Advances in crop fine classification based on Hyperspectral Remote Sensing

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Abstract*—Classification and recognition of crops is an important prerequisite for crop yield estimation and crop growth monitoring. Rapid and accurate acquisition of crop type, spatial distribution and area information can provide basic basis for crop planting structure optimization and structural reform of agricultural supply side. It is of great significance to the formulation of agricultural policy, the development of social economy and the guarantee of national food security. In recent years, hyperspectral remote sensing has been able to fine classify crop types and varieties and obtain spatial distribution maps and planting structure information of crops by virtue of its many bands, abundant spectral information and sensitivity to small spectral differences among ground objects. This paper summarizes the application of hyperspectral remote sensing in crop fine classification, summarizes the hyperspectral data sources commonly used in crop fine classification at home and abroad, such as Hyperion data, environmental satellite data, CASI data and OMIS data, and analyses the applicability of various data. Meanwhile, the methods of crop fine classification using hyperspectral remote sensing are summarized, including decision tree classification, support vector machine classification, multi-classifier integration, spatial-spectral feature classification, hyperspectral data and radar data fusion classification, and the characteristics of various classification methods are analyzed. It was found that the classification accuracy of crop fine classification based on hyperspectral data was higher (better than 90%). But there are still some shortcomings: (1) At present, scholars at home and abroad focus on areas with simple planting structure. Most of the crop types in these areas are rice, wheat and other large-scale food crops, but less on cash crops such as sesame, rape, peanut and so on. (2) Hyperspectral remote sensing has high classification accuracy for regions with fewer crop types, but the classification accuracy needs to be improved in regions with many crop types. (3) Hyperspectral data has a high dimension and a large amount of data processing workload, which is not suitable for fine classification of crops in large-scale areas. Future research directions: (1) Expanding the scope of hyperspectral remote sensing monitoring objects, mainly cash crops. (2) Selecting areas with complex planting structure, fragmented plots, fluctuating topography and various crop types for fine classification of crops. (3) Attaching importance to the essential features of hyperspectral remote sensing fine classification and finding a stable classifier which is generally suitable for crop fine classification. (4) The mechanism of crop fine classification using hyperspectral remote sensing and the method of multi-source data fusion need to be further studied.

***Keywords*—Hyperspectral, Crops, Fine-classification**

I. Introduction

China is a big agricultural country. The information of crop sown area and yield has always been paid attention by the state and governments at all levels. It is the basic basis for ensuring food security and structural reform of agricultural supply side [1]-[2]. With the further development of agricultural reform, there are more and more types of crop planting, and the structure of crop planting is becoming more and more complex. Therefore, timely and accurate acquisition of crop planting area and yield information is of great significance to optimize crop planting structure, formulate agricultural policies scientifically and develop national economy [3]-[4]. Crop classification and identification is the core issue to obtain information of crop planting area and yield, and also an important prerequisite for crop growth monitoring, crop yield estimation and crop pest monitoring [5]. The traditional method of obtaining crop planting area and yield information is mainly based on ground survey statistics. This method consumes a lot of manpower, material resources and financial resources, and the survey period is too long [6]-[7]. As a rapidly developing new science and technology, remote sensing has been widely used in various aspects of agriculture, including crop classification and identification, crop growth monitoring, crop yield estimation, crop pest monitoring, etc. [8]. Hyperspectral remote sensing refers to the use of imaging spectrometer to obtain tens to hundreds of very narrow band information in the visible, near infrared, mid-infrared and thermal infrared bands of electromagnetic spectrum, which constitute a complete and continuous spectral curve [9]-[10]. The bandwidth of multispectral remote sensing is generally 100-200 nm, so the spectral resolution of multispectral remote sensing is low and discontinuous, while the bandwidth of hyperspectral remote sensing is very narrow and the spectral resolution is high [11]. In crop classification and recognition, traditional multi-spectral remote sensing has fewer bands and lower spectral resolution, and some crop types have similar spectral characteristics. Therefore, the classification of these crops will be misclassified [12]. The number of bands obtained by hyperspectral remote sensing is very large, and the spectral information is rich. Therefore, hyperspectral remote sensing can obtain the spectral characteristics and their differences more comprehensively and meticulously, and classify crops more precisely, and the classification accuracy is better than multispectral remote sensing [13].

