Machine Learning Model in HSI-AD

Subjects: Remote Sensing

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In the field of remote sensing, hyperspectral image (HSI) is a ground image collected by advanced sensor technology and imaging system mounted on satellites or other aircraft. Anomaly detection (AD) is a very important sub-branch in machine learning and has important applications in computer vision, data mining, and natural language processing (NLP). HSI-AD refers to the identification of pixels whose spectral characteristics in an image are significantly different from adjacent or global background pixels.

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1. Introduction

1.1. Hyperspectral Image and Applications

In the field of remote sensing, hyperspectral image (HSI) is a ground image collected by advanced sensor technology and imaging system mounted on satellites or other aircraft. By combining the advantages of spectroscopy and digital imaging, the spectral dimension of a hyperspectral image consists of hundreds of continuous narrow bands that are obtained in the visible, near-infrared, short-infrared, midinfrared, and even ultraviolet wavelengths of the electromagnetic spectrum. Spectral resolution refers to the number and width of parts of the electromagnetic spectrum measured by a sensor. HSI can collect more bands than multispectral, thus the details of hyperspectral detection are greater. HSI has the feature of integrating image and spectrum. It can describe both the two-dimensional spatial information of the ground object distribution and the one-dimensional spectral information of the ground object spectral characteristics, forming a three-dimensional data cube of "image-spectrum-merging". Compared with the range where human eyes can only accept visible light, HSI systems collect detailed spectral information which can be used to detect materials which have fine spectral features which may be hard to detect with human vision. Such data exploitation can be performed even with a visible only HSI system, allowing humans to understand and recognize certain characteristics of the target in another way, greatly improving people's perception of the world ability.

Due to the difference in the absorption of different wavelengths of light by different object material components, a certain feature of the object will be very prominent in the image at a specific wavelength, but less prominent in the image at other wavelengths. Therefore, the spectral information can fully reflect the difference in the physical structure and chemical composition of the object. For example, hyperspectral target detection and recognition can effectively identify camouflage in the military, and can effectively evaluate crop growth, yield estimation, vegetation

inspection, and non-destructive testing in agriculture; in geological survey and survey, it can realize the fine identification and survey of mineral resources, and ecological restoration, etc.; in the field of biomedicine, non-contact and non-destructive diagnostic techniques can be used to realize the visualization of different pathological conditions of the organization and the screening and tracking of lesions [1][2][3].

1.2. Anomaly Detection

Anomaly detection is a very important sub-branch in machine learning and has important applications in computer vision, data mining, and natural language processing (NLP). The purpose of anomaly detection is to identify data that does not match normal data or that is significantly different from expected data. The types of abnormal data can be divided into point anomalies, context anomalies, and group anomalies. Learning methods of anomaly detection can be divided into supervised, unsupervised, and semi-supervised learning. Currently, deep learning technology provides great convenience for anomaly detection in the era of big data.

1.3. Hyperspectral Anomaly Detection

HSI-AD refers to the identification of pixels whose spectral characteristics in an image are significantly different from adjacent or global background pixels. "Anomaly" does not specifically refer to a specific feature, it can be a pixel, multiple pixels, a feature, or a variety of different features, as long as it is a feature that is different from the spectral curve of the surrounding background environment—all can be called "abnormal". In practical applications, HSI-AD can be used as a preliminary screening work for target detection, to quickly screen out suspected target features from a large scene, and then match with the prior information of the target spectrum to identify the target features.

For unsupervised methods, since it does not require any prior spectral information of the target and background, HSI-AD is an unsupervised detection method with less dependence on the label of the data set. Compared with other methods, the unsupervised deep learning method can extract more deep features and obtain better detection performance. However, due to the high spectral dimension of HSI, the correlation between the spectral bands is strong, and there is a large amount of information redundancy. Therefore, it is necessary to remove the correlation between the spectral bands through dimensionality reduction and feature extraction from the high-dimensional space to reduce redundant information. Hyperspectral data dimensionality reduction is to use low-dimensional data to represent high-dimensional data reasonably and efficiently. Principal component analysis (PCA) is the most commonly used traditional dimensionality reduction method. However, PCA is a linear transformation, and the nonlinear characteristics of HSI cause the PCA method to have certain limitations.

In practical applications, because the abnormal target is a sparse event with a minor probability relative to the background, the essence of the anomaly detection algorithm is to overcome the problem of inconsistent background distribution and try to make the abnormal target detection in the same distribution of background information. At the same time, it also tries to suppress the interference of background information and highlight abnormal target information.

