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A Review of Hyperspectral Image Classification Based on Joint Spatial-spectral Features

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A Review of Hyperspectral Image Classification Based on Joint Spatial-spectral Features

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Abstract. Hyperspectral image classification technology is a basic work in the application of hyperspectral images. In recent years, with the innovation and development of hyperspectral image classification technology, the method and performance of hyperspectral image classification based on joint spatial-spectral features have made breakthroughs, and have gradually become the focus of researchers. In order to further promote the development of the spatial-spectral feature union class method and improve the classification accuracy of hyperspectral images, this paper summarizes the commonly used spatial-spectral union algorithms. Firstly, the introduction briefly outlines the background and research status of this field. Some common problems in the process of hyperspectral image classification are listed. Finally, some current hyperspectral image classification methods based on joint spatial-spectral features are introduced. The main roles and existing problems of spatial-spectral joint features in the field of hyperspectral image classification are summarized in detail, and the future research directions are prospected.

1. Introduction

Hyperspectral images (HSI) classification technology originated in the early 1980s, when it was not developed rapidly due to insufficient technology and imperfect hardware facilities [1]. It was not until the successful launch of the "Gaofen 5" satellite that researchers' attention to hyperspectral remote sensing technology reached a new height, promoting the development of HSI classification technology, which has been widely used in marine hydrographic detection, ecological and environmental monitoring, fine agriculture and other related fields. It is a three-dimensional cube with many spectral dimensions, which contains rich spatial and spectral information of HSI, which can not only provide effective discriminative properties for classification models, but also alleviate the effects of homogeneous and heterogeneous spectra to a certain extent [2]. However, traditional HSI classification models that utilise only the spectral information of image elements for classification are unable to achieve satisfactory results. Therefore, many HSI classification models with joint spatial-spectral features have been proposed by researchers, such as:the method of kernel fusion [3], Convolutional Neural Networks (CNN) [4], Capsule Network (CapsNet) [5], etc. The essence of spatial-spectral association is to make the classification model discriminative features more expressive by constructing a multi-layer or multi-branch network in which high-dimensional, abstract spatial and spectral feature information is extracted [6]. The study of HSI classification with joint spatial-spectral features is an important research topic now and for a long time to come. In this paper, we first give a brief introduction to HSI classification models and the problems and difficulties, followed by an overview description of the common classification processes for joint spatial-spectral features, mainly briefly describing three classification networks, namely convolutional neural networks (1D+2D-CNN) fusing 1D and 2D features, multicore fusion, and CapsNet, and summarizing the innovations of researchers in these several methods in recent years. Finally, a summary and outlook are provided, specifying the development trend of joint spatial-spectral features in the field of HSI classification.

2. Hyperspectral images classification

2.1. Overview of hyperspectral images classification

The HSI classification process is shown in Figure 1. The classification process consists of the major steps of data input, data pre-processing, feature information extraction and feature map activation, classification model, accuracy evaluation and classification results.

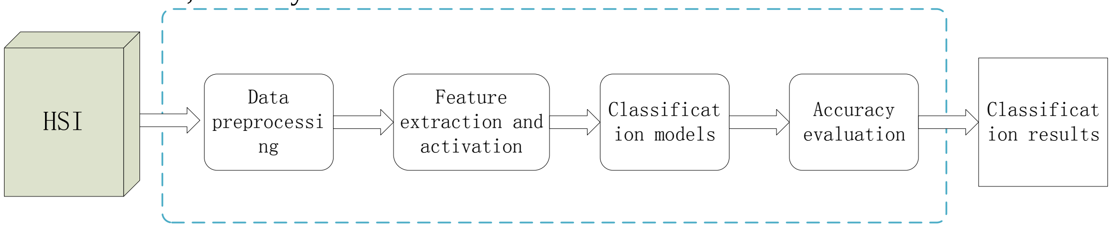

Figure 1. Hyperspectral images classification process

The pre-processing of HSI mainly includes image format conversion, geometric correction, noise reduction, dimensionality reduction, etc. The purpose is to eliminate noise and reduce the complexity of HSI as much as possible to improve the operation efficiency and provide data for the subsequent classification model.

Feature extraction and feature selection is also essentially a dimensionality reduction, a process of finding the optimal solution, and commonly used methods include Principal Components Analysis (PCA), which uses linear transformations to extract features, but hyperspectral data is inherently nonlinear, so linear transformation methods such as PCA can lose a lot of useful information.

