# **A Review of Anomaly Detection in Hyperspectral Remote Sensing Images**

**Abstract:** Hyperspectral remote sensing image anomaly detection technology has important application value in many fields such as resource exploration, environmental monitoring, agriculture, and urban planning. In this paper, the research background, main methods, current challenges, and future development directions of Hyperspectral anomaly detection technology are reviewed. The research background section introduces the advantages of Hyperspectral imaging technology and its application in anomaly detection and points out the limitations of existing methods. The main methods include those based on statistics, data decomposition, sparse representation, and deep learning, each of which has its own unique benefits and application scenarios. The principles of these methods and the measures to improve them are discussed in detail in this article. Hyperspectral anomaly detection faces challenges such as data redundancy and noise, homogeneous and foreign body phenomena, mixed pixel problems, and computational complexity and practicability. To address these challenges, this paper proposes future research directions, including database expansion, multi-source data fusion, and algorithm application. These directions aim to improve the accuracy and robustness of detection and promote the wide promotion of Hyperspectral anomaly detection technology in practical applications. Through the review of the existing research results, this paper provides a reference and guidance for the development of Hyperspectral anomaly detection technology in the future.

**Keywords:** Hyperspectral imaging, anomaly detection, statistical methods, data decomposition, sparse representation, deep learning, multi-source data fusion, practical application

# Introduction

Hyperspectral imaging technology has become an important tool in the field of remote sensing with its ability to capture detailed spectral information in multiple bands. Each pixel has a complete spectral curve that reflects the reflective characteristics of the object at each wavelength, which enables Hyperspectral images to not only provide the geometric shape of the object but also reveal its material composition and chemical properties. This feature makes Hyperspectral imaging widely used in resource exploration, environmental monitoring, agriculture, urban planning, and other fields. Hyperspectral anomaly detection is a key technology that uses Hyperspectral data to identify abnormal targets in images that are significantly different from the normal background.

The importance of Hyperspectral anomaly detection is reflected in its wide range of practical applications. In military reconnaissance, Hyperspectral anomaly detection can identify camouflaged military facilities and concealed weapons and equipment, thereby providing important strategic intelligence. In environmental monitoring, this technology can be used to detect water pollution, identify damaged vegetation, and monitor land use changes. In the agricultural field, Hyperspectral anomaly detection can identify crops attacked by pests and diseases, helping farmers take timely measures to reduce losses. In addition, in disaster emergency response, Hyperspectral anomaly detection can quickly locate disaster-stricken areas and provide timely rescue information.

However, there are many challenges in performing Hyperspectral anomaly detection. First, Hyperspectral data has high dimensionality and large data volume, which makes data processing and analysis extremely complex. How to effectively reduce the dimension and extract useful information becomes a technical difficulty. Secondly, the complex background spectral characteristics and the spectral similarity of abnormal targets increase the difficulty of detection. In addition, the spectral mixing effect will also affect the accuracy of detection, resulting in false detection and missed detection. Therefore, to improve the accuracy and efficiency of Hyperspectral anomaly detection, researchers have proposed a variety of algorithms and methods, including the RX algorithm based on statistics, the method based on subspace decomposition, the technology based on sparse representation, and the method based on deep learning that has developed rapidly in recent years. Each method has its unique advantages and application scenarios, but in practical applications, it is usually necessary to select and optimize according to the specific situation.

In summary, Hyperspectral anomaly detection technology has shown important application value in many fields with its unique advantages. Despite the technical challenges, with the continuous improvement of algorithms and computing power, Hyperspectral anomaly detection technology will play a greater role in future applications. Future research directions will include the development of multi-source data fusion, efficient dimensionality reduction technology, and real-time detection algorithms to further improve the performance and practicality of Hyperspectral anomaly detection.

# **Research Status**

In recent years, Hyperspectral anomaly detection technology has made significant progress in both theoretical methods and practical applications. The following will introduce the current research progress in detail from the aspects of statistical methods, data decomposition methods, sparse representation methods, deep learning methods, multi-source data fusion, algorithm practicalization, and database expansion.