2. Machine Learning Model in Hyperspectral Image (HSI)-Anomaly Detection (AD)

2.1. Traditional Methods

As the prior knowledge of abnormal spectra is difficult to obtain, the abnormality is usually detected by background modeling of hyperspectral data or statistical surface features. Compared with the surrounding environment, the anomaly has two important characteristics that can be used to distinguish it from the background:

(1) Abnormal spectral features are easy to distinguish in the spectral domain;

(2) Abnormalities usually appear in smaller areas;

Therefore, it can be detected by establishing a reference background model or suppressing the background. Traditional modeling methods are divided into three categories: methods based on statistics, representation models, and tensor decomposition.

The Gaussian assumption based on the statistical model (assuming that the background obeys a certain distribution) makes the statistical model mathematically easy to handle. Therefore, the statistical model has been widely used in traditional modeling. A large number of methods are devoted to suppressing the background and establishing the background model. In 1990, Reed and Yu [4] proposed the Reed-Xiaoli (RX) method, which models the background as a Gaussian distribution, and the anomalies are sparse and can be detected from the background by the Mahalanobis distance. Based on the RX method, global GRX [4] and local LRX [5] methods are proposed, which estimate the statistical parameters of the background based on the entire image and dual windows, respectively. However, in practice, due to the complexity of HSI, it is not enough to use Gaussian distribution to simulate background distribution. Therefore, KRX [6], cluster-based (CBAD) [7] and support vector domain description (SVDD) [8] and other methods are proposed.

Representation-based models usually include collaborative representation, sparse representation, and low-rank representation. Among them, the collaborative representation-based detector CRD is based on the theory that background pixels can be well represented by neighboring pixels, but abnormal pixels cannot be well represented. Therefore, even with the participation of abnormal pixels, the background can be modeled adaptively. The Mahalanobis distance method based on low-rank and sparse matrix decomposition uses the LRaSMD technology to distinguish the background from anomalies, explores the low-rank prior knowledge of the background, calculates the statistics of the background, and then uses the difference of Mahalanobis distance to detect abnormal pixels [9].

Based on the theory of tensor decomposition, since HSI is regarded as a third-order tensor cube, the tensor decomposition method can be used to better mine the spectral and spatial characteristics of the spectrum. Since 2017, the application of tensor decomposition methods to solve the HSI-AD problem has become one of the hot spots [10][11][12][13].

In traditional machine learning methods, a common problem is that it is difficult for a feature extraction method to achieve good results in all types of data. The deep learning method solves this problem well and for different types of data, deep learning models can learn features autonomously based on different data.

2.2. Deep Learning-Based Methods

In recent years, deep neural networks have shown strong advantages in the modeling and generalization of complex datasets and can obtain more data features than traditional methods. Deep learning methods have been widely used in multispectral image classification, and some results have been achieved [14][15][16][17][18], but the HSI-AD method based on deep learning has just emerged. There are three commonly used models for anomaly detection, namely, hybrid model, semi-supervised model, and unsupervised model. The hybrid model is mainly used as a feature extractor to extract robust features, which can reduce the dimensional disaster of high-dimensional data, but because it does not improve the surface features of the potential feature layer, it is a sub-optimal choice; the semi-supervised method performs anomaly detection using pretrained model data that only contains normal samples, while the unsupervised model can better explain the characteristics of the data, and is more suitable for data with limited samples and difficult to obtain labels, such as hyperspectral data.

2.3. DBN

Deep belief nets are composed of several layers of restricted Boltzmann machines (RBM). The use of unsupervised learning is similar to the autoencoder, its purpose is to retain the characteristics of the original features as much as possible while reducing the dimensionality of the features. Among them, RBM is a kind of neural perceptron. The output layer of the previous RBM is used as the input layer of the next RBM unit, which is stacked in sequence to form the basic structure of DBN.

2.4. GAN

Generative adversarial network (GAN) is another important network framework for unsupervised anomaly detection technology. The concept of GAN was originally proposed in the zero-sum game framework of game theory and has now become the most common and effective generative model. It generates new data points with certain changes by learning a specific data distribution. GAN consists of a generator model (G) and a discriminator model (D). The generator learns its features from the input data to generate as "true" fake samples as possible to deceive the discriminator, and the discriminator combines the real samples with the samples generated by the generator to identify and judge the authenticity. G accepts random noise as input and generates false data G(z), and D estimates the probability of a real sample. Therefore, the generator wants to fool the discriminator, and the discriminator wants to know the trick of the generator to know that the generator can generate the required data distribution [19][20][21].

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