Choosing a suitable feature extraction and classification model is the key to achieve high classification accuracy. Traditional methods can only extract limited spectral feature information, while the spatial-spectral joint feature classification-based methods can extract not only spectral feature information but also spatial feature information and perform effective feature fusion, which can effectively fit the nonlinear relationship between the classification labels of high HSI and HSI data features for high-dimensional data like HSI to obtain better classification results. On the other hand, the joint spatial-spectral feature classification model integrates feature extraction and feature classification into one framework, which can achieve end-to-end training.

2.2. Research difficulties of hyperspectral images classification problem

HSI has rich spatial and spectral information to provide a strong basis for its classification, but also brings some difficulties for the classification. (1) The large amount of HSI data leads to a large computational effort for HSI-related processing, and how to quickly and accurately classify the image elements to be classified is one of the key issues to be considered when studying HSI classification. (2) The spatial resolution of HSI is lower than the spectral resolution at the nanometer level, and there are some mixed pixels in the image, and the existence of mixed pixels makes the accurate classification of HSI difficult. (3) Due to the wide range of spectral bands, narrow bands, and large number of bands in HSI imaging, which leads to a large correlation between adjacent bands, there will be more redundant information in the images, which has an impact on the classification accuracy, and it is very important to reduce the impact of redundant information on HSI classification. Finally, HSI training samples are small, which is prone to overfitting problems for classification methods with a relatively large number of parameters. It is important to train an efficient classification model with a small number of samples for HSI classification.

3. Classification method based on spatial-spectral features

For the above HSI classification problem. A classification model that utilizes a combination of spatial-spectral features can increase the robustness of the features, providing a solution to these problems. The method based on joint spatial-spectral features can fuse the extracted spectral feature information and spatial feature information before classifying the pixels. Three commonly used joint spatial-spectral feature classification methods are listed below.

3.1. spatial-spectral association method based on multicore fusion

The HSI classification based on the kernel fusion method uses the kernel function to fuse spatial-spectral feature information. The SVM algorithm was first applied to HSI classification by Gualtieri et al. Back in 1999, showing that the SVM algorithm that maps samples to a high-dimensional space using kernel functions can lead to better classification results. However, the early kernel function methods only used spectral feature information and did not consider the spatial context information of image elements. Inspired by kernel learning algorithms, researchers started to try to fuse spectral feature information and spatial feature information in HSI classification problems using multicore fusion techniques. As shown in Fig. 2, this approach uses multicore feature fusion, which first extracts multiscale spectral features by multiscale spatial filtering, followed by representing each feature separately using multicore pairs within the Kernel Sparse Representation Classification (KSRC) to extract deep spatial information, and finally The classification is done by combining the Spatial-spectral information. For example, by fusing spectral features and spatial features through feature weighting, a multi-kernel learning (MKL) method is proposed to fuse spatial-spectral information in the kernel space; a composite kernel is used to construct spatial and spectral kernels respectively, and KSRC is used as the base classifier to achieve classification Fusion of in-device spatial-spectral information.