In recent years, with the development of hyperspectral remote sensing, there have been many methods and classifiers for dimensionality reduction of hyperspectral data, and these methods have been well applied to crop classification and recognition, and some achievements have been achieved. This paper reviews the application of hyperspectral remote sensing in crop fine classification, including the data sources of hyperspectral remote sensing, the methods and effects of crop fine classification, and the shortcomings of hyperspectral remote sensing.

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II. Data Dimension Reduction

There are tens or even hundreds of bands in hyperspectral images. When using hyperspectral data to fine classify crops, if all bands are involved in classification, it will cause the problem of too much calculation. Therefore, before the classification of hyperspectral data, it is necessary to reduce the dimension of hyperspectral data, that is, to transform high-dimensional data into low-dimensional space and then classify [14]. Data dimensionality reduction can remove redundant information, reduce the "dimensionality disaster" to a certain extent, and accelerate the classification speed of classifiers [15]. According to whether the original data is changed or not, data dimension reduction can be divided into two methods: feature extraction and band selection. Band selection is based on non-transform, i.e. several bands are selected from the original band data to form a new subset [16]. The feature of band selection is that it retains the physical information of the original band and does not lose the information of the original data after feature extraction. Feature extraction is a method of mapping hyperspectral data from high-dimensional space to low-dimensional space based on strict mathematical theory, transformation and certain criteria [17]. Although feature extraction reduces the dimension of data to some extent, it also changes the information of original data, and even leads to the loss of original band information [18].

In 2005, Zhao Chunhui [19] and others proposed the dimensionality reduction method of adaptive band selection (ABS). This method calculates the index between bands, and chooses the band according to the size of the index. Then, Bayesian supervised classification of hyperspectral data after band selection is carried out. The results show that the classification accuracy of dimension reduction data is improved by 3.7% compared with that of original data, and the computational complexity is greatly reduced. Wu Hao [20] and others first grouped the bands. On the basis of grouping, the optimal band combination was selected by using the search algorithm combining support vector machine and genetic algorithm, and a comparative experiment was carried out. The experimental results show that compared with other band selection methods, this method has the highest classification accuracy (98.25%) in the case of the least band selection. Chacvez [21] et al. proposed the optimal exponential factor method (OIF), which is to compare the optimal exponential factor to select the band of hyperspectral data. Bajcsy and others [22] put forward a method of band selection based on unsupervised and supervised combination of classification accuracy and computational requirements constraints, and established a band selection system with high computational efficiency and accuracy (computational complexity).

Classical feature extraction methods include principal component analysis (PCA), minimum noise separation transform (MNF), linear discriminant analysis (LDA), etc. In addition, scholars at home and abroad have carried out other methods for feature extraction of hyperspectral data. Chen [23] et al. proposed a new framework for feature extraction and image classification based on depth confidence network, which is a mixture of principal component analysis (PCA), hierarchical learning based finite element method and logical regression (LR). Adriana [24] and others put forward the method of feature extraction based on deep convolution neural network model, which can effectively avoid Hughes phenomenon. Jia [25] et al. proposed a method of data dimension reduction based on discrete wavelet transform. Firstly, the feature based on wavelet transform is extracted from hyperspectral data, and then AP clustering algorithm is used to select the most representative feature from the acquired feature. The experimental results show that the classification accuracy is more accurate than that obtained by using only feature extraction and feature selection. Han [26] et al. proposed a feature extraction method based on spectral clustering and sparse subspace model in 2015.

