CROSS-DOMAIN CNN FOR HYPERSPECTRAL IMAGE CLASSIFICATION

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ABSTRACT

In this paper, we address the dataset scarcity issue with the hyperspectral image classification. As only a few thousands of pixels are available for training, it is difficult to effectively learn high-capacity Convolutional Neural Networks (CNNs). To cope with this problem, we propose a novel cross-domain CNN containing the shared parameters which can co-learn across multiple hyperspectral datasets. The network also contains the non-shared portions designed to handle the dataset-specific spectral characteristics and the associated classification tasks. Our approach is the first attempt to learn a CNN for multiple hyperspectral datasets, in an end-to-end fashion. Moreover, we have experimentally shown that the proposed network trained on three of the widely used datasets outperform all the baseline networks which are trained on single dataset.

Index Terms— Hyperspectral image classification, Convolutional Neural Network (CNN), shared network, cross-domain, domain adaptation

1. INTRODUCTION

The introduction of convolutional neural network (CNN) has brought forth unprecedented performance increase for classification problems in many different domains including RGB, RGBD, and hyperspectral images. [1, 2, 3, 4] Such performance increase was made possible due to the ability of CNN being able to learn and express the deep and wide connection between the input and the output using a huge number of parameters. In order to learn such a huge set of parameters, having a large scale dataset has become a significant requirement. When the size of the given dataset is insufficient to learn a network, one may consider using a larger external dataset to better learn the large set of parameters. For instance, Girshick et al. [2] introduced a domain adaptation approach where the network is trained on a large scale source domain (ImageNet dataset) and then finetuned on a target domain (object detection dataset).

When applying CNN to hyperspectral image classification problem, we also face the similar issue as there are no large scale hyperspectral dataset available. A typical hyperspectral image classification data only contains between 10k and 100k pixels where very small portion of those pixels are being used for training. In order to tackle such data scarcity issue, we need a way to make use of multiple hyperspectral dataset (domain).

There are several challenges that arise when devising an approach which can be applied to multiple hyperspectral domains. First of all, all the hyperspectral datasets contain different wavelength range and spectral reflectance bands. Furthermore, applying a domain adaptation approach [2] is infeasible as a large scale auxiliary dataset for the hyperspectral image classification is not available.

Therefore, we have developed a novel cross-domain CNN architecture which simultaneously performs network learning and classification on multiple hyperspectral datasets. The architecture consists of three components: dataset-specific hyperspectral analysis layers, shared convolutional layers, and dataset-specific classification layers. In the front-end portion, “dataset-specific hyperspectral analysis layers” are present to analyze the spatial-spectral information. The back-
end is built with the “dataset-specific classification layers” which performs the classification for different datasets. These two components are connected by the “shared convolutional layers” which learns the common information across the domains. All three components are being optimized in an end-to-end fashion. The information acquired from multiple datasets is fed through the layers concurrently during training, which leads to the better learning of the shared convolutional layers via dataset augmentation. The overall CNN architecture is depicted in Figure 1.

In this paper, we have used the three mostly used hyperspectral datasets (Indian Pines, Salinas, and University of Pavia) to demonstrate the effectiveness of having a cross-domain CNN. The experimental results show that our novel architecture outperforms the baseline networks (i.e., only one dataset used to train the network) by about 1.5% to 3% consistently in terms of classification accuracy.

The contributions of our approach are listed as below.

1. First attempt to learn a CNN with multiple hyperspectral datasets.
2. A novel cross-domain CNN optimized in an end-to-end fashion.
3. Consistent classification accuracy increase on all datasets.

2. THE PROPOSED METHOD

Figure 2 shows the proposed cross-domain CNN architecture.

**Backbone CNN architecture.** For each dataset-specific stream in the proposed architecture, we have used the modified version of the 9-layered hyperspectral image classification CNN introduced by Lee and Kwon [4]. The modification has been carried out by adding a batch normalization (BN) layer after each convolutional layer while removing all the local response normalization layers. By introducing the BN layers, we can bypass the process of data normalization for both training and testing.

The backbone CNN contains the sequentially connected multi-scale filter bank, one convolutional layer, two residual modules and three convolutional layers. Each multi-scale filter bank [5] consists of $1 \times 1$, $3 \times 3$, and $5 \times 5$ filters to analyze the spatial-spectral characteristics. Each residual module [3] includes two convolutional layers.

**Cross-domain CNN architecture.** The multi-scale filter bank in each dataset-specific stream, which is responsible for analyzing the spatial-spectral characteristics, is assigned as the “dataset-specific hyperspectral analysis layers”. The last three convolutional layers function as the “dataset-specific classification layers”. The remaining layers in the middle of the architecture which consist of the second convolutional layer and two residual modules are assigned as the cross-domain “shared convolution layers”.

