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REINFORCEMENT LEARNING BASED ON HYPERSPECTRAL IMAGE CLASSIFICATION USING BINARY ENTROPY METHODS

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ABSTRACT:-

Hyperspectral image (HSI) classification has become a hot topic in the field of remote sensing. In general, the complex characteristics of hyperspectral data make the accurate classification of such data challenging for traditional machine learning methods. In addition, hyperspectral imaging often deals with an inherently nonlinear relation between the captured spectral information and the corresponding materials. In recent years, deep learning has been recognized as a powerful feature-extraction tool to effectively address nonlinear problems and widely used in a number of image processing tasks. Motivated by those successful applications, deep learning has also been introduced to classify HSIs and demonstrated good performance. This paper presents a systematic review of deep learning-based HSI classification literatures and compares several strategies for this topic. Specifically, we first summarize the main challenges of HSI classification which cannot be effectively overcome by traditional machine learning methods, and also introduce the advantages of deep learning to handle these problems. Then, we build a framework which divides the corresponding works into spectral feature networks, spatial-feature networks, and spectral-spatial feature networks to systematically review the recent achievements in deep learning-based HSI classification. In addition, considering the fact that available training samples in the remote sensing field are usually very limited and training deep networks require a large number of samples, we include some strategies to improve classification performance, which can provide some guidelines for future studies on this topic. Finally, several representative deep learning-based classification methods are conducted on real HSIs in our experiments.

Keywords:- Hyperspectral image, deep learning, classification, feature extraction.

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1. INTRODUCTION

In recent years, people have only begun to obtain hyperspectral remote sensing images with high spatial resolution and high spectral resolution relatively easily. Because hyperspectral images have strong resolving power for fine spectra, they have a wide range of applications in environmental [1], military [2], mining [3], and medical fields [4]. The acquisition of hyperspectral images depends on imaging spectrometers installed in different spaces. The imaging spectrum was established in the 1980s. It is used to image in the ultraviolet, visible, near-infrared, and mid-infrared regions of electromagnetic waves. The imaging spectrometer can image in many continuous and very narrow bands, so each pixel in the used wavelength range can get a fully reflected or emitted spectrum. Therefore, hyperspectral images have the characteristics of high spectral resolution, many bands, and abundant information. The processing methods of hyperspectral remote sensing images mainly include image correction [5], noise reduction [6], transformation [7], dimensionality reduction, and classification [8]. Unlike ordinary images, hyperspectral images are rich in spectral information, and this spectral information can reflect the physical structure and chemical composition of the object of interest, which is helpful for image classification. Hyperspectral image classification is the most active part of the research in the hyperspectral field [9].

Hyperspectral imaging sensors often provide hundreds of narrow spectral bands from the same area on the surface of the earth. In hyperspectral images (HSIs), each pixel can be regarded as a high-dimensional vector whose entries correspond to the spectral reflectance in a specific wavelength. With the advantage of distinguishing subtle spectral difference, HSIs have been widely applied in many fields [1]–[5]. Based on the recent studies published in [6], HSI classification (i.e., assigning each pixel to one certain class based on its spectral characteristics) is the most vibrant field of research in the hyperspectral community and has drawn broad attentions in the remote sensing field. In HSI classification tasks, there exist two main challenges: 1) The large spatial variability of spectral signatures and 2) The limited available training samples versus the high dimensionality of hyperspectral data. The first challenge is often brought by many factors such as changes in illumination, environmental, atmospheric and

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temporal conditions. The second challenge will result in illposed problems for some methods and reduce the generalization ability of classifiers.

A. RELATED WORKS

In the early stage of the study on HSI classification, most methods have focused on exploring the role of the spectral signatures of HSIs for the purpose of classification. Thus,numerous pixel-wise classification methods (e.g., neural net-works [7], support vector machines (SVM) [8], multinomial logistic regression, and dynamic or random sub-space) have been proposed to classify HSIs. In addition, some other classification approaches have focused on designing an effective feature-extraction or dimension-reduction technique, such as principle component analysis(PCA) , independent component analysis (ICA) [15],and linear discriminant analysis (LDA) [16]. However, the classification maps obtained by these pixel-wise classifiers are unsatisfactory since the spatial contexts are not considered.Recently, spatial features have been reported to be very useful in improving the representation of hyperspectral data and increasing the classification accuracies. More and more spectral-spatial features-based classification frameworks have been developed, which incorporates the spatial contextual information into pixel-wise classifiers. For example, in, extended morphological profiles (EMPs) were used to exploit the spatial information via multiple morphological operations. Multiple kernel learning (e.g., composite kernel and morphological kernel was designed to explore the spectral-spatial information of HSIs.