III. Classification Based on Statistical Features

The classification of hyperspectral data can be divided into two main categories: one is based on statistical characteristics of data, the other is based on spectral characteristics of objects [9]. Classification methods based on statistical features include supervised classification and unsupervised classification. Supervised classification needs some prior knowledge, and classifies unclassified areas by determining discriminant functions and rules. Supervisory classification methods for crop fine recognition based on hyperspectral data include maximum likelihood classification, minimum distance method, decision tree, support vector machine and neural network. Unsupervised classification means that data can be classified directly without any prior knowledge, but the accuracy of classification is often inaccurate. The main methods include K-means clustering, iterative self-organizing data analysis (ISODATA), etc. [27]. This paper mainly summarizes the supervised classification methods for the fine classification and recognition of crops.

According to the spectral characteristics of hyperspectral images of rice growing period, Zhang Feng [28] and others used the hybrid decision tree classification method to classify rice varieties in Jintan seed farm of Changzhou City, Jiangsu Province. The overall classification accuracy reached 94.9%. Liu Liang [29] and others used hierarchical classification method to extract and mine crop information in Shunyi District of Beijing. This method is oriented to the application target, and divides the complex information extraction process into relatively simple sub-processes, and the classification accuracy of each crop reaches more than 95%. Galva˜o [30] and others used EO-1 satellite hyperspectral data to establish a discriminant model by stepwise regression analysis to identify and classify five sugarcane varieties in southeastern Brazil. The classification accuracy was 87.5%. With the development of pattern recognition technology, artificial neural network (ANN) algorithm has been widely used in the fine classification of crops. However, when ANN is used for fine classification, the training sample time is too long [31]. Then in order to solve the problem of artificial neural network in hyperspectral data classification, the kernel learning algorithm represented by Support Vector Machine (SVM) was applied to hyperspectral image classification. Melgani [32] and others used two different support vector machines: linear support vector machine without kernel transform and non-linear support vector machine based on Gauss Radial Basis Function (SVM-RBF). The classification accuracy of corn and soybean was 87.1% and 93.42%, respectively. Du [33] and others combined Hyperion data with AVIRIS data, and used a new binary tree support vector machine classification method based on inter-class separability to classify crops, water bodies, roads and so on in the image, which verified the effectiveness of the method.

Tarabalka [34] combined SVM with Markov Random Field (MRF) to classify wheat, soybean, oat and maize. Firstly, probabilistic support vector machine (PSVM) is used to classify three hyperspectral images at the pixel level. Then, Markov random field regularization is used to refine the classification results obtained in the first step.

In addition, there are many other classification methods based on statistical characteristics applied to hyperspectral crop fine classification. Yu Ming [35] et al. based on AVIRIS hyperspectral data as data source, proposed a method of crop fine classification based on conditional random field, and compared this method with minimum distance method and support vector machine classification. The results show that the classification accuracy of conditional random field is 16% and 2% higher than that of minimum distance method and support vector machine respectively, and the classification accuracy of each crop is better than 94%. Semih [36] et al. firstly selected the most important features using random forest algorithm, then applied a classification method based on non-linear statistical features — nuclear Fukunaga-Koontz transform, to fine classify 16 crops on AVIRIS hyperspectral images, the overall classification accuracy was 84%. Jike [37] et al. proposed a kernel supervised ensemble classification method, which combines the advantages of ensemble feature learning (rotating forest) and kernel supervised learning (kernel orthogonal normalized partial least squares). This method is applied to AVIRIS and ROSIS hyperspectral images to classify and recognize soybean and wheat. The experimental results show that the accuracy of integrated classification based on nuclear supervision is the highest, but the classification accuracy is affected by training samples. Xue [38] et al. proposed a new sparse graph regularization (SGR) method. CASI/SASI hyperspectral images were used to classify and recognize eight crops in Heihe River Basin of Gansu Province, including wheat, potato and broccoli. The classification accuracy was 87.84%. This method is suitable for the case of fewer training samples, and it has strong anti-noise ability.

