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Applications of Hyperspectral Remote Sensing in Ground Object Identification and Classification

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Abstract

Hyperspectral remote sensing has become one of the research frontiers in ground object identification and classification. On the basis of reviewing the application of hyperspectral remote sensing in identification and classification of ground objects at home and abroad. The research results of identification and classification of forest tree species, grassland and urban land features were summarized. Then the researches of classification methods were summarized. Finally the prospects of hyperspectral remote sensing in ground object identification and classification were prospected.

Keywords

Hyperspectral Remote Sensing, Ground Object Identification and Classification, Statistical Model, Spectral Matching

1. Introduction

Hyperspectral remote sensing is one of the most important achievements in the field of remote sensing in 1980s. Hyperspectral remote sensing technology object is to acquire related data about objects by many narrow bands of electromagnetic waves [1]. It can get a lot of very narrow and continuous spectrum image data in the ultraviolet, visible and near infrared, infrared and thermal infrared region. Thus, the spectral dimension is added on the basis of the traditional two-dimensional remote sensing, and a unique three-dimensional remote sensing is formed. Spectral measurements of large amounts of surface material on the Earth indicate that different objects exhibit different spectral reflectance and radiation characteristics. The characteristics cause the absorption peak and the reflection peak whose wavelength width was about 5 ~ 50 nm. The physical connotation is the lattice vibration of different molecules, atoms and ions, which causing spectral emission and absorption at different wavelengths, thus resulting in different spectral features [2]. So hyperspectral remote sensing can be more convenient to identify the various features [3], and provides a new technical method for ground object identification and classification. And with its high spectral resolution and multi band advantages, it has gradually become an inevitable choice for ground object identification and classification.

2. Applications of Hyperspectral Remote Sensing in Ground Object Identification and Classification

At present, the research of hyperspectral remote sensing technology in ground object identification and classification applications mainly includes the following aspects:

2.1. Application of Hyperspectral Remote Sensing in Forest Tree Species Identification and Classification

The traditional artificial field survey of forest resources is time-consuming and laborious, and the accuracy of forest identification is not high by using multispectral remote sensing. It is necessary to identify tree species by using subtle spectral differences between the hyperspectral pixels. Some scholars at home and abroad have used hyperspectral data to identify and classify forest tree species. Martin *et al.* [4] identified red pine, white pine, spruce, and swamp forest, Norway spruce and other 11 species through the establishment of a relationship between AVIRIS hyperspectral data and the different chemical constituents of the tree species leaves. The results showed the validity of the hyperspectral remote sensing technology in forest species identification and classification; Goodenough *et al.* [5] used the ETM multispectral data, ALI hyperspectral data and Hyperion hyperspectral data to classify 5 species of forest species such as hemlock, fir, North American cedar, alder and small dry pine in Victoria, Canada. The results showed that the hyperspectral data was more accurate than the multispectral data for forest type identification; Peng Gong *et al.* [6] utilized CASI hyperspectral imagery to identify six conifers by differential techniques in California, USA, demonstrating the great potential of hyperspectral remote sensing technology in tree species identification and classification research; Tan *et al.* [7] took advantage of Hyperion data to identify the forest species in Wangqing Forestry Bureau of Jilin Province and compared with the forest tree species identification models of ALI and ETM multispectral remote sensing data. The results showed that the hyperspectral classification had the best effect on forest tree identification and classification. In addition, hyperspectral remote sensing data combined with a variety of methods could improve the accuracy of forest tree species identification. Junming Li *et al.* [8] used HJ-1A remote sensing images to classify the typical tree species of Quercus mongolica, Betula platyphylla and larch in Wangqing Forestry Bureau of Jilin Province, the classification accuracy reached 88.33% by combining with the terrain slope and DEM data; Xiaomei Li *et al*. [9] utilized CHRIS hyperspectral remote sensing images to classify forest types in Changbai Mountain. The classification accuracy was 84.60% using support vector machines; Chengqi Cheng *et al*. [10] classified hyperspectral multiple channels into the same class according to the similarity of information content from the statistical point of view. Different species were identified in two dimensional statistical spaces using the principal component analysis method and the score difference between different factors on the first and second principal component. Six species of paper mulberry, qingshandong, metasequoia, pine, moso bamboo and bamboo were divided into three groups, which indicated that the hyperspectral could realize the fine classification of forest tree species.

