Classification of Hyperspectral Images using a fusion of Spectral and Spatial Features

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Abstract

The high dimensional attribute of Hyperspectral Imaging (HSI) allows for high performance detection of objects or materials in a variety of fields, such as within remote sensing. The large range of spectra within each pixels of the image is used within classification to predict the presence of certain materials as those materials exhibit unique spectral characteristics. Traditional HSI classification methods utilized only the spectral characteristics of the image as the features. More recently, researchers have proposed the use of spatial-spectral features for classification that incorporate spatial characteristics for classification of multiple objects and material within an image. However, some of these advanced methods suffer from issues such as the curse of high dimensionality and or even overfitting. This paper explores the various papers that propose spatial-spectral features as part of their classification methods. Additionally, the paper implements and compares the performance of a two spatial-spectral HSI classification methods. The results of this comparison in terms of performance and metrics is discussed within the paper below.

1 Introduction

HYPERSPECTRAL IMAGING (HSI) is an computer vision modality that combines standard 2D imaging with spectroscopy to acquire a three-dimensional hypercube [1]. Compared to the standard 2D optical images, HSI hypercubes consists of three dimensions; two spatial, and one spectral. This spectral dimension consists of vectors that represent the spectral response of each pixel. Compared to multispectral imaging, such as RGB color cameras, hyperspectral images provides information from a wide range of the electromagnetic spectrum (typically from Ultraviolet to Infrared) [2]. HSI systems are mainly composed of a light source, wavelength dispersion devices, and area detectors. In modern hyperspectral image acquisition systems, the light from target surfaces are reflected into a set of lenses and dispersion elements which collimate and distribute the light into several wavelengths. The distributed light is then captured by 2D detector arrays which discretize and quantify the spectral information into hypercubes [3].

One of the traditional applications of HSI is for geospatial mapping and mineral identification. Sophisticated spectrometers are fit onto high-altitude aircrafts which fly over land regions of interest, and acquire hyperspectral images for geospatial analysis. More recently, HSI also been used in other applications such as for medical image diagnosis.

One of the key advantages of hyperspectral imaging is that it provides an ability to identify and characterize the chemical composition of objects in an image using their spectral responses. Certain materials reflect different wavelengths of light different and exhibit unique spectral reflectance curves which can be used to identify them and quantify their abundance within an image. This property of HSI makes it ideal for image classification purposes. The goal of Hyperspectral Image Classification is to accurately characterize the material composition of pixels within hyperspectral images and assign them a class label. This characterization can be used to build classification maps that indicate where certain constituents are present within the scene [2]. Although spectral features can be used to segment materials with good accuracy, materials are often misclassified due to the spectral similarity with another material in the same image. Additionally, analysing the spectra of each pixel can get computationally complex. The inclusion of spatial segmentation in the classification process based on the 2D image of the scene can allow for more accurate and efficient classification of materials that are clustered together [4].

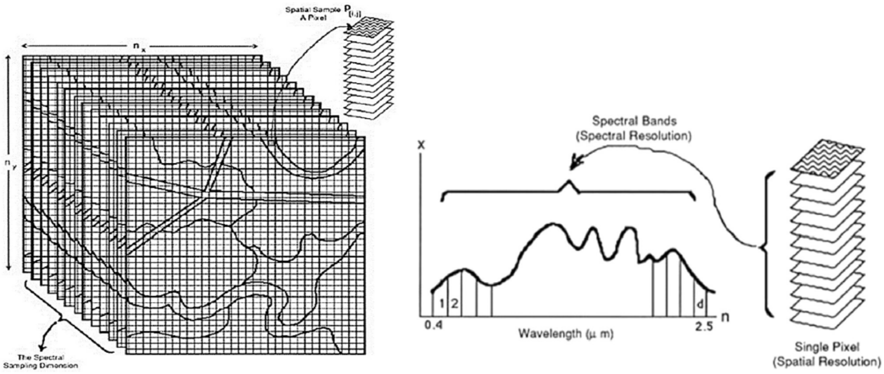

Figure 1: Breakdown of a Hyperspectral Image []

The idea behind incorporating spatial features in HSI classification is that neighboring pixels in an image that have similar or the same spectral characteristics have a high probability of belonging to the same class or type of material. Extracting spatial features that represent the shape and texture of materials or objects within the image can allow for the inclusion of valuable contextual information during the classification or prediction process.

There are various ways spatial features can be fused with that of spectral features. Fusion of spatial and spectral features in the recent literature can be generalized into two categories; preprocessing-based, and postprocessing-based.

1.1 Preprocessing-based Fusion

Typically, an HSI image classifier model consists of preprocessing the image first to clean the image of noise and extract meaningful features, the the image is fed to a classifier for classification. Preprocessing-based fusion relies on the extraction of spatial features prior to the classification stage. Specifically, spatial features that represent the morphology of objects in the image are first acquired using spatial filtering and feature extraction methods. The classification process for this method can be divided into phases; 1) spatial and spectral feature extraction from HSI, and 2) classification of such features using standard classifiers such as support vector machines (SVM). The first phase of this process is key as that is where the fusion of features is done.

