高光谱遥感影像异常检测综述

# **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.

摘要

高光谱遥感图像异常检测技术在资源勘探、环境监测、农业和城市规划等多个领域具有重要应用价值。本文综述了高光谱异常检测技术的研究背景、主要方法、当前面临的挑战以及未来发展方向。研究背景部分介绍了高光谱成像技术的优势及其在异常检测中的应用，并指出了现有方法的局限性。主要方法包括基于统计学、数据分解、稀疏表示和深度学习的方法，其中每种方法都有其独特的优点和应用场景。本文详细讨论了这些方法的原理和改进措施。高光谱异常检测面临的数据冗余和噪声问题、同物异谱和异物同谱现象、混合像元问题以及计算复杂度和实用性等挑战。为应对这些挑战，本文提出了未来的研究方向，包括数据库扩展、多源数据融合和算法实用化。这些方向旨在提高检测的准确性和鲁棒性，推动高光谱异常检测技术在实际应用中的广泛推广。通过对现有研究成果的综述，本文为未来高光谱异常检测技术的发展提供了参考和指导。

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

关键词

高光谱成像，异常检测，统计学方法，数据分解，稀疏表示，深度学习，多源数据融合，实用化

研究背景

高光谱成像技术以其在多个波段捕捉详细光谱信息的能力，成为遥感领域的重要工具。每个像素点都拥有一条完整的光谱曲线，反映了地物在各个波长上的反射特性，这使得高光谱图像不仅能够提供地物的几何形态，还能揭示其物质成分和化学性质。这一特性使高光谱成像在资源勘探、环境监测、农业、城市规划等领域具有广泛应用。而高光谱异常检测则是利用高光谱数据，识别出图像中与正常背景显著不同的异常目标的一项关键技术。

高光谱异常检测的重要性体现在其广泛的实际应用中。在军事侦察中，通过高光谱异常检测，可以识别出伪装的军事设施和隐蔽的武器装备，从而提供重要的战略情报。在环境监测中，该技术可以用于检测水体污染、识别受损的植被以及监控土地利用变化。在农业领域，高光谱异常检测能够识别出病虫害侵袭的作物，帮助农民及时采取措施，减少损失。此外，在灾害应急中，高光谱异常检测可以快速定位受灾区域，提供及时的救援信息。

然而，进行高光谱异常检测也面临诸多挑战。首先，高光谱数据具有高维性和大数据量，这使得数据处理和分析变得异常复杂，如何有效地降维和提取有用信息成为技术难点。其次，复杂的背景光谱特性和异常目标的光谱相似性增加了检测的难度。此外，光谱混合效应也会影响检测的准确性，导致误检和漏检。因此，为了提高高光谱异常检测的精度和效率，研究人员提出了多种算法和方法，包括基于统计学的RX算法、基于子空间分解的方法、基于稀疏表示的技术以及近年来发展迅速的基于深度学习的方法。每种方法都有其独特的优势和应用场景，但在实际应用中，通常需要根据具体情况进行选择和优化。

综上所述，高光谱异常检测技术以其独特的优势，在多个领域展现了重要应用价值。尽管面临技术上的挑战，但随着算法和计算能力的不断提升，高光谱异常检测技术将在未来的应用中发挥更大的作用。未来的研究方向将包括多源数据融合、高效降维技术和实时检测算法的开发，以进一步提升高光谱异常检测的性能和实用性。

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.

研究进展（现状）

近年来，高光谱异常检测技术在理论方法和实际应用方面均取得了显著进展。以下将从基于统计学的方法、基于数据分解的方法、基于稀疏表示的方法、基于深度学习的方法、多源数据融合以及算法实用化与数据库拓展几个方面，详细介绍当前的研究进展。