2.2. Application of Hyperspectral Remote Sensing in Grassland Identification and Classification

As a dynamic and complex natural resource, the grassland must be analyzed the features of the spectral characteristics and spectral characteristics of different objects in the same band, in order to achieve the identification, monitoring and classification of the grassland community species [11]. Because of the high spectral resolution and multi band advantages of hyperspectral remote sensing data, more precise vegetation spectral information was provided, which could be used to identify and classify grassland more accurately. Some scholars have analyzed the hyperspectral characteristics of different grasslands, which provided a basis for identification and classification of grassland. Schmidt *et al*. [12] studied the difference eight grass such as Brachiaria and yellow back grass using statistical analysis, distance analysis and continuum removal spectral analysis method by spectrophotometer under laboratory conditions, providing a theoretical basis for the identification and classification of grassland using hyperspectral technology; Chunmei Zhang *et al*. [13] used Hyperion hyperspectral image data to analyze the grassland spectrum of the Jinchang arid region in the Shiyang River Basin, and obtained a series of spectral characteristics of the grassland in the area, which provided a basis for grassland vegetation cover extraction and grassland classification and extraction. Some scholars have begun to use hyperspectral data to identify and classify grassland. Fenfen Guo *et al*. [14] divided the research area into 5 types (Swamp meadows, alpine meadows, alpine steppe, desert grasslands and bare land) using SPCA-MLC and HIS-SAM two classification methods combined with field samples based on HJ1A-HSI hyperspectral data in the northern part of Xainza county. The accuracy of the two kinds of classification was more than 80%, which proved the great potential of HJ1A-HSI hyperspectral data in realizing the high precision classification of Tibetan grassland; Di Cheng *et al*. [15] analyzed the spectral characteristics of the Stellera chamaejasme community in Haibei state of Qinghai Province using the HJ-HSI hyperspectral data and identified and extracted the Stellera chamaejasme. The extraction accuracy was 78.46%, which proved the availability of hyperspectral data in the field of identification of Stellera chamaejasme.

2.3. Application of Hyperspectral Remote Sensing in Urban Object Identification and Classification

Due to the complexity and similarity of urban features, hyperspectral data could best reflect its high spectral resolution characteristics in this field, and could distinguish urban features with similar spectral characteristics, including asphalt, water, vegetation and Roof material composition. Scholars at home and abroad have begun to explore the use of hyperspectral technology to identify and classify urban objects. Ben-Dor *et al.* [16] analyzed the city spectral library of 400 - 1100 nm and discussed the important bands to distinguish the urban object. It was considered that the near infrared, shortwave infrared and hot infrared bands were important bands reflecting the main physical and chemical characteristics of urban features, and the identification of urban features was verified. Mori *et al.* [17] analyzed the spectral data of roof and pavement between 350 - 2500 nm. It was found that the roofing material had similar spectral characteristics in the visible light band, but there were obvious differences in the infrared band, and the pavement material was unique in the infrared band. Furthermore, the applicability of remote sensing technology in urban surface object classification was discussed; F.A. Kruse *et al.* [18] identified and mapped the surface materials of Boulder, Colorado, including buildings, roofing materials, paving materials, vegetation, and some minerals using SAM method and MTMF method based on the AVIRIS data, the availability of hyperspectral data in urban object identification and classification was proved. Domestic Junshi Xia *et al.* [19] extracted the impervious layer ratio of Xuzhou City using linear spectral mixture model based on two Hyperion hyperspectral remote sensing data of 2004 and 2006, compared with the TM multi spectral data extraction results, the advantages of hyperspectral remote sensing data in extraction of urban impermeable layer are demonstrated; Wei Tao *et al.* [20] used high-resolution SPOT panchromatic images to fuse the Hyperion hyperspectral image data, on this basis analyzed the spectral characteristics of common urban features, and then used SAM method to identify and Classify urban features, and the ground statistical error was only 11.61%.

3. Research Progress of Hyperspectral Remote Sensing Image Classification Methods

With the development of imaging spectrometer technology, the classification research of hyperspectral remote sensing image is deepening. There are two kinds of hyperspectral remote sensing image classification methods. One is image classification method based on statistical mode. The other is based on ground spectral matching image classification method.

3.1. Image Classification Method Based on Statistical Mode

The traditional statistical model of image classification method can be divided into supervised classification and unsupervised classification according to whether have the classification data of known training samples [21]. Hyperspectral image classification methods are mostly developed from the two traditional classification methods. In recent years, new methods have been introduced into the classification of hyperspectral data, such as fuzzy discriminant, neural network, decision tree and support vector machines.