2. DATASETS OF HYPERSPECTRAL IMAGES (HSIs)

HSIs captured by airborne and space borne sensors are very useful in many applications like remote sensing [3], land-cover [4], agriculture [5] etc. These sensors collect reflective portion of electromagnetic spectrum containing hundreds of narrow spectral bands and this reflective portion creates a unique spectral signature for an object. This allows the identification of various materials on earth surface by the unique spectral signature. As the sensors capture HSIs are very expensive, only few HSI datasets are publicly available [5]. Also, the task of creating ground truth and pixel-labelling is exorbitant and time-demanding [1] and consequently only a few labelled HSIs samples are available for research work. Moreover, the DL-based

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models need an adequate number of training samples for parameter tuning during the training phase [2]. Thus, the availability of very less number of HSI samples makes the classification task very challenging [3]. Nevertheless, some of the HSI datasets are publicly available and in this section three most popular datasets i.e., Pavia University, Indian Pine, and Salinas are discussed.

2.1. Dataset of Indian Pine

Dataset of Indian Pine has been captured as first dataset by airborne-visible-infrared-imaging spectrometer (AVIRIS) sensor over a site in northwestern, Indiana, USA [8]. The spatial resolution of image is 20m with a spatial size of 145×145 pixels. The spectral range of the acquired image is 0.4- 2.5µm with a sum of 224 number of spectral bands. However, after removing water absorbed and noisy bands, only 200 spectral bands are utilized in experiments. Also, the image contains 16-classes with total 10366-samples in the dataset as depicted in Table 1.

Table 1. Samples and groundtruth classes of Indian Pine Dataset

Sr. No.	Class	Samples
1	Oats	20
2	Corn	237
3	Woods	1265
4	Wheat	205
5	Alfalfa	46
6	Grass-trees	730
7	Soybean-mintill	2455
8	Corn-mintill	830
9	Grass-pasture	483
10	Soybean-clean	593
11	Soybean-notill	972
12	Corn-notill	1428
13	Hay-windrowed	478
14	Stone-steel-towers	93
15	Grass-pasture-mowed	28
16	Buildings-grass-trees-drives	386
	Total	**10366**

2.2. Dataset of Pavia University

Reflective-optics-spectrographic-imaging-system (ROSIS) sensor was used to capture Pavia university dataset over the Pavia University, northern Italy [85]. The image contains a spatial resolution of 1.3m with a spatial size 610×340 pixels. The original image contains total 115 spectral bands in a spectral range 0.43-0.86µm. However, a

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total of 103 spectral bands are utilized in experiments after discarding noisy bands. Also, total of 9-classes having 42776-samples are available in the dataset as shown in Table 2.

Table 2. Samples and groundtruth classes of Pavia University Dataset

Sr. No.	Class	Samples
1	Trees	3064
2	Gravel	2099
3	Asphalt	6631
4	Bitumen	1330
5	Shadows	947
6	Meadows	18649
7	Bare soil	5029
8	Painted metal sheets	1345
9	Self-blocking bricks	3682
	Total	**42776**

3. HYPERSPECTRAL IMAGES CLASSIFICATION

The HSI classification process is shown in Figure 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.

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

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extraction and classification model is the key to achieve high classification accuracy.

