Hyperspectral Image Classification using Convolutional Neural Networks

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ABSTRACT: Hyperspectral sensors, such as AVIRIS, HyMap, ROSIS, HYDICE, and Hyperion, can simultaneously acquire hundreds of contiguous bands. hyperspectral data is superior to the multi-spectral sensors with providing rich spectral information. It can be regarded as a spectral cube data, where there are two spatial dimensions and one spectral dimension. However, the large amounts of spectral bands also bring a challenge for hyperspectral data analysis. How to effectively use these spectral information is vital to the application of the hyperspectral data in objection recognition and urban planning. In most research on hyperspectral image analysis, feature exploring and machine learning models training are two main strategies. Except for traditional spectral features, people devoted into exploring the texture features, spatial features, frequency features, in order to find more features that can promote the classification accuracies on hyperspectral data. For machine learning models, more research pay attention on the kernel-based machine learning for hyperspectral image classification, such as support vector machine (SVM) and Kernel Fisher Discriminator (KFD). Meanwhile, feature extraction and selection is used to reduce the dimension of the hyperspectral data, and then traditional machine learning model, for example Bayes classifier, Decision Tree, and so on. These state-of-the-art dense hyperspectral image classification methods need to separate the classification work into two stages including features obtaining and model training. In addition, the texture and spectral features are usually taken into account individually. Deep learning can integrate these aspects together in order to improve the efficiency of the hyperspectral image classification. In this paper, there are include two part. One is that we use the convolutional neural networks (CNNs) to learn contextual features with multiple scales by convoluting different two-dimensional filter. And then, vector field model (VFM) is used to integrate different spectral band into one layer at the same scale. The second one is that we use one-dimensional filter to convolute the spectral signature to get spectral features. The experimental result shows that the new method has the better performance for hyperspectral image classification.

1. INTRODUCTION

Hyperspectral sensors can acquire hundreds of contiguous spectral bands that is superior to the multi-spectral sensors because of its offering rich spectral information. Meanwhile, the large amounts of spectral bands also bring a challenge for hyperspectral image analysis, specially hyperspectral image classification. This problem is called as the Hughes phenomenon[1] or the curse of dimensionality [2], where the high dimensionality of data leads to an increase in the number of training samples. Therefore, finding effective features has been a significant research field for hyperspectral image analysis and application.

In order to reduce the influence from the Hughes phenomenon, dimensionality reduction is usually used to hyperspectral image analysis. Commonly used algorithms include principal components analysis (PCA)[3], independent component analysis (ICA) [4-5], linear discriminant analysis (LDA)[6-7], mutual information [8-9], minimum noise fraction (MNF)[10-11], genetic algorithm (GA) [12], projection-based methods[13-14] and band add-on (BAO)[15]. After dimensionality reduction, traditional multi-spectral remote sensing image classification methods, such as maximum likelihood (ML) [16-17] and Bayes classification method[18], are used to complete the following classification.

Other popular approaches are kernel-based algorithms, such as support vector machines (SVM)

[19-21] and kernel Fisher discriminants (KFD) [22-23], for hyperspectral image classification. The advantage is that kernel-based approaches can be used to analyze hyperspectral data directly, without dimensionality reduction and bands selection.

Recently, kinds of neural networks, including CNN [24], deep belief network (DBN) [25] and stacked auto encoder (SAE) [26], have been applied into hyperspectral image analysis. deep convolutional neural networks (CNN) [27] have been extensively used for a wide range of visual perception tasks, such as object detection, action/activity recognition, etc. Deep learning can integrate these aspects together in order to improve the efficiency of the hyperspectral image classification.

In this paper, there are include two part. One is that we use the convolutional neural networks (CNNs) to learn contextual features with multiple scales by convoluting different two-dimensional filter. And then, vector field model (VFM) is used to integrate different spectral band into one layer at the same scale. The second one is that we use one-dimensional filter to convolute the spectral signature to get spectral features.

