D) method [4]; Zhao et al proposed a method for spectral global and spatial nonlocal tensor decomposition [5]. Chang et al proposed a method of introducing residual filtering and multi-channel filtering into the generation of countermeasure networks [6]. Common noises include Gaussian noise, impulse noise, dead line, stripe noise and Poisson noise [7]. In this paper, the mixed noise (Gaussian noise, impulse noise and stripe noise) in the image is regarded as additive noise, and the low rank decomposition is carried out according to the spectral global correlation and spatial non-local similarity of the hyperspectral image. Then, the norm constrained sparse noise is used to reduce the noise. Finally, the global RX detection is carried out on the reconstructed hyperspectral image after noise reduction.

2. Theoretical Model

2.1 Global Low Rank Decomposition of Spectrum Based on Hysime Subspace Estimation
In the current dimensionality reduction methods of hyperspectral image data, it is usually assumed that the dimension of the subspace is known, and the noise is i.i.d Gaussian noise, these methods have great limitations [8]. Because the dimension of the subspace should be determined according to the characteristics of the data itself, and the noise in most hyperspectral data is mixed. Hyperspectral signal subspace recognition is a signal subspace estimation method based on feature decomposition, simple and unsupervised (that is, without any prior parameters). This method is mainly based on the idea of minimum mean square error. through the estimation of signal and noise correlation matrix, the residual statistics after median filtering are used to estimate the optimal eigendirection quantum set of signal subspace [9].

The spectral vector of the hyperspectral image can be represented by the pre-learned subspace, which makes full use of the low rank characteristic of the hyperspectral data [10]. Therefore, the hyperspectral image can be decomposed into a k-dimensional subspace. This is a good approximation in most hyperspectral images [11].The degradation models of hyperspectral images are as follows:

\[ Y = EZ + S + N. (X = EZ) \]  

Where X represents a clean hyperspectral image (without noise), E represents the basis matrix of the subspace, Z represents the coefficient matrix about E, S represents sparse noise (including impulse noise and stripe noise), and N represents Gaussian noise.

2.2 Low Rank Decomposition Based on Spatial Nonlocal Similarity
The common image denoising method based on non-local similarity is the basis of ordinary image denoising. Using the spatial self-similarity of hyperspectral images, we find similar blocks from different regions of the image. Based on this, we can use the denoising methods of ordinary images for reference. The block matching is carried out on the low-dimensional hyperspectral image, and the 3murd tensor group needed in the denoising model is obtained by using K-SVD algorithm. The specific steps include the following four steps:

1) Using HySime to determine subspace;
2) Extracting similar 3-D blocks from Images;
3) Expand each 3-D block \( Z_i \in R^{s \times s \times k} \) into a 2-D matrix of \( s^2 \times k \) size.;
4) Stack all 3-D blocks

The estimated 3-D tensor is:

\[ \hat{L}_i = \arg \min \frac{1}{\sigma^2_i} \| P_{\hat{L}_i} - L_{\hat{L}_i} \|_F + \kappa (L_{\hat{L}_i}) \]  

Where, \( \kappa (L_{\hat{L}_i}) \)it is the sum of the singular values of the 3murd tensor expansion matrix.
2.3 Hyperspectral Image Denoising Model
Because impulse noise and stripe noise are sparse in space, they are expressed as an additive sparse term by modeling, and the $L_1$ norm is used to limit the noise term in the sparse term, so as to suppress Gaussian noise. After estimating the 3-D low-rank tensor from the previous step, the hyperspectral image denoising model is as follows:

$$\{E, Z, S\} = \arg \min_{E, Z, S} \frac{1}{2} P - E Z - S P F_i^* + \lambda P S P_i^* + \lambda \sum_i \frac{1}{\sigma_i^2} P Z - Q_i Z_i^* . \quad E^* E = I_i$$ (3)

The Augmented Lagrange Method is used to iteratively solve the model. It includes the following three aspects:

1. Constantly iterate to update feature images $S$
2. Constantly iterate to update sparse noise $Z$
3. Constantly iterate to update the subspace $E$

2.4 GRX Anomaly Detection
Global Reed-Xiao Detector is a classical algorithm in the field of hyperspectral anomaly detection, which is simple, effective and time-consuming. It assumes that both the target data and the background data follow the Gaussian distribution, on this basis, the mean and covariance matrix of the background are analyzed, and the anomaly detection is carried out through the pre-set judgment threshold. The expression of the RX algorithm is:

$$RX(s) = \begin{cases} (s - \mu_b)^T C_b^{-1} (s - \mu_b) & \geq \epsilon, \text{target} \\ < \epsilon, \text{background} & \end{cases}$$ (4)

Where $s$ is the input image spectrum, $\mu_b = \frac{1}{M} \sum_i x_i$ is the mean value of the background sample, and $C_b = \frac{1}{M} \sum (x - \mu_b)(x - \mu_b)^T$ is the covariance matrix of the background sample.