## 2.1 Statistical Methods

Statistical-based methods were an early focus of research in the field of Hyperspectral anomaly detection. Such methods detect anomalous targets by assuming that the background spectrum obeys some statistical distribution and based on this model. The classical RX (Reed-Xiaoli) detector is one of the most commonly used methods, which assumes that the spectral distribution of the background pixels obeys a multivariate normal distribution, and identifies the anomalous targets by calculating the Mahalanobis distance of each pixel from the background statistical distribution. The advantage of this method is its solid theoretical foundation and relatively simple calculation.

However, in practice, due to the complexity and diversity of the background spectra, the background pixels often do not obey the Gaussian distribution completely, which affects the detection performance of the RX detector. Therefore, researchers have proposed various improvements: Kwon and Nasrabadi (2005) proposed the KRX[1] (Kernel-RX) algorithm, which improves the differentiation between anomalous targets and background pixels and the detection accuracy by introducing a kernel function to map Hyperspectral data into a high-dimensional feature space; Zhou et al. (2016) proposed on the basis of KRX the CKRX [2] (Cluster Kernel RX) algorithm, which reduces the computational amount of the algorithm by performing clustering operation on background pixels and replacing all pixels with cluster centers, and performs anomaly detection by a fast feature decomposition algorithm; Matteoli et al. (2014) proposed LRX[3] (Local-RX) algorithm, which adopts a local adaptive kernel density estimation method to effectively model the background data and reduce the background noise interference, thus improving the anomaly detection accuracy; Guo et al. (2014) proposed the WRX[4] (Weighted-RX) algorithm, which better evaluates the background information by decreasing the anomaly/noise pixel weights and increasing the background pixel weights, thus improving the anomaly detection accuracy; Guo et al. (2014) proposed the LF-RX ( Linear Filter-Based RX) algorithm, which obtains a more accurate estimation of the background covariance matrix by filtering the anomaly/noise pixels, providing more realistic anomaly detection results.

## **2.2 Methods Based on Data Decomposition**

Data representation-based Hyperspectral anomaly detection algorithms are a type of detection method that utilizes the intrinsic structural features of Hyperspectral image data. Such algorithms extract useful information from the image by decomposing the raw data into several components, e.g., through techniques such as principal component analysis (PCA) or singular value decomposition (SVD). The core of anomaly detection is to identify pixels or regions that are significantly different from the normal data distribution. The anomaly detection algorithms based on data decomposition are Chen et al. (2011) proposed the sparse representation-based algorithm SRD [5], where the target pixels can be expressed by a sparse linear combination of the training data. Li et al. (2015) proposed the sparse representation algorithm BJSR[6] for background union, where the background pixels are utilized to construct the dictionary set and estimate the sparse coefficient matrix, and the anomalies are judged by the reconstruction error of the pixels. Vafadar and Ghassemian (2018) proposed the improved co-expression detection algorithm CRBORAD[7], which removes outliers by statistical methods before co-expression to improve the model accuracy. Li and Du (2014) proposed the co-expression-based anomaly detection method, which utilizes the spatial relationship between Hyperspectral pixels, and the anomalous pixels can't be spatially adjacent to the pixels are expressed. Improvement of SRD and CRD by other scholars: several scholars have further researched and improved on the basis of sparse expression and co-expression.

## **2.3 Methods Based on Sparse Representation**

Hyperspectral anomaly detection based on data decomposition is a method for recognizing and detecting anomalous targets in images by decomposing high-dimensional spectral data into low-dimensional features or sparse representations. The principles include techniques such as principal component analysis (PCA), nonnegative matrix factorization (NMF), independent component analysis (ICA), and dictionary learning, which make anomalous targets more salient in the simplified feature space by extracting the main features and removing redundant information.PCA preserves the main information of the data by linear transformation, and NMF decomposes the physically significant components by utilizing nonnegativity. ICA separates mixed signals through independence, and dictionary learning highlights anomalous targets through sparse representation. These methods not only improve detection accuracy but also reduce noise and computational complexity.