(1) Fuzzy classification

The fuzzy classification holds that a pixel is separable, that is, a pixel can belong to a class to some extent while at the same time belong to another class. The degree of this class relation is represented by the degree of membership of the pixel [22]. Its basic idea is to make the absolute membership in the ordinary set flexible, so that the membership degree of the image pixel is expanded from the value of the original {0,1} to any value in the [0,1] interval. Therefore, the fuzzy classification technique is suitable for the probabilistic description and processing of hyperspectral image [23]. Xiuyuan Zhang *et al.* [22] used EO-1Hyperion data to classify the water, the forest land and the artificial land object based on RF fuzzy classification method, the classification accuracy achieved above 87%.

(2) Neural network classification

The spectral information and spatial information of all kinds of features in the image are analyzed and selected. The feature space is divided into subspaces which do not overlap each other. Then the individual pixels in the image are normalized into the subspaces. When dealing with hyperspectral data, the initialization of parameters is difficult, and it is easy to appear local optimization and over learning phenomenon. The training process is slow [24]. Junna Yu *et al.* [25] studied the classification of the common neural networks and hyperspectral images and searched for efficient hyperspectral remote sensing image classification methods.

(3) Decision Tree classification

As a supervised classification method based on spatial data mining and knowledge discovery, decision tree is an efficient method for hyperspectral image classification. Its basic idea is that the remote sensing data set is subdivided step by step according to certain rules, and each sub class with different attributes is obtained [26] [27]. There are three kinds of decision trees, that is, single change decision tree, changeable decision tree and hybrid decision tree. Among them, the hybrid decision tree is the most complex, the most effective and the most powerful classification algorithm [23]. Chenwei Xu *et al.* [28] used vegetation data in spectral data to classify vegetation based on the spectral tree-based decision tree classification method and achieved good results.

(4) Support Vector Machine classification

The biggest advantage of the Support Vector Machine [29] method is not limited by the data dimensionality and the finite sample size. In order to map data to a higher dimension of space, each category needs to select a kernel function. In the new space, a linearly separated hyperplane can be established as the decision boundary [30]. Kun Tan *et al.* [31] used the hyperspectral remote sensing image classification method based on Support Vector Machine to classify hyperspectral images of Changping area in Beijing with an accuracy of 76.9%, and achieved good results. In order to improve the classification accuracy, some scholars combined Support Vector Machine with other classification methods. For example, Patra *et al.* [32] combined Support Vector Machine with the neural network of self-organizing map to form a new semi-supervised hyperspectral data classification method; Tan *et al.* [33] used Mean Shift segmentation and Support Vector Machine combination, and achieved a good classification effect.

3.2. Based on Ground Spectral Matching Image Classification Method

Different ground objects have different spectral characteristics. Using the spectral curves reflecting the physical spectral properties of ground objects, the ground features are extracted and the surface information is extracted by matching the known spectral data in the spectral library.

(1) Minimum distance matching between spectra

Spectral distance matching is the method of calculating the distance between the position spectrum and the reference spectral value. Then, the method is classified according to the minimum distance principle. The distance between the spectra can be Euclidean distance, Mahalanobu distance and Pagoda distance. This method is most sensitive to noise, so it is necessary to denoise the spectrum before matching.

(2) Spectral angle matching

Spectral angle matching is achieved by calculating the matching angle between the observed spectrum and the reference spectrum to reflect the matching degree between the objects, so as to achieve the purpose of classification and identification of objects. The smaller the angle, the more similar the spectrum and the higher the degree of matching, the more accurate classification and identification [34]. Supposing hyperspectral data has n bands, the reference vectors are $Y[Y_1, Y_2$, and $Y_3, \cdots, Y_n\}$, the test vectors are $X[X_1, X_2, X_3, \cdots, X_n\}$, the angle between them is

$$\cos A = \sum_{i=1}^{n} X_i Y_i \bigg/ \sqrt{\left(\sum_{i=1}^{n} X_i^2\right)\left(\sum_{i=1}^{n} Y_i^2\right)} \tag{1}$$

Spectral angle matching is insensitive to solar irradiance, albedo and topography, and can weaken these factors to a certain extent. It has been widely used in classification and identification of ground features. Xiang Yu *et al.* [35] used spectral angle matching, correlation coefficient method and spatial distance method to identify mangrove species. The accuracy of spectral angle matching was as high as 80%, which meet the needs of practical application.

(3) Code matching

In order to quickly find and match specific targets in the spectral library, the spectral curves are encoded to match the coding results. Relatively simple is spectral two valued coding, including segmentation, two value coding, single threshold coding, multi threshold coding. Since the details of the spectral information are lost in the process of coding, only coarse classification and identification are applied. Peijun Du *et al.* [36] proposed four value coding and ten value coding and optimized the choice between data compression, computational complexity reduction and the improvement of the matching results accuracy, and achieved good experimental results.