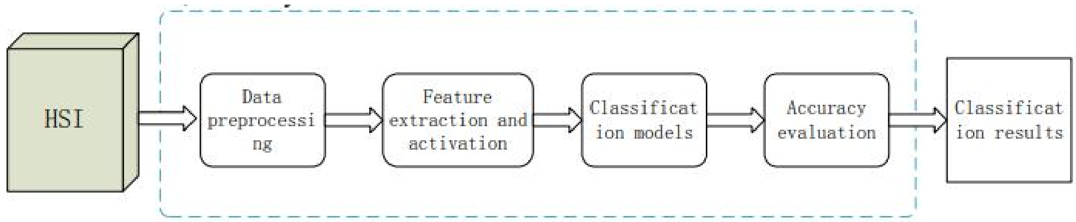

Figure 1. Hyperspectral images classification process

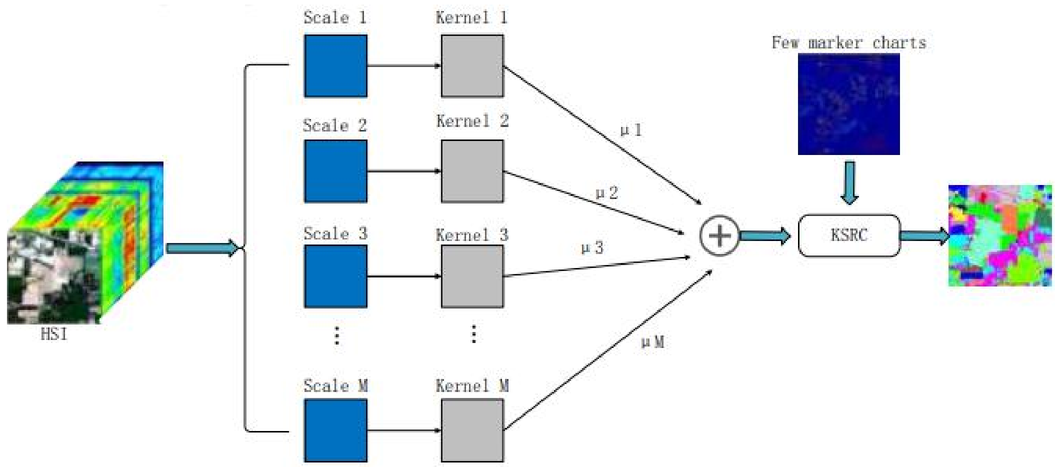

Figure 2. Hyperspectral images classification model based on multicore fusion

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.

4. DEEP LEARNING

In recent years, hyperspectral image classification methods have introduced spatial information of hyperspectral images. This type of method is simply referred to as hyperspectral image classification methods based on spatial-spectral joint features. Deep learning originates from artificial neural networks. Compared with artificial neural networks, deep learning has a stronger pumping ability. Deep learning models have deeper layers, which also helps to extract feature information. This section

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mainly introduces convolutional neural networks (CNN) in deep learning [9, 15], deep belief network (DBN), and Stacked Autoencoder (SAE).

4.1. CNN. Classification method based on spectral features:

Hyperspectral images have very rich spectral information and extremely high spectral resolution. Each pixel can extract one-dimensional spectral vectors. These vectors are composed of spectral information. Classification using only one-dimensional spectral vectors is called a classification method based on spectral information. In the classification method based on spectral information, generally, the pixel

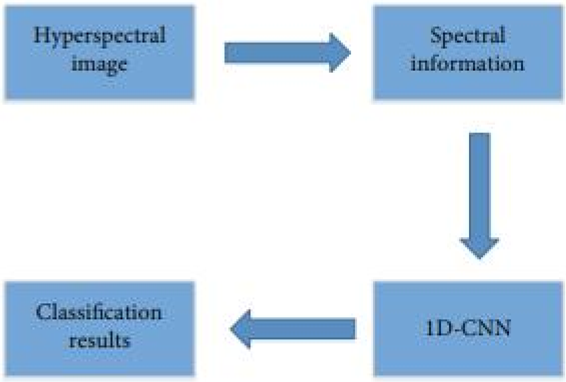

Figure1 : Schematic diagram of 1D-CNN

is used to extract spectral information or to obtain certain specific features from spectral information through feature extraction to classify. Using CNN to classify spectral features of hyperspectral images is to use one-dimensional CNN (1DCNN) to extract spectral features and classify them. The process is shown in Figure 1.

