SPECTRAL-SPATIAL HYPERSONSPECTRAL IMAGE CLASSIFICATION VIA
BOUNDARY-ADAPTIVE DEEP LEARNING

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ABSTRACT

Deep learning based hyperspectral image (HSI) classification have recently shown promising performance. However, complex network architecture, tedious training process and effective utilization of spatial/contextual information in deep network limits the application and performance of deep learning. In this paper, for an effective spectral-spatial feature extraction, an improved deep network, spatial adaptive network (SANet) approach is proposed which exploits spatial contextual information and spectral characteristics to construct a more simplified deep network which leads to more powerful feature representation for effective HSI classification. SANet is established from the simple structure of a principal component analysis network. First spatial structural information is extracted and combined with informative spectral channels followed by an object-level classification using SANet based decision fusion approach. It integrates spatial-contextual outcome and spectral characteristics into a SANet framework for robust spectral-spatial HSI classification. Integration of local structural regularity and spectral similarity into simplified deep SANet has significant effect on the classification performance. Experimental results on popular standard HSI datasets reveal that proposed SANet technique produce better classification results than existing well known techniques.

1. INTRODUCTION

Hyperspectral image (HSI) classification is one of the most vital and primary task in remote sensing image analysis. Significant improvements in spectral and spatial resolution of the Remote sensing sensors has further broaden the scope and application. Some of the application includes underground mineral discovery, farming, city planning, environmental management, and surveillance. However, besides this exceptional level of spectral-spatial detail has opened doors for numerous new applications, it also resulted in shifting HSI classification problem to a more challenging level, as captured images now cover extremely complex spatial structures and inter-pixel mixed spectral relations, making HSI classification a challenging task. This situation has motivated the researcher to develop several spectral-spatial classification techniques in the last decade by utilizing the different classifiers [7] and exploiting the spectral-spatial information [17][10].

Recently deep learning based architectures have shown promising performance in HSI classification [16] after being applied successfully in Artificial intelligence [5]. Deep learning extracts more abstract and deep features through a layered training process and exploit the structure by minimizing the mean-square error of all the samples from different classes hence results into improved performance. Stacked auto encoder and its variations [3][6][15] are proposed to learn the deep features. Another improved framework based on deep belief network (DBN) and its variations [4] are proposed which shows improved performance. Another type of deep learning algorithm, convolutional neural networks (CNN) for HSI classification are also presented in [11]. However, complex connections of different layers in deep architecture demands to train several parameters in the presence of limited training data which is not desirable as training data is the main limitation in HSI. Moreover, training process is a time consuming process in in deep learning. Furthermore, these architectures are unable to exploit the spatial contextual information along with the spectral features. In recent studies it has been demonstrated that incorporation of spatial information plays a vital role in the classification accuracy [6].

This paper presents a deep learning based spatial-adaptive network (SANet) that exploits the spatial and spectral features with limited training data for effective HSI classification. Proposed technique is rooted from principal component analysis (PCA) network (PCANet) [2] which is a simpler network that has demonstrated its effectiveness in traditional RGB images [2]. Paper involves following three keys concepts: First, Hyper-segmentation based adaptive boundary adjustment technique is employed [14] to group the pixel with similar spatial contextual features; Second, high dimensionality issue is addressed by incorporating a feature selection technique [13]; Third, resulted spatial and spectral features are exploited through multi-layer based PCANet which results into
improved HSI classification performance. Remaining paper is organized as follows. Section 2 describes the detailed description of the proposed Spatial-adaptive PCANet (SANet) classification technique. Experimental results are presented in section 3 while conclusion is drawn in section 4.

2. SANET BASED HSI CLASSIFICATION

In general, SANet based HSI classification consists of two parallel phases. In the first phase, to reduce the complexity, feature selection approach is utilized to extract the most informative and discriminative bands. In order to extract the spatial features, adaptive boundary adjustment based hyper-segmentation is applied and the resulted segments are vectorized and fused with spectral signature. In the second phase, resulted spectral and spatial information is fed to PCANet for effective deep feature extraction and support vector machines is used to obtain the final classification results. Detailed process is described in Fig 1. Next section briefly describes PCANet and then we explain how we have modified it to work for HSI feature extraction. Finally, extracted spatial contextual information and spectral features are combined before feeding them to PCANet for improved HSI classification performance.

