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Target Detection of Hyperspectral Images

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Abstract. Hyperspectral imaging can detect targets that cannot be detected in broadband remote sensing, greatly improving the ability to describe and distinguish ground object categories. However, the increase in band dimensionality also brings many problems, such as insufficient samples, high dimensionality, and a large amount of redundant information, which poses a huge challenge to feature extraction in hyperspectral images. This article reviews hyperspectral image feature extraction algorithms from four aspects: dimensionality reduction, feature extraction, feature matching, and image synthesis. Elaborated on the advantages and disadvantages of various algorithms. This article reviews classification algorithms for remote sensing images from two aspects: feature space method and spectral matching method. Elaborated on the iteration and comparison of traditional algorithms and new technologies. At the same time, from the perspective of the drone industry, the difficulties faced by existing algorithms and the development trend of hyperspectral images were elaborated. It is particularly critical to select accurate methods based on actual data in specific applications.

Keywords. hyperspectral images, feature extraction, classification, UAV

1. Introduction

Hyperspectral images contain rich spectral characteristics and ground object information, which improve spectral resolution while retaining high spatial resolution[1]. Hyperspectral images can be used to detect and identify the types of ground objects that cannot be found in traditional panchromatic and multi-spectral remote sensing. They play an important role in the global advanced earth observation remote sensing system and have become the main force of land, ocean and atmosphere observation.

Hyperspectral images contain hundreds of bands and preserve rich spatial and spectral information. The increase of the band dimension also brings many problems. The large number of bands leads to a surge in the computational complexity of image processing, and the computational efficiency of the algorithm decreases. On the other hand, the correlation between the bands interferes with the accuracy of feature extraction. The uniqueness of high-dimensional data has a significant impact on the performance of supervised classifiers [2].

During the flight, the area covered by a single UAV image is not large due to the limitations of external environmental factors such as flight height and terrain, and multiple single images need to be stitched to cover the entire research area later . The image POS data obtained during the drone flight is only the center point position, and

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the positioning accuracy is not high. If you add control points to each cell based on the center coordinates, the workload will be extremely large. At the same time, this method does not take into account the scale change and rotation angle that will occur during the flight, which will affect the quality of image stitching. Some scholars have performed orthorectification on the DEM constructed by combining the hyperspectral data of the UAV with the panchromatic image, and then performed image stitching and color leveling. This method is only suitable for scenes where full-color images can be obtained simultaneously. Therefore, an efficient and accurate UAV hyperspectral image stitching method is imminent.

A UAV is an unmanned aircraft that flies by wireless remote control or planning a route. It generally consists of a power system, a flight control system, a wireless communication remote control system, and a payload (weapon, reconnaissance equipment). The combination of UAV and remote sensing technology, that is, UAV remote sensing, overcomes the limit of remote sensing monitoring of crops in a small area near the ground, and also overcomes the influence of satellite images by time resolution and spatial resolution. UAV remote sensing is widely used in agriculture, ecological environment, new rural construction planning, natural disaster monitoring, public safety, water conservancy, mineral resources exploration, surveying and mapping with its advantages of all-day, real-time, high resolution, flexible mobility, and high cost performance.

However, most scholars at home and abroad use the UAV remote sensing platform to apply it to the fields of crop monitoring and mineral resource detection, but few people use the UAV platform to carry imaging hyperspectral sensors to study the same ground objects at different heights. Changes in spectral reflectance and rapid identification of ground objects in different periods at different heights.

Our paper makes notable contributions summarized as follows:

1. This paper reviews the hyperspectral image feature extraction algorithms from four aspects: hyperspectral data dimensionality reduction, feature extraction, feature matching and image synthesis. The design ideas, advantages and disadvantages of various algorithms are described in detail.

2. In this paper, the classification algorithms of remote sensing images are reviewed from two aspects: feature space-based method and spectral matching method. The iterations and comparisons from traditional algorithms to new technologies are expounded.

3. In the UAV industry, this paper expounds the difficulties faced by the existing algorithms and the development trend of hyperspectral images.