Common methods based on matrix decomposition include LRR (Low-Rank Representation), RPCA (Robust Principal Component Analysis), and Go-Dec. First Liu (2013) proposed the LRR[8] method, which reveals the intrinsic structure of the data through low-rank representation, and was initially used for subspace clustering, and then the method was used by many researchers for Hyperspectral anomaly detection problems. Xu et al. (2016) proposed the LRaSR[9] (Low-Rank and Sparse Representation) method, which combines low-rank and sparse representation to represent background pixels by a low-rank matrix of the background dictionary while mining spectral local features.Qu et al. (2018) proposed the ADLR[10] (Abundance and Dictionary-based Low-Rank decomposition) method, which considers the mixed image element problem, which obtains end-element abundance vectors by spectral unmixing to construct dictionaries and reduce noise interference.Ning et al. (2019) PAB-DC [11](Potential Anomaly and Background Dictionary Construction) method, which constructs a dual dictionary of background and potential anomalies to more accurately discriminate between the background anomaly and noise pixels. Cheng and Wang (2020) proposed a low-rank representation detection algorithm GTVLRR[12] (Graph and Total Variation Regularized Low-Rank Representation) method based on graph and total variation regularization, which combines graph regularization and total variation regularization to preserve the spatial relationship of Hyperspectral data and improve the detection accuracy.

Candès et al. (2011) proposed the RPCA[13] method: the data is decomposed into a low-rank matrix and a sparse matrix, which effectively extracts the noise and enhances the robustness to disturbances such as illumination and occlusion. Subsequently, Zhu et al. (2019) method HSRAD[14] (Hybrid Statistics and Representation-based AnomalyDetector), which combines statistical methods with matrix decomposition, initially detects anomalies through low-rank sparse matrix decomposition, and then optimizes it through co-expression algorithms, the algorithm finally Li et al. (2021) proposed the LSDM-MoG[15] method considering that the noise information contained in the traditional matrix decomposition algorithm seriously interferes with the detection of anomalous targets, which combines the low-rank sparse decomposition with the hybrid Gaussian model to distinguish between the noise and anomalous part of the sparse matrix. Feng et al. (2022), on the other hand, combined the matrix decomposition with the density peak coexpression, which can more effectively utilize the matrix decomposition, and the coexpression-based AnomalyDetector. which can more effectively utilize the low-rank component in the matrix decomposition results, and finally fused the two detection results through an entropy-based adaptive fusion algorithm to achieve better results[16].

Zhou and Tao (2011) proposed the Go-Dec[17] method, which further refines the data decomposition compared to RPCA, including the low-rank matrix, sparse matrix, and noise matrix, and reduces the model complexity and improves the solution efficiency by constraining the rank and sparsity of the matrix. Sun et al. (2014) then applied the method to Hyperspectral anomaly detection, which can improve the speed of anomaly detection.

## **2.4 Methods Based on Deep Learning**

With the improvement of computational power and the development of deep learning technology, deep learning-based methods show strong potential in Hyperspectral anomaly detection. They are mainly categorized into convolutional neural networks (CNN) and generative adversarial networks (GAN).CNN extracts spatial and spectral features of Hyperspectral data through multilayer convolution, which improves detection accuracy.GAN, on the other hand, learns the background distribution of Hyperspectral data through the generative adversarial process, which more accurately distinguishes the anomalous target and background.