2.1. Spatial Feature Extraction through Adaptive Hyper-segmentation

Feature extraction procedure should consider two important aspects: 1) There is a high probability that pixels which are closer in feature space may share the same class 2) There is a high probability that pixels which are closer in spatial space may share the same class. By considering these facts, we have improved PCANet for discriminative spectral-spatial feature extraction. PCANet considers every pixel independently without considering its relationship with neighbouring pixels. We improve this limitation of PCANet by providing it with the spatially similar group of pixels which have a strong relationship in spatial domain through effective hyper-segmentation.

Target of the hyper-segmentation is to group the pixels with similar spatial characteristics in the neighbouring region. Size and shape of each segment can be adaptively modified till the actual structural boundary is encountered. Moreover, the resulted segments have the spectral and spatial consistency as required by the above mentioned facts. HSI image is segmented initially into $N$ segments each of size $R$ on a grid of size $S$ and centre of each segment is defined by taking the mean of the segment. Then major dominant spatial feature in each segment is computed along with the gradient value of each segments’ boundary pixel and straightness factor. Similarity measure is evaluated based on the following energy function and boundary of each segment is evolved based on the similarity measure value. This process is repeated till no pixel changes its segment.

$$A(p, g_i) = \sqrt{|x_p - g_i|^2 + \lambda \tilde{n}_i(p)|Grad(p)|} \quad (1)$$

The detailed process can be found in [14]. Band selection approach [13] is applied first in which most informative bands with discriminative information are kept.
2.2. SANet based Spectral-Spatial classification Network

2.2.1. PCANet

PCANet is recently proposed for single image classification [2]. PCANet is designed to address the complexity of CNN. Most important improvement in PCANet, in comparison with CNN is the replacement of data adopting convolution filter banks between layers with PCA filters. Hence complex optimization procedure is evaded. Moreover, binary quantization (hashing), histogram features, and linear SVM are also implemented to simplify traditional deep learning methods such as CNN. PCANet consists of three main components: PCA filters, binary hashing and histogram features. More details can be found in [2].

PCA filters are used to construct a layer-wise network. PCANet first collect all the vectorized patches of size $S_1 \times S_2$ around each pixel of input image $I$ to form a matrix $Y$. The same matrix for each image is collected and then combined:

$$Y = [y_1, y_2, ... y_N]$$

where $N$ is the number of images. The error can be minimized through:

$$\arg \min_{V \in R(s_1 \times s_2) \times M_1} [Y - VV^TY]_F^2, s.t. V^TV = E_{M_1}$$

where $E$ is an identity matrix with size $M_1 \times M_1$, $V$ are the principal eigen vectors of $YY^T$, and $M_1$ denotes the number of principal eigen vectors. Filter can be expressed as:

$$W_m^{1} = \text{mat}(s_{1}s_{2}) (q_{m}(YY^T)) m = 1, 2, ..., M_1$$

Where $M_1$ is the number of filters in a first layer and $\text{mat}(.)$ converts a vector into a matrix. The first PCANet layer can be acquired as:

$$I_m^i = I_i \ast W_m^{1}, i = 1, 2, ..., N.$$  

Similarly, second layer of PCANet can be acquired using the same process. The PCANet would output $M_1M_2$ images number of filters in the second layer are $M_2$. Aforementioned process can be repeated to build a multi-layer PCA network. It is suggested by the authors that four layers i.e., one input layer, two convolution layers and one output layer are enough for most tasks.

Binary quantization is performed after establishing a network. Each of the $M_1$ image is divided into many blocks and histogram of each block is computed. Resulted histograms are stacked into a vector. This vector is the resulted feature expression.

2.2.2. Spectral-Spatial Classification

PCANet is an image classification approach. To modify the network, the spectral-spatial information which is concatenated in the previous step into a vector is first reshaped into a 2-D image through data imaging process. Let $Z_i$ shows the final concatenated spectral-spatial vector the imaging form of $Z$ can be represented as:

$$z_i \text{ reshape } Z_i^{Spec}$$

Finally in order to classify the resulted features, SVM classifier is employed.

3. EXPERIMENTAL ANALYSIS AND PERFORMANCE COMPARISONS

In order to demonstrate the classification performance of the proposed technique, it was evaluated on two well know standard and diverse real hyperspectral images captured by two different sensors namely, Indian Pine and Pavia University datasets. There selection is supported by the fact that most of the existing techniques have evaluated there techniques on these datasets [9]. Both the datasets propose challenging classification due to presence of both rural and urban areas as well as small man made and natural structures. Brief description of each dataset is given in the next section.