2. UAV Environment Modeling

Since it is difficult to directly obtain high-precision spatial information from remote sensing images, the lag of remote sensing information analysis has caused great waste of resources. It is necessary to improve the analysis and recognition accuracy of remote sensing images. As shown in Figure1, this part expounds the current research results of hyperspectral images from three aspects: data dimensionality reduction, feature extraction, feature matching and image synthesis.

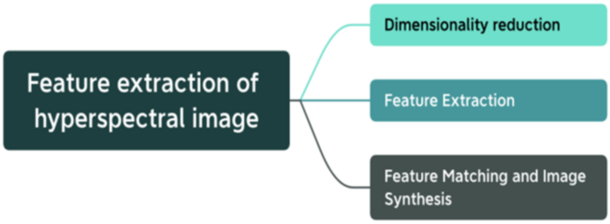

Figure 1. Feature extraction of hyperspectral image

2.1. Dimensionality Reduction

The high dimensionality of hyperspectral imagery improves the ability to monitor targets, but the correlation between data also brings a lot of redundancy. Redundant information affects the performance of discrimination, and also leads to a surge in data processing costs. It is necessary to reduce the dimensionality of hyperspectral data before further processing [3].

Dimensionality reduction algorithms for hyperspectral data can be divided into two categories: band selection and feature extraction. Band selection refers to selecting the band or band combination that can best reflect the target information from hundreds of bands in hyperspectral data [4, 5]. Feature extraction is the recombination and optimization of the bands, and the effect of dimensionality reduction is achieved by projecting the original hyperspectral bands into a new low-dimensional space. The integrity of the information needs to be guaranteed during the reassembly process.

There have been a lot of studies on the dimensionality reduction of hyperspectral data from the perspectives of band selection and feature extraction. Kooper [6] et al. refined the band selection method into supervised and unsupervised based band selection methods, and further divided the unsupervised band selection methods into methods based on information, clustering and band reconstruction. The supervised-based band selection method needs to import prior knowledge, such as training samples or target spectral characteristics, before performing band selection. Based on prior knowledge, the result of band selection is more pertinent. The mainstream supervised band selection methods include Sequence Forward Selection (SFS) [7], Sequence Floating Forward Selection (SFFS) [8], and roughness band selection methods [9, 10]. Unsupervised band selection methods are mainly divided into three categories, the methods based on the amount of information [11, 12], the methods based on clustering [13] and the methods based on the least error of the band reconstruction. The method based on information content selects the standard band combination according to the metric, mainly including the optimal index method (OIF), the adaptive band selection method (ABS), the entropy and joint entropy method, the collaborative Variance matrix eigenvalue method, maximum information band selection method (MI) [11]. The OIF method mainly selects the band by calculating the standard deviation and correlation coefficient of the band combination, and usually selects the band combination with a larger standard deviation. MI adopts a search strategy in the entire dataset to search for bands with large information contribution, and remove the bands with the smallest contribution [11]. Clustering-based methods classify hyperspectral bands according to given clustering rules, including hierarchical-based clustering, K-means clustering, and neighbor propagation clustering, etc. Hierarchical clustering is a commonly used band selection method that employs hierarchical clustering that occurs layer by layer from the bottom up for analysis. The method based on the smallest band reconstruction error operates on all bands or band combinations according to the band linear mixture model, and selects the band or combination with the smallest error as the characteristic band, including the information dispersion method (ID), the first spectral derivative (FSD) et al.

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2.2. Feature Extraction

The extraction methods of hyperspectral image feature points based on scale-invariant features mainly include scale-invariant feature transform (SIFT) and accelerated robust feature algorithm (SURF). The SIFT algorithm, proposed by Lowe et al. in 1999, is a robust feature point extraction algorithm with strong matching ability. Since the SIFT algorithm builds a multi-layer pyramid model, the extracted feature points are more stable, and even if the ground elevation or flight height changes during the flight, it will not affect the feature point extraction due to different scales. At the same time, the SIFT algorithm takes the main direction of the feature points as a reference index, so that the extracted feature points have strong rotation invariance. In addition, the algorithm maintains certain invariance to illumination changes during flight, affine transformation and projection transformation during matching, which enhances the matching ability of the algorithm.