IV. Classification based on Spectral Information

The basis of identifying crop types by hyperspectral remote sensing is that the absorption, radiation characteristics and spectral curves of different crop types are different. Spectral matching is to study the similarity between two spectral curves to complete the classification of crops, that is, to achieve fine classification of crops through small spectral differences between crops [39]. Among them, the commonly used methods are spectral angle matching method (SAM), matching classification based on ground object spectral library, calculating unknown and known spectral distances and matching minimum distances, etc..

Rao [40] classifies rice, sugarcane, pepper and cotton in Andhra Pradesh, India, using two spectral databases based on hyperspectral data at canopy and pixel scales as reference spectra. The overall classification accuracy is 86.5% and 88.8%, respectively. However, this method is suitable for crops with large spectral differences. For crops with similar spectrum, the classification results of this method are not ideal. Bhojaraja [41] and others used spectral angle mapping (SAM) classification method to extract areca nut area from Hyperion hyperspectral data in Kanataka, India, with an accuracy of 73.68%. Guo Hui [42] and others defined the wavelet packet information entropy eigenvector spectral angle classification method (WPE-SAM). The corn, celery and broccoli were classified and calculated in the Alina hyperspectral image. The feasibility of WPE-SAM method was analyzed and compared with the spectral angle mapping (SAM) classification method. The results show that the overall classification accuracy is improved from 78.62% of SAM to 78.66% of WPE-SAM, and the average classification accuracy is increased from 83.14% to 84.18%.

V. Other classification methods

A. *Classification Based on Spatial-Spectral Features*

The two main classification methods summarized above are classification based on spectral information of ground objects and classification based on statistical characteristics of data. These classification methods often fail to take into account the spatial characteristics of hyperspectral data besides abundant spectral information, which leads to the phenomenon of "salt and pepper" in the classification results[43]. Combining spatial features with spectral information is one of the hotspots in hyperspectral image classification. This paper reviews the application of spatial-spectral feature based classification in crop fine classification.

Wang Junshu [44] and others proposed an incremental classification algorithm for hyperspectral remote sensing images, INC_SPEC_MPext, which combines spectral and spatial structure information. On AVIRIS data, the classification methods based on spectral, spatial information and spectral spatial feature fusion were applied to fine classification and recognition of maize, soybean and wheat. The results show that the classification cost of INC_SPEC_MPext is the lowest when the training samples are limited, and the classification accuracy of INC_SPEC_MPext is 5.92% and 3.22% higher than that of spectral information and spatial information. Wu Jian [45] and others used NDVI threshold method to extract vegetation information, then used minimum noise transform to reduce the dimension of Hyperion hyperspectral image, and used a hyperspectral image vegetation classification method combining spatial and spectral information to complete the vegetation classification in the study area, with the classification accuracy of 90.3%. Chen [46] and others proposed that spectral spatial information be integrated into hyperspectral image classification, and the kernel-based ELM classification method was used to classify soybean, rice and wheat on AVIRIS images. The experimental results show that the classification accuracy of this method is better than that of traditional pixel classifier, support vector machine based on Gabor filter and support vector machine based on multi-hypothesis (MH) prediction under the condition of small sample training. Li [47] et al. proposed a hyperspectral image classification method based on multi-feature fusion strategy to fine classify maize and soybean in AVIRIS images. In this method, spectral spatial features are extracted by spectral spatial feature learning (SSFL), and texture features of local binary pattern (LBP) images are fused with spectral spatial features. Finally, hyperspectral images are classified by Kelm Extreme Learning Machine (KELM).

B. *Multi-classifier ensemble classification*

With the introduction of ensemble learning into remote sensing, a new classification method, multi-classifier ensemble classification, appears in hyperspectral image classification. The application of single classifier is often limited by various conditions, and ensemble learning can synthesize the results of multiple single classifiers to obtain the most satisfactory classification results .