基于统计学的方法

基于统计学的方法是高光谱异常检测领域的早期研究重点。这类方法通过假设背景光谱服从某种统计分布，并基于此模型检测异常目标。经典的RX（Reed-Xiaoli）检测器是最常用的方法之一，它假设背景像素的光谱分布服从多元正态分布，通过计算每个像素与背景统计分布的马氏距离来识别异常目标​​。这种方法的优点在于其理论基础扎实且计算相对简单。然而，实际应用中，由于背景光谱的复杂性和多样性，背景像素往往不完全服从高斯分布，从而影响了RX检测器的检测性能。因此，研究人员提出了各种改进措施，如局部RX（LRX）检测器，通过在局部区域内估计背景统计参数，提高了检测的灵活性和准确性​​。

基于数据分解的方法

为了克服高光谱数据的高维性和冗余性问题，基于数据分解的方法成为研究热点。这些方法通过降维技术提取主要特征，减少数据处理的复杂度。主成分分析（PCA）是最常用的降维方法之一，通过提取数据的主成分，保留主要信息，去除噪声和冗余。独立成分分析（ICA）则通过寻找相互独立的成分，对数据进行分解，特别适用于分离混合光谱信号​​。此外，非负矩阵分解（NMF）在高光谱数据分析中也得到了应用，通过将数据分解为非负基矩阵和系数矩阵，NMF可以更好地解释光谱数据的物理意义。例如，采用NMF的方法，可以有效分离出背景和异常成分，从而提高检测精度​​。

基于稀疏表示的方法

稀疏表示方法近年来在高光谱异常检测中受到广泛关注。这类方法利用高光谱数据的稀疏特性，假设异常目标在数据中出现的频率较低，因此可以通过稀疏矩阵表示背景和异常目标。稀疏表示算法通常包括构建过完备字典和稀疏编码两个步骤。背景联合稀疏表示（BJSR）算法是其中的代表性方法之一，它通过利用背景像素构建字典集，并估计稀疏系数矩阵，计算重构误差来识别异常目标。这种方法不仅可以提高检测的精度，还能有效处理复杂背景，提高检测的鲁棒性。

基于深度学习的方法

随着计算能力的提升和深度学习技术的发展，基于深度学习的方法在高光谱异常检测中表现出强大的潜力。卷积神经网络（CNN）通过多层卷积提取高光谱数据的空间和光谱特征，提高了检测精度。生成对抗网络（GAN）则通过生成对抗过程，学习高光谱数据的背景分布，更准确地区分异常目标和背景。例如，Deep CNN模型结合GAN的方法，在处理复杂背景和光谱混合时，展现了强大的检测能力。具体来说，深度学习方法能够自动提取高阶特征，减少了人工特征工程的复杂性，提高了检测的自动化程度和鲁棒性。

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.

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.

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.

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.

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.

难点挑战（发展方向）

**高光谱遥感图像异常检测面临许多挑战，但也展现了广阔的发展前景。以下是目前高光谱异常检测研究中的主要挑战和未来的发展方向。**

**挑战**

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.

**发展方向**

**数据库扩展：目前高光谱异常检测算法的性能验证主要依赖于少数公开的数据库，这些数据库的数据量和多样性有限。因此，扩展和丰富高光谱异常检测数据库，将有助于更全面地评估和提升算法性能​​。**

**多源数据融合：单一高光谱数据有时无法提供足够的信息来准确检测异常目标。未来的研究趋势是融合多源遥感数据（如雷达、LiDAR等）以及地面测量数据，以增强异常检测的鲁棒性和精确性。例如，通过将高光谱数据与雷达数据结合，可以利用其互补的特性，提高检测效果​​。**

**算法实用化：为了在实际应用中推广高光谱异常检测技术，研究人员需要开发更加高效、易用的检测算法。包括发展低计算复杂度的快速算法，以及将采集设备与处理设备高度集成的一体化便携式异常检测系统。此外，基于深度学习的跨平台框架（如TensorRT、ncnn等）的应用，将有助于实现高光谱异常检测算法的实时性和可部署性​​。**

**总之，高光谱遥感图像异常检测领域虽然面临诸多挑战，但通过数据库扩展、多源数据融合和算法实用化等方向的研究，可以大大提升检测效果和实用性。这些发展方向不仅有助于解决现有问题，也为高光谱异常检测技术的广泛应用提供了坚实的基础。**

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.

总结