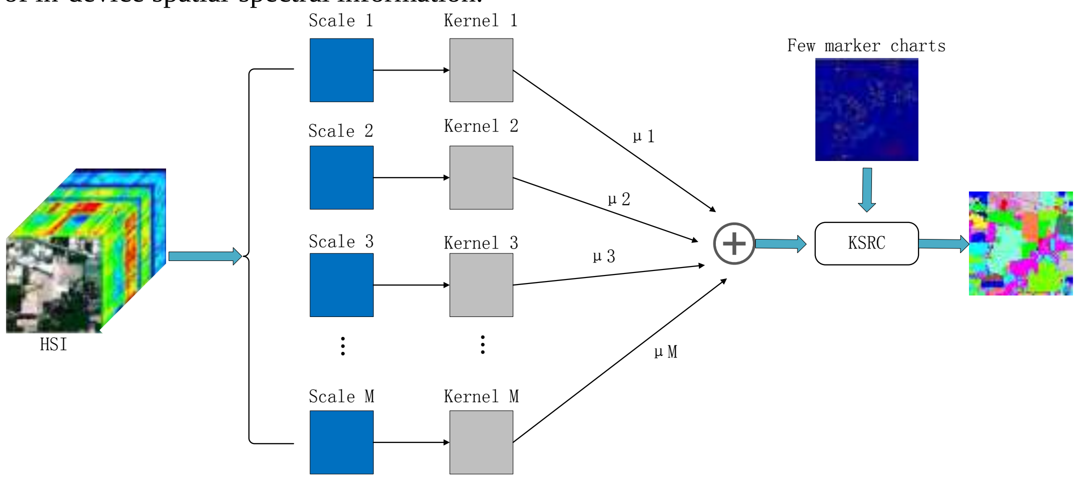

Figure 2. Hyperspectral images classification model based on multicore fusion

3.2. 1D+2D-CNN based spatial-spectral union method

The CNN model is one of the most commonly used models in the field of HSI classification. As shown in Figure 3, the method uses a CNN with a dual-branch structure. First, the model performs PCA dimensionality reduction on the input HSI data. Use 1D-CNN to extract spectral information on the dimensionally reduced images. Then further use 2D-CNN to extract deeper spatial information. The classification is done by fusing the extracted spatial and spectral information. For example, Yang et al. [7] proposed a dual-channel CNN with spectral channel and spatial channel, and used the dual-channel to extract spectral and spatial features respectively for classification, and achieved superior results; Hu Li et al. [8] used the atrous convolution model fused by 1D-CNN and 2D-CNN to extract spatial-spectral feature information respectively, and then used a weighted fusion method to perform feature fusion on the features, and finally complete the classification.

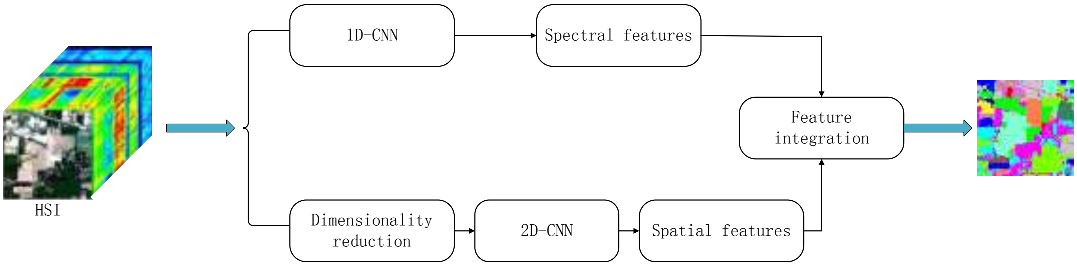

Figure 3. 1D+2D-CNN based spatial-spectral classification model

3.3. Capsule network-based spatial-spectral association method

Since CNNs limit the ability of the model at a certain depth. A new network architecture was proposed by Sabout et al [9], namely CapsNet. the capsule network replaces the pooling layer of the CNN, which in turn preserves the spatial information of the input data. As shown in Fig. 4, the architecture uses two branches to extract the spatial and spectral information of the HSI, respectively, in the way of the classical Capsule Neural Network CapsNet. to prevent the data set from being too large, the network is preprocessed accordingly for both branches. Fewer capsules are obtained using 1D and 2D constrained windows (1D-ConvCaps, 2D-ConvCaps) to reduce the training pressure during dynamic routing. The final subdivision labels are computed by cascading Markov Random Fields (MRF).

