# **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 methods are the early research focus in the field of Hyperspectral anomaly detection. This type of method assumes that the background spectrum obeys a certain statistical distribution and detects abnormal targets based on this model. The classic RX (Reed-Xiaoli) detector is one of the most commonly used methods. It assumes that the spectral distribution of background pixels obeys a multivariate normal distribution and identifies abnormal targets by calculating the Mahalanobis distance between each pixel and the background statistical distribution. The advantage of this method is that it has a solid theoretical foundation and is relatively simple to calculate. However, in practical applications, due to the complexity and diversity of the background spectrum, background pixels often do not completely obey the Gaussian distribution, which affects the detection performance of the RX detector. Therefore, researchers have proposed various improvement measures, such as the local RX (LRX) detector, which improves the flexibility and accuracy of detection by estimating background statistical parameters in a local area.

## **2.2 Methods based on data decomposition**

To overcome the high dimensionality and redundancy problems of Hyperspectral data, methods based on data decomposition have become a research hotspot. These methods extract the main features through dimensionality reduction technology and reduce the complexity of data processing. Principal component analysis (PCA) is one of the most commonly used dimensionality reduction methods. By extracting the main components of the data, the main information is retained and noise and redundancy are removed. Independent component analysis (ICA) decomposes the data by finding independent components, which is particularly suitable for separating mixed spectral signals. In addition, non-negative matrix factorization (NMF) has also been applied in Hyperspectral data analysis. By decomposing the data into non-negative basis matrices and coefficient matrices, NMF can better explain the physical meaning of spectral data. For example, the NMF method can effectively separate the background and abnormal components, thereby improving the detection accuracy.

## **2.3 Methods based on sparse representation**

Sparse representation methods have received widespread attention in Hyperspectral anomaly detection in recent years. This type of method uses the sparse characteristics of Hyperspectral data and assumes that the frequency of abnormal targets in the data is low, so the background and abnormal targets can be represented by sparse matrices. Sparse representation algorithms usually include two steps: building an over-complete dictionary and sparse coding. The background joint sparse representation (BJSR) algorithm is one of the representative methods. It uses background pixels to construct a dictionary set, estimates the sparse coefficient matrix, and calculates the reconstruction error to identify abnormal targets. This method can not only improve the detection accuracy but also effectively handle complex backgrounds and improve the robustness of detection.

## **2.4 Methods based on deep learning**

With the improvement of computing power and the development of deep learning technology, methods based on deep learning have shown great potential in Hyperspectral anomaly detection. Convolutional neural networks (CNNs) extract spatial and spectral features of Hyperspectral data through multi-layer convolutions, improving detection accuracy. Generative adversarial networks (GANs) learn the background distribution of Hyperspectral data through a generative adversarial process to more accurately distinguish abnormal targets from backgrounds. For example, the Deep CNN model combined with the GAN method has shown strong detection capabilities when dealing with complex backgrounds and spectral mixtures. Specifically, deep learning methods can automatically extract high-order features, reduce the complexity of artificial feature engineering, and improve the automation and robustness of detection.

# **Difficulties and Challenges (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**

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.

**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.

**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**

**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.

**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.

**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.

1. **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.