CNN to extract spatial features. The classification is completed by combining the class prediction scores of both the streams. Similarly, in [13], another hybrid framework for multi-feature based HSI classification is proposed which uses PCA to reduce dimensionality, guided filters to get spatial features and a sparse AE to extract high level features. The authors in [14], have proposed a batch-based training scheme for AEs to exploit spectral-spatial features and these features are merged via a mean pooling scheme. Likely, a classification framework, exploiting spectral-spatial, is developed in [15] to utilize stacked sparse AE for feature extraction and random forest classifier for final classification. Furthermore in [16], the authors have used a threefold feature learning scheme proposed in [17] to implement an efficient

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multilayer extreme learning machine-based AE framework. In work [18], the authors have addressed the issue of high inter-class-similarity and high intra-class-variability.

Here a stacked model is used to learn discriminative features via imposing a local fisher discriminant regularization. In the work proposed in [19], extended morphological profiles are utilized to incorporate spatial information within the spectral information obtained from spectral segments. The proposed scheme has been very effective in terms of time complexity. Recently, [18], a k-sparse denoising AE is knitted with spectral-spatial features is employed for HSI-classification. In this work, the spatial features are obtained through restricted spatial information in order to reduce intra-class variability of spatial features.

5. EXPERIMENTS

In this section, we mainly conduct a comprehensive set of experiments from four aspects. Firstly, a series of experiments are designed to demonstrate the advantages of deep learning on HSI classification over traditional methods. Secondly, the classification performance of several recent state-of-the-art deep learning approaches is systematacially compared. Thirdly, we visualize the learned deep features and network weights to further explore the “black box”. Finally, the effectiveness of strategies included in Section IV is further analyzed. To complete our experiments, three benchmark HSIs are used, i.e., the Houston, University of Pavia, and Salinas images. The three images are introduced in the following subsection.

Experimental Data Sets

The Houston data was distributed for the 2013 IEEE Geoscience and Remote Sensing Society (GRSS) data fusion contest. This scene was captured in 2012 by an airborne sensor over the area of University of Houston campus and the neighboring urban area. The size of the data is 349×1905 pixels with a spatial resolution of 2.5 m. This HSI consists of 144 spectral bands with wavelength ranging from 0.38 to 1.05 μm and includes 15 classes.

Compared Methods

In this review, we have investigated several recent stateof-the-art deep learning-based approaches, including 3D-CNN [6], Gabor-CNN [9], CNN with pixel-pair features

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(CNNPPF) [6], siamese CNN (S-CNN), 3D-GAN , and the deep feature fusion network (DFFN) [7], for HSI classification. Specifically, the 3D-CNN exploits 3-D convolutional filters to directly extract spectral-spatial features from the original hyperspectral cube. However, the network architecture adopted in 3D-CNN is relatively simple and the correlation between different layers is neglected. The DFFN adopts the DRN [10], which can be considered a more powerful network, to extract more discriminative features. In addition, the features from different-level layers are further fused to explore the correlation between layers. The main drawback of DFFN is that the optimal feature fusion mechanism depends on a hand-crafted setting with abundant experiments. In the GaborCNN, the Gabor filtering is first utilized as a preprocessing technique to extract
spatial features of HSIs.

Classification Results

The first experiment was performed on the Houston data set. In this experiment, the training samples were given according to the 2013 GRSS data fusion contest. The amount of training and test samples per class is shown in Table I. The classification maps obtained by different methods. From this figure, we can see that the classification maps obtained by the SVM and JSR methods are not very satisfactory since some noisy estimations are still visible. By contrast, other methods perform much better in removing "noisy pixels" and deliver a smoother appearance in their classification results. By comparing two filtering-based methods, i.e., EPF and GaborCNN, we can see that the classification map of EPF seems to be over-smoothing, but the Gabor-CNN preserves more details in edges. Apart from visual comparison, Table IV gives quantitative results of various methods on the image, where three metrics, i.e., overall accuracy (OA), average accuracy (AA), and Kappa coefficient, are adopted to evaluate the classification performance.