2. METHOD

We use a fully deep convolution neural network that is comprised of a series of convolution and pooling layers. Deep learning models stem from artificial neural network, usually include more than three layers, in order to get robust performance. There are many applications fields, such as image classification and targets recognition.

Convolutional Neural Networks (CNN) belong to a multilayer deep learning model, where it consists of multiple convolution and pooling layers, and one logistic regression layer. Because CNNs can be used to extract robust and invariant features from data, it is a better tool for image classification, object recognition than other deep learning models.

In the procedure of CNNs for image classification, features vector can be first obtained by using convolution and pooling. Then, classifiers is used to perform the hyperspectral image classification.

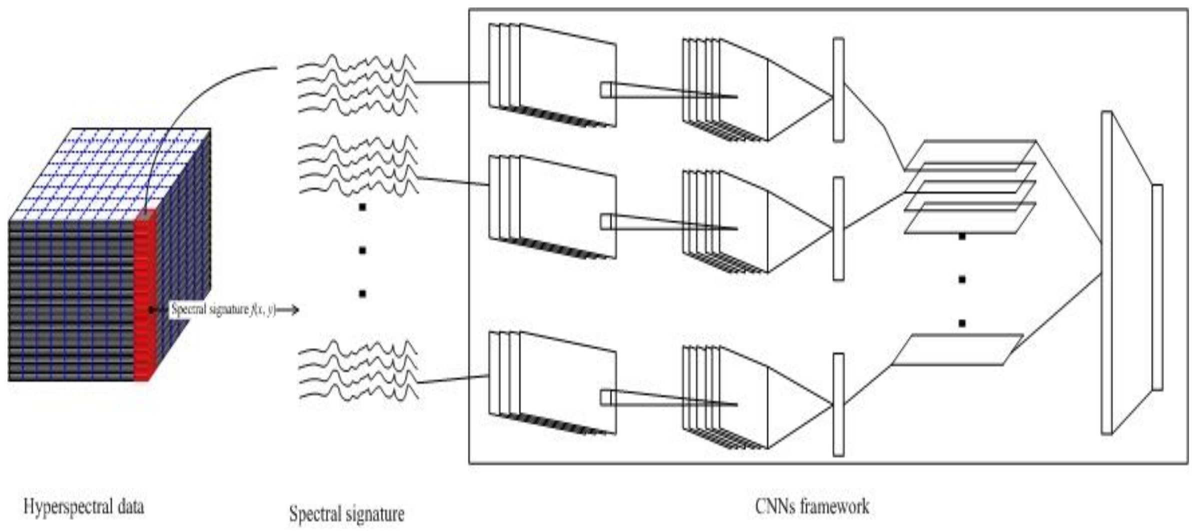
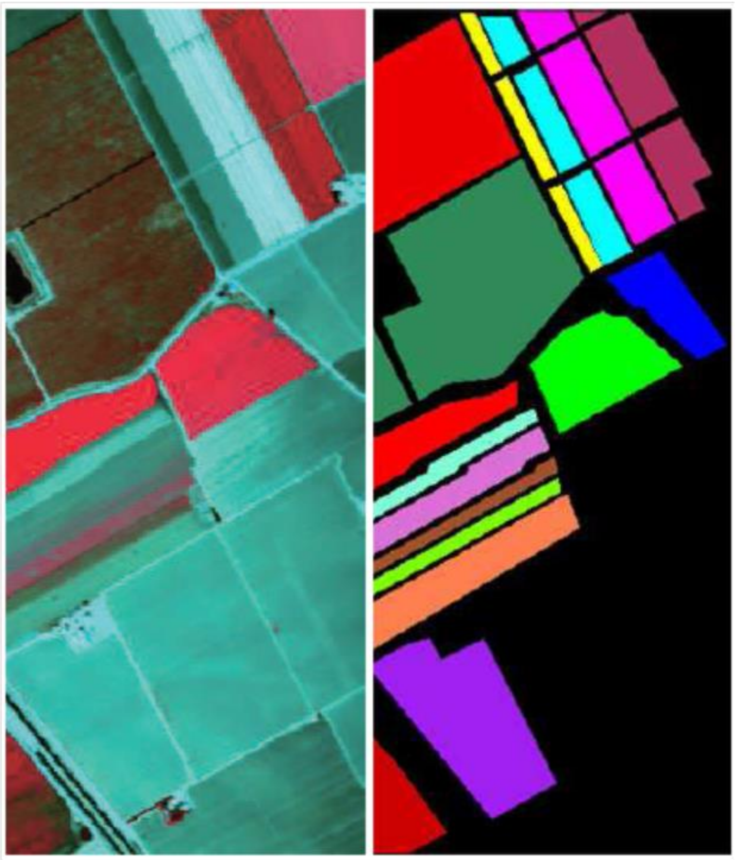