The Accelerated Robust Feature Algorithm (SURF) was proposed by Bay et al. in 2006. It is a fast feature detection algorithm developed on the basis of the SIFT algorithm. The SURF algorithm uses the local maxima of the approximate Hessian matrix determinant to locate the position of the point of interest, and uses the integral image for the convolution operation, which improves the rate and robustness of feature point extraction.

As shown in Fig.2, hyperspectral images can be regarded as a cube of data obtained by combining innumerable bands, and have the characteristics of large amount of information and high spectral resolution. The existing hyperspectral remote sensing image classification methods mainly include image classification based on feature space and image classification based on spectral matching.

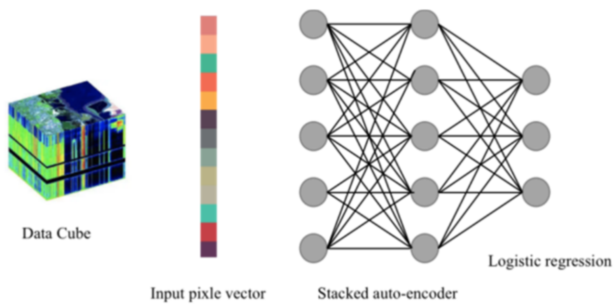

Figure 2. SAE connected with a subsequent logistic regression classifier

According to whether the training samples need the known prior knowledge of the images to be classified, the commonly used image classification methods based on feature space can be divided into two forms: supervised classification and unsupervised classification. This part introduces the classification methods of remote sensing images from five aspects: minimum distance classification, maximum likelihood classification, clustering algorithm, fuzzy classification and deep neural network.Compared with traditional manual methods, deep learning techniques can extract features, such as texture and edge information, from raw data layer by layer, as shown in Fig.3.

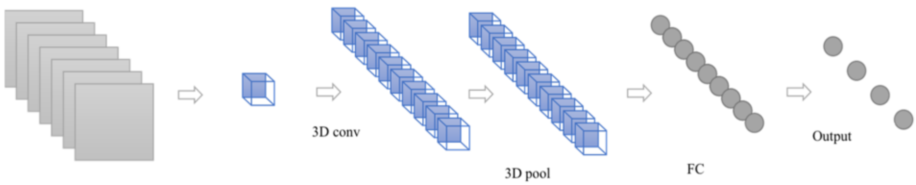

Figure 3. 2D CNN model structure for hyperspectral classification

3. Experiment and Result Analysis

In this section, we conducted a detailed test of the performance of the algorithm on hyperspectral images captured on drones, and quantitatively analyzed the results. Our dataset comes from the flight data of DJM 210. The dataset contains various scenarios, such as open areas, residential areas, streets, and parks. The 5G module is provided by China Mobile.

The experimental results are shown in Table 1. We analyzed the performance of 2D CNN, 3D CNN, and DDPG+3D CNN. From the results, it can be seen that the mode of DDPG+3D CNN has significant advantages, capturing image features more accurately and performing accurate classification.

Table 1. Comparison of different target detection algorithms

Model / Search Space	Map (%)		Latency (ms)			Madds (B)	Params
	Valid	Test	CPU	EdgeTPU	DSP		
2D CNN	23.6	23.1	138	*	25.1	0.65	5.58
3D CNN	25.6	26.1	185	18.5	*	0.92	2.50
DDPG+3DCNN	24.3	23.8	120	16.4	23.4	0.53	1.29

4. Conclusion

In this paper, the technology in the field of hyperspectral is reviewed from the aspects of hyperspectral image feature extraction technology and hyperspectral image classification technology. These include iterations from traditional processing techniques to new technologies. This paper sorts out and analyzes the advantages and disadvantages of each method and its application status. It is particularly critical to select an accurate method in combination with actual data in specific applications.

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