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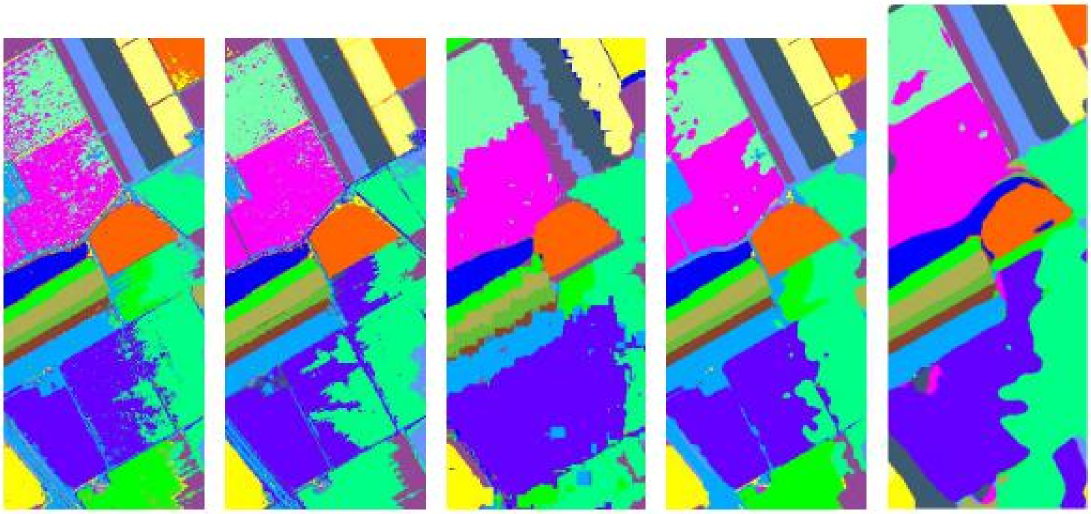

(a) SVM (b) EMP (c) JSR (d) EPF (e) 3D-CNN

Figure 3 :

TABLE 3: THE CONFIGURATION OF CNN MODEL

Layer No.	Type	Size	Feature maps
1-3	Convolution	3×3	16
4-5	Convolution	3×3	32
6-7	Convolution	3×3	64
8	Pooling	3×3	64
9	Fully connected	-	200
10	Fully connected	-	16

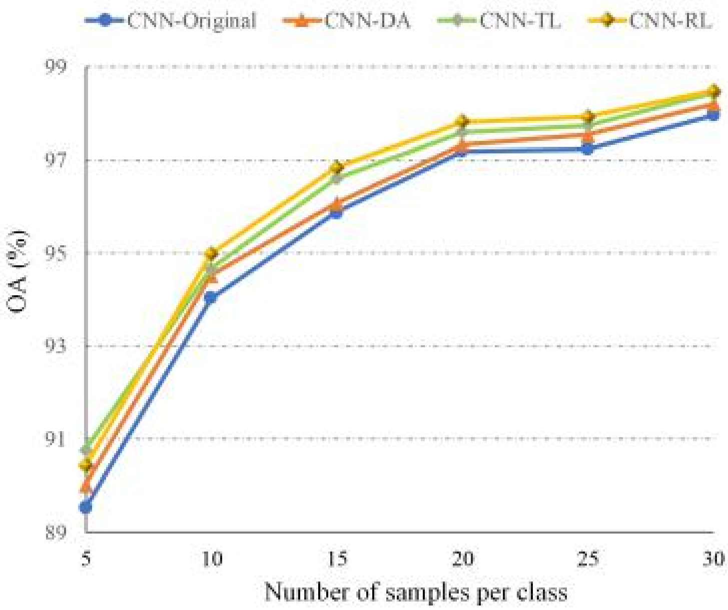

Figure 4 : values obtained by different methods versus number of samples.

6. CONCLUSION

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Classification and recognition of hyperspectral images are important content of hyperspectral image processing. This paper discusses several methods of hyperspectral image classification, including supervised and unsupervised classification and semi-supervised classification. Although the supervised and unsupervised classification methods described in this article have their respective advantages to varying degrees, there are limitations in the application of various methods. For example, supervised classification requires a certain number of prior conditions, and human factors will affect the classification results have an impact. Therefore, based on different application requirements, combined with the acquisition of hyperspectral images with massive information, multiple methods need to be combined with each other in order to achieve the desired classification effect. With the development of hyperspectral image technology, hyperspectral image classification has been widely used. Existing theories and methods still have certain limitations for more complicated hyperspectral image classification. Therefore, researching more targeted hyperspectral image classification methods will be an important research direction in the future.

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