Li et al. (2017) introduced a convolutional neural network (CNN) into Hyperspectral anomaly detection for the first time and proposed the CNND[18] (CNN-based Detector) method. The method first takes the difference pixel pairs and the like pixel pairs as input data and jointly inputs them into the CNN for training. Then, the mean values of the pixel to be measured and its surrounding pixels are input into the trained CNN to determine whether there is an anomaly. Song et al. (2019) proposed a DBSCAN[19] (Density-Based Spatial Clustering of Applications with Noise) method, which accurately extracts the abundance map of Hyperspectral data through CNN, and the abundance map is more effective in distinguishing the background from the anomalous pixels compared to the original data, and subsequently obtains a spectral dictionary through density spatial clustering, which is combined with a low-rank decomposition method to realize anomaly detection. Fu et al. (2021) transformed the anomaly detection problem into a plug-and-play detection framework, DeCNN-AD[20] ( Denoising CNN-Anomaly Detection), which reduces the background noise in the original data through CNN regularization constraints, and subsequently constructs an optimized dictionary through clustering to ultimately achieve anomaly detection. Wang (2020) proposed a network called Auto-AD[21] (Autonomous Hyperspectral Anomaly Detection). Hyperspectral Anomaly Detection Network), which reconstructs the background by a fully convolutional autoencoder (AE) with jump connections and suppresses the anomaly reconstruction by using an adaptive weighted loss function so that the anomalies are revealed in the form of reconstruction errors. Experimental results show that the method is effective in anomaly detection on public airborne datasets and UAV airborne Hyperspectral datasets.

Hyperspectral anomaly detection methods based on Generative Adversarial Networks (GANs) have been widely studied in recent years. Jiang et al. (2020c) proposed a method semiDRX[22] (semi Dual RX) that combines a dual RX detector with a semi-supervised GAN. This method first utilizes the original RX algorithm to initially identify anomalous and background pixels and then inputs these data into a semi-supervised GAN to extract more accurate anomalous and background pixels, and finally obtains the final anomaly detection results by the fine RX detector. Jiang et al. (2020b) developed a GAN anomaly detection algorithm based on the unsupervised salient reconstruction constraints HADGAN[23] (unsupervised discriminative reconstruction-constrained Generative Adversarial Network for HAD). The algorithm imposes significant reconstruction constraints on the GAN through a self-encoder, learns the background pixel distribution more accurately, reduces the interference of anomalous targets in the background, and ultimately detects the anomalous targets through a joint null-spectral approach. Li et al. (2022b) proposed a method combining sparse coding and GAN, sparseHAD[24] (sparse coding- inspired generative adversarial network for Hyperspectral Anomaly Detection) to achieve weakly supervised anomaly detection. Subsequently, Li et al. (2022c) proposed a joint dual-GAN approach to reconstruct the background distribution more realistically[25]. The first GAN is used to extract the low-dimensional background feature maps, and the second GAN combines the spatial information and utilizes the previous background feature maps to obtain denser and more accurate background features, and ultimately obtains the final anomaly detection results through the null-spectrum combination method. In addition, there are other scholars who have conducted further research in this direction and explored more GAN-based Hyperspectral anomaly detection methods.