3.1. Dataset Description

3.1.1. Indian Pine: AVIRIS dataset

Indian Pine data set was acquired by Airborne Visible Infrared Imaging Spectrometer sensor over the Northwestern Indiana. It consists of spatial size of $145 \times 145$ with a ground resolution of 17m. Out of total 224 bands, 24 water absorption bands near 1400 and 1900 nm are removed resulting
3.1.2. Pavia University: ROSIS dataset

Pavia University dataset was collected by Reflective Optics System Imaging Spectrometer sensor over the University of Pavia, Italy. It consists of spatial size of $610 \times 340$ and 103 spectral channels. It comprises of 9 land cover classes. Mostly, it includes man made structures. False color composition and ground truth is shown in Fig 3.

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*Overall Accuracy* 84.18 88.63 86.85 91.48
*Average Accuracy* 80.08 85.26 89.95 93.09
*Kappa Coefficient* 0.6852 0.7366 0.8495 0.9075

### 3.2. Parameter Setting

Labeled data for each class is randomly distributed into training and testing data in the ratio 1:9 for fair comparison. Moreover, the defaults PCANet network parameters setting [2] are adopted by SA Net i.e., one input layer, one output layer, two
convolution layers with patch size of $7 \times 7$, and overlap ratio of 0.8. Small changes in the parameter values don’t have much influence on the classification results as narrated by [2]. In order to evaluate the classification performance, following evaluation criteria is employed:

1. **Overall Accuracy (OA):** OA represents the number of HSI pixels that are correctly classified divided by the total number of test samples taken.

2. **Average Accuracy (AA):** AA calculates the mean of the classification accuracies of all classes.

3. **Kappa Coefficient:** It determines the agreement between the final classified map and the actual ground truth map. It is generally considered to be more accurate measurement as it takes into consideration the agreement occurring by chance [1].

### 3.3. Compared Techniques

As proposed technique is based on deep learning based architecture, we compare it with the existing recently proposed deep learning based HSI classification methods such as Stacked auto encoder (SAE-LR) [3], Convolution neural network (CNN) [8] and Recurrent neural network (RNN) [12].

### 3.4. SANet based Spectral-Spatial Classification Results

In this section, we investigate the effectiveness of proposed SANet for hyperspectral image feature extraction and classification. Tables 1 and 2 indicates that the SANet-based feature extraction approach always delivers the best performances of OA, AA, and Kappa for two data sets. In order to have a fair comparison, we utilized 10% of the training samples to find the best parameters of feature extraction methods.

In Pavia University dataset, SAE-LR and SANet method have shown close results, and the SANet outperforms SAE-LR slightly because the number of training samples in Pavia dataset is comparatively large. That shows more training data would result in to better performance. Indian Pine dataset is considered a challenging dataset due to its low spatial resolution ad presence of mixed pixels. Quantitative results of each class for Indian Pine along with other techniques are shown in Table 1. As can be seen from the table, proposed spectral spatial feature extraction technique has a significant effect on the classification accuracy’s of each class. Hence it also outperforms other techniques in OA, AA and $k$. Visual classification result for each class for Indian Pine and Pavia University are shown in Fig 4. Although some faults are still detected, the overall performance of SANet is good.

### 4. CONCLUSION

In this paper, We have introduced a new simplified deep learning SANet approach for HSI classification by analyzing a state-of-the-art deep learning model and addressing its concerns by construction. Despite its outstanding learning capability, complex layered architecture and overlooking the spatial information limit the capability of deep learning in remote sensing context. We therefore proposed SANet, a simplified deep network based architecture that replaces inner-layer convolution filter banks with PCA filters hence reduces the complexity by avoiding the optimizing process. Moreover, spatial information is exploited through hyper-segmentation and integrated with spectral characteristics. SANet then utilizes the multi-layer deep learning network to effectively exploit the hyper-segmentation based spatial features and selected spectral features within and among segmented regions. Experimental results on two real and challenging datasets reveals an improved classification performance specially in small structural regions. One of the future track is to reduce the training samples and further improving the performance.

### 5. ACKNOWLEDGMENT

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### 6. REFERENCES