Set the threshold to $\epsilon$, if $RX(s) \geq \epsilon$, the abnormal target exists; otherwise, it does not exist. The essence of RX algorithm is actually an energy detection algorithm, which detects abnormal targets by calculating the Mahalanobis distance between the measured spectral pixels and the background sample.

3. Experimental Analysis

3.1 Dataset
The data set used in this paper comes from the sub-images of AVRIS hyperspectral images at San Diego Airport in California. It includes pure hyperspectral images and real hyperspectral images with artificial mixed noise.

In order to simulate hyperspectral data with noise, three kinds of data sets with noise are artificially generated, which are Gaussian noise, impulse noise and dead line. Among them, impulse noise chooses a typical common salt and pepper noise. In the first case, zero-mean Gaussian noise is added to all bands, and the variance of Gaussian noise is randomly sampled from 0.1 to 0.2. In the second case, Gaussian noise is added to each frequency band, while 20% salt and pepper noise is added. In the third case, Gaussian noise and salt and pepper noise are added, and three deadlines are added.
In addition, select a real hyperspectral image data PAVIACENTRA data set. PAVIACENTRA is a part of the selected region with a size of 150x150x102. This real hyperspectral image has Gaussian noise, impulse noise and dead lines in some bands.

3.2 Simulated Data Experiment

The comparison algorithms selected in the experiment include: GRX algorithm, UNRS algorithm, CRD algorithm and LSAD algorithm. In order to save space and computing time, this paper only introduces the comparison between the algorithms in the first case, while other methods use BM3D denoising for simple preprocessing [12].

| Method   | Parameters          |
|----------|---------------------|
| GRX      |                     |
| UNRS     | $win_{out} = 7$, $win_{in} = 3$, $\lambda = 0.01$ |
| CRD      | $win_{out} = 7$, $win_{in} = 3$, $\lambda = 0.01$ |
| LSAD     | $win = 5$         |
| SLD-RX   | $k = 5$           |

According to the experimental results, the effect of anomaly detection LSAD algorithm (AUC=0.94, t=401.23s) is the best, but it takes the longest. The SLD-RX algorithm (AUC=0.93, t=18.59s) proposed in this paper is slightly better than UNRS algorithm (AUC=0.91, t=2.18s) and CRD algorithm (AUC=0.90, t=2.02s) for anomaly detection, but it takes a long time. Compared with the original GRX algorithm (AUC=0.84, t=0.74s), it takes more time, but the accuracy of anomaly detection is higher.
The experimental results show that the mixed noise has a great influence on the accuracy of anomaly detection in the simulation experiment. Although other algorithms have been simply preprocessed by BM3D denoising, the accuracy of anomaly detection is lower than that of anomaly detection in pure hyperspectral images. It can be seen that the denoising performance of this algorithm is also better than that of general denoising.

Fig 4. Results of simulated data detected by different methods (a) UNRS (b) CRD (c) GRX (d) LSAD (e) SLD-RX

3.3 Real Data Experiment
Several bands of Pavia hyperspectral images are randomly selected (for example, band 9, 19, 29, 29 and 49) to observe the possible types of noise. As shown in figure 5, different types of noise may exist in different bands of the original hyperspectral image.

Fig 5. Pavia contains noise type: (a) Gaussian noise (b) salt and pepper noise (c) Gaussian noise + dead line (d) salt and pepper noise + dead line (e) dead line (f) denoised Pavia image

The comparison algorithm selected by the real hyperspectral image data experiment and the set experimental parameters are the same as the simulation experiment. In order to increase the experimental contrast, the experimental contrast algorithm does not carry out denoising pre-processing.

The experimental results of SLD-RX algorithm on real hyperspectral data are similar to those of simulated data. Although this algorithm takes a long time, it has a great improvement in detection accuracy compared with the original RX algorithm. At the same time, because of the comparison of UNRS algorithm and CRD algorithm, it is obviously better than LSAD algorithm in time-consuming algorithm.

Fig 6. ROC curve of real data

From the experimental results, it can be seen that there are many types of noise (Gaussian noise, impulse noise, stripe noise, dead line, etc.) in the original hyperspectral image data under the influence of natural conditions and image acquisition instruments. This algorithm can effectively eliminate the influence of noise on hyperspectral image anomaly detection and improve the efficiency and accuracy of anomaly detection.
4. Summary

In this paper, a hyperspectral anomaly detection algorithm based on subspace low-rank decomposition is proposed to improve the efficiency and accuracy of the anomaly detection algorithm by removing the mixed noise that interferes with the image anomaly detection in hyperspectral images. Based on the existence of multiple subspaces in hyperspectral images, subspace representation is used to reduce data dimensions, reduce the amount of data processing and computation, and enhance the low rank of spectral dimensions. At the same time, considering the spatial non-local similarity of the hyperspectral image, the K-SVD algorithm is used to decompose the non-local similar blocks in the subspace into three-dimensional tensors. On this basis, the image preprocessing denoising model in anomaly detection algorithm is established. Finally, a simple RX algorithm is used to realize hyperspectral image anomaly detection. On the whole, the algorithm takes less time and has higher detection accuracy, so it has certain advantages compared with other methods.

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