### 3. EVALUATION

**Evaluation Settings.** We have used three hyperspectral datasets (Indian Pines, Salinas, and University of Pavia) for the experiments. The Indian Pines dataset includes $145 \times 145$ pixels and 220 spectral reflectance bands which cover the range from 0.4 to 2.5 $\mu$m with a spatial resolution of 20 m. The Indian Pines dataset has 16 classes but only 8 classes with relatively large numbers of samples are used. The Salinas dataset contains 16 classes with $512 \times 217$ pixels and 224 spectral bands and a high spatial resolution of 3.7 m. Salinas dataset shares the frequency characteristics with the Indian Pines dataset as the same sensor (AVIRIS) was used for the data acquisition. The University of Pavia dataset provides 9 classes and $610 \times 340$ pixels with 103 spectral bands which cover the spectral range from 0.43 to 0.86 $\mu$m with a spatial...
Table 1: Selected classes for evaluation and the numbers of training and test samples.

(a) Indian Pines

| Class            | Training | Test  |
|------------------|----------|-------|
| Corn-notill      | 200      | 1228  |
| Corn-mintill     | 200      | 630   |
| Grass-pasture    | 200      | 283   |
| Hay-windrowed    | 200      | 278   |
| Soybean-notill   | 200      | 772   |
| Soybean-mintill  | 200      | 2255  |
| Soybean-clean    | 200      | 393   |
| Woods            | 200      | 1065  |
| **Total**        | **1600** | **6904** |

(b) Salinas

| Class                             | Training | Test  |
|-----------------------------------|----------|-------|
| Broccoli green weeds 1            | 200      | 1809  |
| Broccoli green weeds 2            | 200      | 3526  |
| Fallow                           | 200      | 1776  |
| Fallow rough plow                 | 200      | 1194  |
| Fallow smooth                     | 200      | 2478  |
| Stubble                           | 200      | 3759  |
| Celery                            | 200      | 3379  |
| Grapes untrained                  | 200      | 11071 |
| Soil vineyard develop             | 200      | 6003  |
| Corn senesced green weeds         | 200      | 3078  |
| Lettuce romaines, 4 wk            | 200      | 868   |
| Lettuce romaines, 5 wk            | 200      | 1727  |
| Lettuce romaines, 6 wk            | 200      | 716   |
| Lettuce romaines, 7 wk            | 200      | 870   |
| Vineyard untrained                | 200      | 7068  |
| Vineyard vertical trellis         | 200      | 1607  |
| **Total**                         | **3200** | **50929** |

(c) University of Pavia

| Class            | Training | Test  |
|------------------|----------|-------|
| Asphalt          | 200      | 6431  |
| Meadows          | 200      | 18449 |
| Gravel           | 200      | 1899  |
| Trees            | 200      | 2864  |
| Sheets           | 200      | 1145  |
| Bare soils       | 200      | 4829  |
| Bitumen          | 200      | 1130  |
| Bricks           | 200      | 2482  |
| Shadows          | 200      | 747   |
| **Total**        | **1800** | **40976** |

Table 2: Classification accuracy.

| Dataset          | Individual CNN | Cross-Domain CNN | Gain |
|------------------|----------------|------------------|------|
| Indian Pines     | .907           | .922             | +.015|
| Salinas          | .893           | .908             | +.015|
| University of Pavia | .921    | .953             | +.032|

Class resolution of 1.3 m. For the Salinas dataset and the University of Pavia dataset, we use all classes because both datasets do not contain classes with a relatively small number of samples. Each dataset has been randomly partitioned into train and test sets according to Table 1.

Classification Accuracy. As shown in Table 2, the proposed cross-domain CNN outperforms the individual networks on the Indian Pines, Salinas, and University of Pavia by 1.5%, 1.5%, and 3.2%, respectively. Note that the individual networks have been trained without the shared portion of the network.

4. CONCLUSION

In this paper, we have introduced a novel cross-domain CNN which can concurrently learn and perform the hyperspectral image classification for multiple datasets. As the shared portion of our network is being trained using multiple hyperspectral datasets, the proposed approach is more effective in optimizing the high capacity CNN than the cases where only a single dataset (domain) is being used. Our approach is the first attempt to exploit multiple hyperspectral datasets for training a CNN in an end-to-end fashion. We have experimentally demonstrated that using the shared layers across the domains brings notable classification accuracy improvements when compared to the individually trained cases.

5. REFERENCES

[1] Saurabh Gupta, Ross Girshick, Pablo Arbeláez, and Jitendra Malik, “Learning rich features from RGB-D images for object detection and segmentation,” in ECCV, 2014.

[2] Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik, “Region-based convolutional networks for accurate object detection and segmentation,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 38, no. 1, pp. 142–158, 2016.

[3] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, “Deep residual learning for image recognition,” in CVPR, 2016.

[4] Hyungtae Lee and Heesung Kwon, “Contextual deep CNN based hyperspectral classification,” in IGARSS, 2016.

[5] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich, “Going deeper with convolutions,” in CVPR, 2015.