Figure 1. Proposed classification framework for HSI classification using CNNs

The hyperspectral image is a data cube. The spectral bands on each pixel can be considered as a one-dimensional signature. Multi-scale one-dimensional filters are used to filtering the original signature, such that multi-scale filtering result can be obtained, and be considered as two-dimensional signature or one-band image. Then, we construct multiple convolution and pooling layer for the CNNs framework for the classification for hyperspectral image.

3. EXPERIMENT AND RESULTS

The second experimental hyperspectral data, which is AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) image, was acquired over Salinas Valley, California in 1998. The full image contains 217×512 pixels and 220 bands with a range of spectral from 0.4 to 2.45μm. And it was taken at a low altitude with the spatial resolution of 3.7m. The data set shown in Figure 2(a), presents a vegetation classification scenario including broccoli, corn and lettuce romaine. The main advantage of this data set is that there is a ground truth map (Figure 2(b)) of the hyperspectral image including sixteen land-cover classes prepared at the time of image acquisition. The details of the land cover classes and sample number is listed in Table 1.



(a) (b)

Figure 2. (**a**) False color hyperspectral remote sensing image over the Salinas Valley (using Bands 68, 30 and 18); (**b**) ground truth of the labeled area with sixteen classes of land cover: Broccoli Green Weeds 1, Broccoli Green Weeds 2, fallow, fallow rough plow, fallow smooth, stubble, celery, grapes untrained, soil vineyard developed, corn senesced green weeds, romaine lettuce 4 wk, romaine lettuce 5 wk, romaine lettuce 6 wk, romaine lettuce 7 wk, vineyard untrained and vineyard vertical trellis. Note that wk here means week; (**c**) the legend of the classes for land cover of ground truth.

Table 1 Ground truth classes for the Salinas Valley scene and their respective samples number.

Bands	Spatial resolution	Spectral scope
C1	Brocoli green weeds 1	2009
C2	Brocoli green weeds 2	3726
C3	Fallow	1976
C4	Fallow rough plow	1394
C5	Fallow smooth	2678
C6	Stubble	3959
C7	Celery	3579
C8	Grapes untrained	11271
C9	Soil vinyard develop	6203

C10	Corn senesced green weeds	3278
C11	Lettuce romaine 4wk	1068
C12	Lettuce romaine 5wk	1927
C13	Lettuce romaine 6wk	916
C14	Lettuce romaine 7wk	1070
C15	Vinyard untrained	7268
C16	Vinyard vertical trellis	1807
Total		54129

We take the KNN, linear SVM, and the proposed CNNs as the experimental methods. The experiment results are shown in Table 2. It can be seen that our proposed method can obtain the best performance in hyperspectral image classification.

Table 2 Experiment results.

Method	KNN	Linear SVM	CNNs
Accuracy	85.78%+0.6594%	86.12%+1.3524%	91.23%+0.8562%

4. CONCLUSION

In conclusion, a CNN based algorithm is proposed for hyperspectral remote sensing image classification. In the proposed algorithm, the spectral bands on each pixel is considered as a spectral signature. First, we use the convolutional neural networks (CNNs) to learn contextual features with multiple scales by convoluting different two-dimensional filter. Second, we use one-dimensional filter to convolute the spectral signature to get spectral features. The experimental result shows that the new method has the better performance for hyperspectral image classification.

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