(4) Matching based on spectral characteristic parameters

The meaningful spectral feature parameters are extracted from the spectral curves, and the image pixels are classified and identified by a few parameters matching. This method can effectively identify the spectra with typical spectral absorption or radiation characteristics. Kruse *et al.* [37] defined spectral absorption parameters with the longest absorption half wavelength length, wavelength position and absorption depth of spectral absorption characteristics. Among them, the spectral derivative technique could be differentiated not only to eliminate the effects of baseline drift and high frequency noise, but also to amplify the fine peaks and valleys in the original spectrum, making the spectral curve inflection point and the wavelength position at the maximum and minimum reflectivity easier to identify and Analysis [38]. The formulas for the first or second derivative of the reflectance were

$$R'(\phi_i) = \frac{R(\phi_{i+1}) - R(\phi_{i-1})}{2\Delta\phi} \tag{2}$$

$$R''(\phi_i) = \frac{R'(\phi_{i+1}) - R'(\phi_{i-1})}{2\Delta\phi} \tag{3}$$

(Among, ϕ_i was the wavelength value of each band; $\Delta\phi$ was the interval of wavelength ϕ_i to wavelength ϕ_{i-1}; R' was the first derivative of the reflectance at wavelength i; R'' was the second derivative of the reflectance at wavelength i).

4. Prospect

The application of hyperspectral remote sensing in object identification and classification is irreplaceable because of its unique advantages. The research of hyperspectral remote sensing image classification technology has become increasingly mature. But it is also needed to do the following aspects of research.

(1) Establish a complete object spectrum database

In the actual application process, the spectral data in database is an important parameter for object identification and classification. The typical terrain spectrum and matching parameters over the past 20 years have been collected in the

"China Typical Standard Spectrum Database", but the spectrum database still need to improve. At the same time, the composition and structure of soils, vegetation and other structures are susceptible to the effects of components and the environment, resulting in the variation of the spectral characteristics of the features. Therefore, researchers need to study the spectral variation of standard ground objects in different environments, and establish and perfect the ground spectrum database. It can provide accurate reference data for remote sensing research personnel, improve the level of processing of remote sensing information, promote the application of hyperspectral remote sensing technology in object identification and classification, and also lay a solid foundation for subsequent quantitative remote sensing inversion.

(2) Fusion of multi-source images

In remote sensing imaging systems, spatial resolution and spectral resolution are often not available at the same time. Because the spectral bandwidth of the hyperspectral imaging system is narrow and a large instantaneous field of view must be used to collect enough light quantum to maintain acceptable signal and the high spatial resolution system must widen the spectral channel. Therefore, in the current remote sensing imaging system, one must sacrifice another in order to obtain high spatial resolution and high spectral resolution [39]. The spectral resolution of hyperspectral remote sensing image is up to nanometer level. But the spatial resolution is just passable. China's environmental satellite launched in 2008 equipped with hyper spectral imager HSI has 115 bands, the spectral resolution of 5 nm, but the spatial resolution of 100 meters, which for the identification of the ground of small areas is undoubtedly a big challenge. Therefore, the fusion of high spatial resolution and hyperspectral resolution image both maintain spatial resolution information and ensure the integrity of the spectrum to improve the classification and feature extraction effectiveness, expand the hyperspectral image in the field of identification and classification applications.

(3) Mixed pixel decomposition of hyperspectral data

Due to the limited spatial resolution of hyperspectral data and the complexity of the distribution of surface matter, the single pixel contains multiple terrain spectra, which affects the accuracy of remote sensing image classification and the effect of target detection [40]. The key problem of mixed pixel decomposition is the selection of endmember spectra and the solution of nonlinear mixed [41]. How to use the prior knowledge and spatial support information of the imaging area to extract the pure end element and how to better solve the nonlinear mixed objects in some smaller scale fields will become the key to obtain fine identification and classification results to provide a more detailed data base for feature identification and classification studies.

5. Conclusion

The hyperspectral remote sensing image has played an important role in the application of object identification and classification. China intends to launch the high 5 satellite detector with hyperspectral and spatial resolution of 30 meters, which makes it possible to study land cover change using our aerial hyperspectral image. This paper described the current application in object identification and classification and summarized the classification method of hyperspectral images. On this basis, the future development of the application in this field was predicted. Hyperspectral remote sensing applied to object identification and classification is still a relatively new field, and the hardware and software environment has not reached the level of maturity. However, with the development of remote sensing technology, the acquisition, processing, identification and classification of hyperspectral image data will be able to fly qualitatively.

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