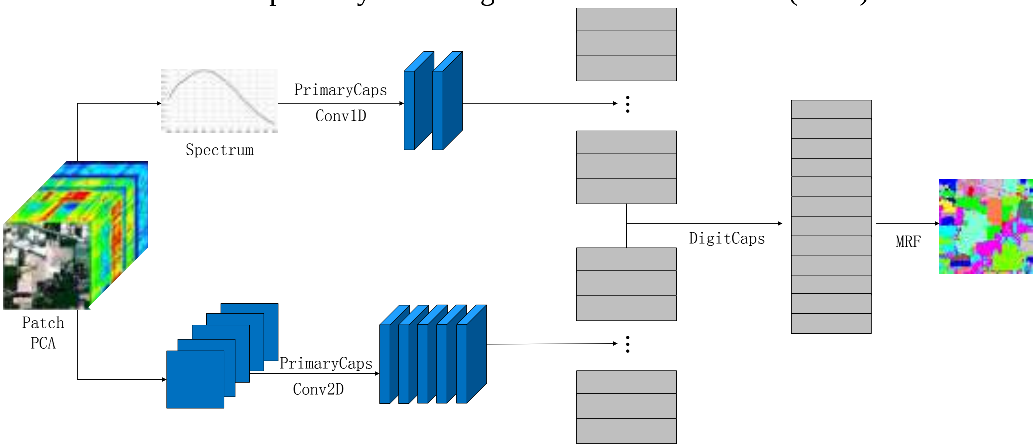

Figure 4. 1D+2D-CNN based spatial-spectral classification model

4. Summary and Outlook

With the continuous development of HSI processing technology, the application of HSI is becoming more and more extensive. HSI classification as a fundamental work has been the focus of research in the field of remote sensing, and this work has good application prospects and a relatively solid theoretical foundation, and its development will also have a relative impact on the subsequent HSI processing. This paper summarizes and summarizes the HSI classification models of joint spatial-spectral features commonly used in recent years. In addition, the combination of attention mechanism, migration learning, hybrid network and other strategies can make up for the shortcomings of hyperspectral data such as high dimensional characteristics, scarcity of training samples and data nonlinearity, which can better improve the classification.

Although the spatial-spectral joint feature method based on CNN model has achieved good results in the field of HSI classification, and the classification accuracy is also improving. However, efforts are still needed in the following directions.

Commonly used classification methods, which are based on specific, publicly available datasets, often have poor generalization ability of HSI classification algorithms due to different data collection and sensors, different time of day, different lighting conditions and differences in atmospheric environment. Therefore, how to use migration learning techniques to overcome the differences between different datasets is one of the key issues that need to be addressed for HSI classification to move toward practical applications.

There are often many parameters in the classification method, more training samples are needed, the algorithm complexity is high, and the adjustment of hyperparameters is inconvenient. These shortcomings are limited by the theoretical study of the algorithm and the high-dimensional nature of HSI itself. Therefore, how to improve the robustness and time efficiency of the algorithm is also the direction of future research.

The main issues to be considered when extracting the joint spatial-spectral features are, among others, the size of the spatial neighborhood, the size, structure and complexity of the network. The existing methods mainly rely on multiple comparative experimental analyses to select the appropriate parameters. How to guide the selection of spatial neighborhood size and the design of network size based on the spatial resolution, spectral resolution and acquisition scene of HSI itself is an issue worthy of attention.

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References
[1] Wang X, Mu Z, Song R, et al. 2020 A Hyperspectral Image NSST-HMF Model and Its Application in HS-Pansharpening *IEEE Transactions on Geoscience and Remote Sensing* **99** pp 1-15
[2] Wang Q C, Fu G Y, Wang H Q, et al. 2018 Fusion of multi-scale feature using multiple kernel learning for hyperspectral image land cover classification Guangxue Jingmi Gongcheng *Optics and Precision Engineering* **26(4)** pp 980-988
[3] Szytula A and Leciejewicz J 1989 *Handbook on the Physics and Chemistry of Rare Earths* vol 12, ed K A Gschneidner Jr and L Erwin Amsterdam Elsevier p 133
[4] Lee H, Kwon H 2017 Going Deeper With Contextual CNN for Hyperspectral Image Classification *IEEE Trans Image Process* **26(10)** pp 4843-4855
[5] Yin J, Li S, Zhu H, et al. 2019 Hyperspectral Image Classification Using CapsNet With Well-Initialized Shallow Layers *IEEE Geoence and Remote Sensing Letters* **7** pp 1-5
[6] Ghamisi P, Benediktsson J A, Sveinsson J R 2014 Automatic Spectral–Spatial Classification Framework Based on Attribute Profiles and Supervised Feature Extraction *IEEE Transactions on Geoscience & Remote Sensing* **52(9)** pp 5771-5782
[7] Yang J, Zhao Y, Chan C W, et al. 2016 Hyperspectral image classification using two-channel deep convolutional neural network *IGARSS 2016 - 2016 IEEE International Geoscience and Remote Sensing Symposium* IEEE
[8] Gao H, Lin S, Yang Y, et al. 2018 Convolution Neural Network Based on Two-Dimensional Spectrum for Hyperspectral Image Classification *Journal of Sensors* **2018** pp 1-13
[9] Choi J, H Seo, Im S, et al. 2019 Attention Routing Between Capsules *2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)* IEEE