## **2.5 Other Methods**

Meanwhile, Hyperspectral anomaly detection has been explored in somewhat different directions in recent years. For example, Zhang et al. (2022) proposed a Hyperspectral anomaly detection algorithm based on fractional Fourier transform (FrFT), FrFT-TRX[26], which improves the differentiation between the target and the background by better utilizing the spatial properties of the test points by using the tensor RX (TRX) algorithm in the fractional Fourier domain. Li et al. (2022) proposed an end-to-end trainable deep single-class classification network ssDSVDD[27] for Hyperspectral anomaly detection, which selects background samples to train the minimum enclosing hypersphere by density clustering method, realizes the unification of feature learning and anomaly detection, fuses both spectral and spatial features, and reduces the negative impact of redundant bands by a band-attention module. Xiang et al. (2021) proposed a method that fuses a visual attention model and adaptive weighted background subtraction for the Hyperspectral anomaly detection method HVAM[28]. Taghipour et al. (2021) proposed a Hyperspectral anomaly detection method HVAAD[29] based on a visual attention mechanism, which extracts spatial and spectral features by fusing bottom-up and top-down attention mechanisms. Wang et al. (2022) proposed a method named SST-Former[30], a joint spectral-spatial-temporal transformer for Hyperspectral image change detection, which effectively improves the detection performance through position coding, spectral transform encoder, class labeling, and spatial transform encoder, as well as a temporal transformer and a multilayer perceptron, and verifies its superiority on multiple datasets. Li et al. (2024) proposed a one-step detection paradigm method TDD[31], which realizes a Hyperspectral anomaly detection model without iterative reconstruction of the background by designing anomaly sample simulation strategies and global and local self-attention modules, which verifies its superior detection performance and liability on multiple public datasets. To solve the challenge of accurately constructing the low-rank distribution of background pixels and sparse distribution of anomaly pixels in Hyperspectral image anomaly detection, Guo et al. (2023) proposed an anti-noise hierarchical mutual irrelevance induced discriminative learning AHMID[32] method, which enhances the distinguishability of the background and the anomaly and the noise-resistant performance using the structural irrelevance constraints, the first-order statistical constraints, dispersion constraints, and the mixed noise model. He et al. (2023) proposed a Hyperspectral anomaly detection method based on convolutional transformer self-encoder CTA [33], which combines a clustering module and a self-encoder module, utilizes the integration of convolution and transformer for local and global feature extraction, and explores the background and anomaly information through the clustering module to enhance the differentiability of anomalies. Li et al. (2023) proposed a new Hyperspectral anomaly detection method AETNet[34], which learns spatial context features through a single-training generalized anomaly enhancement network and stochastic masks without the need to adjust parameters or retrain for new scenes, and combines with plug-and-play model selection module and a large-scale benchmark dataset, HAD100, to achieve the optimal balance between the detection accuracy and the inference speed, and to remain competitive under different sensor devices. Duan et al. (2023) proposed an unsupervised isolated forest Hyperspectral oil film detection method, HOSD[35], which achieves high accuracy through noise reduction, dimensionality reduction, probability estimation, and optimization. Shen et al. (2022) proposed a double sparse constraint-based target detection method, DSC[36], which combines the spectral by decomposing the background and target images and optimizing the coefficient matrix similarity and clustering to construct a dictionary, which achieves target highlighting and background suppression. Luo et al. (2023) proposed the Cross-AD[37] method, which captures the local similarity and global difference of camouflaged targets through horizontal and vertical adaptive background estimation and enhances the detection of large-scale imitations and dense vegetation through improved Cross-Box and Cross-Index algorithms environments, achieving an optimal balance between execution time and detection performance.

In summary, it can be seen that the research on Hyperspectral anomaly detection is still hot in recent years, focusing on obtaining more spatial information through full convolution, retaining enough spatial and spectral information by unifying the null spectrum, and obtaining more features to improve the accuracy of anomaly detection. Meanwhile, a Transformer is also applied to Hyperspectral anomaly detection to obtain considerable results.

## 2.6 Algorithm and Source Code

Table 2-1 Hyperspectral anomaly detection algorithm and open source code

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| Algorithm | Source Code |
| DeCNN-AD | https://github.com/FxyPd/DeCNNAD |
| sparseHAD | https://github.com/JiangThea/HAD |
| Auto-AD | https://github.com/RSIDEA-WHU2020/Auto-AD |
| HAD-AHMID | https://github.com/HalongL/HAD-AHMID |
| HTD-IRN | https://github.com/shendb2022/HTD-IRN |
| CTA | https://github.com/hzhdhz/CTA |
| AETNet | https://github.com/ZhaoxuLi123/AETNet |
| HOSD | https://github.com/PuhongDuan/HOSD |
| IEEE\_TGRS\_SSTFormer | https://github.com/yanhengwang-heu/IEEE\_TGRS\_SSTFormer |
| DSC | https://github.com/shendb2022/DSC |
| Cross-AD | https://github.com/XingshiLuo/Cross-AD |
| TDD | https://github.com/Jingtao-Li-CVer/TDD |

# **Challenges and Development Directions**

Hyperspectral remote sensing image anomaly detection faces many challenges, but also shows broad development prospects. The following are the main challenges and future development directions in the current research on Hyperspectral anomaly detection.