Fan Liheng [48] and others proposed a method based on band grouping and classifier integration to classify maize, soybean, wheat and other crops on AVIRIS data. The original spectral space of hyperspectral remote sensing image is classified according to the similarity information between bands. A new spectral group is formed by randomly extracting one band from each class, and the difference between different spectral groups is increased by limiting the number of the same bands in different spectral groups. The new spectral group is used as the feature subset of the training classifier. The maximum likelihood classifier is trained in the feature subset. The final integrated classifier is synthesized by simple majority voting method. The classification accuracy of this method is 97.76%. Soviet Red Army [49] et al. proposed a multi-classifier dynamic integration algorithm based on five basic classifiers, such as support vector machine. The algorithm was applied to two hyperspectral images for classification experiments. The experimental results show that the multi-classifier dynamic integration algorithm can maintain a high classification accuracy (better than 90%). Ceamanos [50] et al. proposed a classifier set based on support vector machine to classify maize, soybean and wheat from AVIRIS data. Firstly, the bands are divided into several groups, and each group is classified by support vector machine. Then all the outputs are fused by additional support vector machine classifiers. The classification accuracy is 90.8%. Xia [51] and others integrated the rotating forest and Markov random field extracted from local features, and used AVIRIS hyperspectral data to classify soybean, oat and other crops. Kumar [52] and others used the classical AdaBoost algorithm and bagging algorithm in the multi-classifier system combined with the multi-classifier model based on support vector machine to classify and recognize cabbage and cabbage on AVIRIS hyperspectral data. The classification accuracy was 96.8%.

C. *Classification Application Based on Multi-source Remote Sensing Data*

Hyperspectral data can also be combined with information extracted from multispectral data or radar data for fine classification of crops. Shi Feifei [53] and others used spectral characteristic variables extracted from HJ-1A HSI hyperspectral data and NDVI time series extracted from GF-1 data as multi-source data to classify crops in Huangshui watershed of Qinghai Province by using classification decision regression tree (CART) and support vector machine (SVM), with classification accuracy of 88.2% and 84.5, respectively. Yang Sirui [54] and others fused hyperspectral images with LiDAR data, and classified wheat and barley in Heihe River basin with sparse polynomial logistic regression classifier. The classification accuracy can reach 94.5%. Liu [55] and others put forward the object-based image analysis (OBIA) paradigm, which combines hyperspectral data and LiDAR data to classify maize, pepper, potato and other crops with a precision of 90.33%. Dalponte [56] and others used hyperspectral images and LiDAR data to classify forest vegetation in complex areas. They mainly used support vector machine (SVM) combined with Gauss maximum likelihood (GML-LOOC) to classify forest vegetation. The classification accuracy was 89.2%.

VI. Conclusions

The research on crop fine classification based on hyperspectral remote sensing has made some achievements in data sources, data dimension reduction methods and classifiers at home and abroad. Hyperspectral remote sensing has also been widely used in crop fine classification and recognition. However, hyperspectral remote sensing still has some shortcomings in crop fine classification, which needs further study.

1) Scholars at home and abroad mostly study areas with simple planting structure. Most of the crops in these areas are mainly wheat, rice and other large-scale food crops. There are few studies on fine classification of crops in areas with complex planting structure. When using multi-spectral remote sensing to classify and recognize crop varieties, fragments and topographic fluctuations, the classification accuracy is often low. Therefore, it is very important to study the fine classification of crop types and varieties in these areas by using the rich spectral information of hyperspectral.

2) Hyperspectral remote sensing has been widely used in crop fine classification and recognition due to its advantages of multi-band and rich spectral information. However, it also brings many problems, such as high dimension of hyperspectral data, large data redundancy, strong inter-band correlation, and large workload of data processing. Therefore, finding a dimension reduction method and classifier that can speed up the hyperspectral data processing is of great significance for the future hyperspectral remote sensing fine classification of crops at large regional scale.

In future research, we should expand the scope of hyperspectral remote sensing monitoring objects, and select areas with complex crop planting types or conduct hyperspectral fine classification of crop varieties. To improve the universality and stability of the classifier, the mechanism of hyperspectral crop fine classification and the method of multi-source data fusion were further studied.

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