## **3.1 Challenge**

### **3.1.1 Data Redundancy and Noise Issues**

Hyperspectral data usually contain hundreds of bands, and there is high redundancy and noise between these bands. This redundancy not only increases the complexity of data processing but also may lead to a decrease in detection accuracy. To solve this problem, many studies have used methods such as principal component analysis (PCA) and robust principal component analysis (PCA) for dimensionality reduction and band selection to improve the efficiency and accuracy of the algorithm.

Same-object different-spectrum and different-object same-spectrum phenomenon: The spectral characteristics of the same material under different conditions may be different (same-object different-spectrum), while the spectral characteristics of different materials under certain conditions may be similar (different-object same-spectrum). This phenomenon makes anomaly detection more complicated. For example, some studies have alleviated this problem by combining spectral and spatial feature fusion methods.

### **3.1.2 Mixed Pixel Problem**

A pixel in a Hyperspectral image may contain mixed spectra of multiple materials, which makes detection more difficult. To address this problem, researchers have proposed various spectral unmixing methods, such as non-negative matrix factorization (NMF) and convolutional neural network (CNN) unmixing, to separate pure endmember spectra, thereby improving detection accuracy.

### 3.1.3 Computational Complexity and Practicality

Many Hyperspectral anomaly detection algorithms have high computational complexity and slow operation speed, making them difficult to promote in practical applications. In recent years, with the development of deep learning, some research has been devoted to developing fast algorithms with low computational complexity and trying to deploy them on embedded platforms to improve the practicality of the algorithms.

## **3.2 Development Directions**

### 3.2.1 Database Expansion

Currently, the performance verification of Hyperspectral anomaly detection algorithms mainly relies on a few public databases, which have limited data volume and diversity. Therefore, expanding and enriching the Hyperspectral anomaly detection database will help to more comprehensively evaluate and improve the performance of the algorithm.

### 3.2.2 Multi-source Data Fusion

Single Hyperspectral data sometimes cannot provide enough information to accurately detect abnormal targets. The future research trend is to fuse multi-source remote sensing data (such as radar, LiDAR, etc.) and ground measurement data to enhance the robustness and accuracy of anomaly detection. For example, by combining Hyperspectral data with radar data, their complementary characteristics can be used to improve the detection effect.

### **3.2.3 Algorithm Practicalization**

To promote Hyperspectral anomaly detection technology in practical applications, researchers need to develop more efficient and easy-to-use detection algorithms. This includes the development of fast algorithms with low computational complexity and integrated portable anomaly detection systems that highly integrate acquisition equipment with processing equipment. In addition, the application of cross-platform frameworks based on deep learning (such as TensorRT, CNN, etc.) will help to achieve the real-time and deployability of Hyperspectral anomaly detection algorithms.

In summary, although the field of anomaly detection in Hyperspectral remote sensing images faces many challenges, the detection effect and practicality can be greatly improved through research in areas such as database expansion, multi-source data fusion, and algorithm practicality. These development directions not only help solve existing problems but also provide a solid foundation for the widespread application of Hyperspectral anomaly detection technology.

# Conclusion

Hyperspectral remote sensing image anomaly detection technology has shown important application value in many fields such as resource exploration and environmental monitoring due to its rich spectral information. This paper reviews the research background, main methods, challenges and future development direction of Hyperspectral anomaly detection technology. Although existing methods have made significant progress in detection accuracy and efficiency, the high dimensionality, redundancy and noise problems of Hyperspectral data still exist. In addition, the common phenomena of different spectra of the same object and the same spectrum of different objects, as well as the problem of mixed pixels in practical applications, increase the complexity of detection. Future research should focus on database expansion, multi-source data fusion and the development of fast algorithms with low computational complexity to improve the robustness and practicality of the algorithm. With the continuous improvement of deep learning technology and computing resources, Hyperspectral anomaly detection technology will become more intelligent and efficient, further promoting its widespread popularization and development in practical applications.

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