1.2 Postprocessing-based Fusion

Similar to Preprocessing-based fusion methods, postprocessing-based methods have two phases. However, rather than fusing features prior to classification, the fusion is done after the classification stage. Specifically, the spectral features is used to perform pixel-wise classification of the entire image. Then the resulting output is regularized using spatial filters to obtain a spectral-spatial classification output. This way, spatial features are fused with output of the spectral classification stage rather than fusing the spatial and spectral features directly. Recent work has looked into utilizing multiple classifiers from both the spectral and spatial features such that the output of each can then be fused using a decision process.

2 Literature Survey

The advancement in the field of HSI classification has showed the fusion of spatial and spectral features can be done in various ways. One of such is feature stacking, where the spatial and spectral features are extracted independently. Principal component analysis (PCA) can be used to extract the principal components of the HS image. Then, features for each principle component are extracted and stacked into a feature vector which is then fed into a classifier to obtain a classification map. Spectral features are extracted using algorithms such as PCA and Linear Discriminant Analysis, whereas spatial feature can be extracted using gabor filters, attribute filters, and other morphological feature extraction methods. In [], Mura et al. employ such a method by incorporating attribute filters (AFs) to extract attribute profiles (APs) that contain contextual spatial features. The attribute profiles are obtained using the following equation, where γ refers to the thinning filter and φ refers to the thickening filter applied to the morphological attributes:

$$AP_{a_k}(y_j) = \{\varphi_n(y_j), \ldots, \varphi_1(y_j), y_j, \gamma_n(y_j), \ldots, \gamma_1(y_j)\};$$
$$j = 1, 2, \ldots, m; k = 1, 2, \ldots, s$$

The APs are then concatenated together to obtain Extended APs (EAPs). Finally the a extended vector consisting of all the EAPs, or EMAP, is constructed by concatenating all the EAPs:

$$EMAP(x) = \left\{ EAP_{a_1}(x), EAP_{a_2}(x), \ldots, EAP_{a_s}(x) \right\}$$

The EMAP feature are stacked on the spectral feature set and then fed into a Multinomial Linear Regression classifier. Although this method is simple in nature, it suffers from the exclusion of hidden contextual information present within joint spectral and spatial features. Additionally, stacking both the spectral features of each pixels and the spatial features of an entire image can lead to a feature-set of high dimension and result in computational complexity.

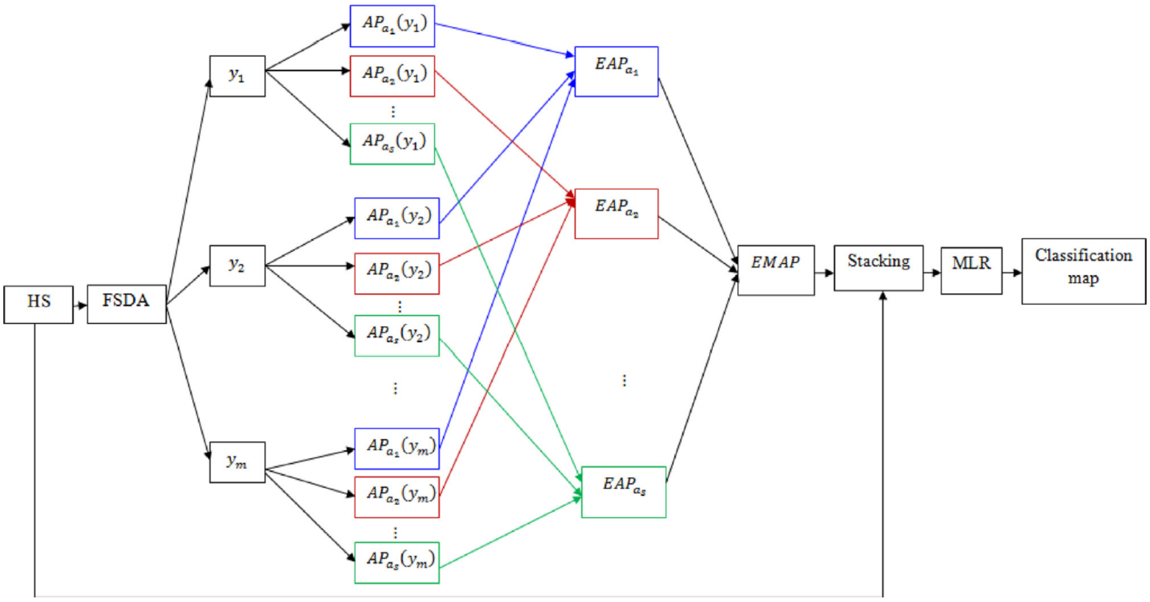

Figure 2: Example of feature stacking method using EMAPs []

Kernel-based relaxation classifiers are another elegant way of incorporating spatial features using postprocessing filters. Kernel composites allows the mapping of non-linear features into a higher dimensional space where the data is linearly separable. Shambulinga et al. present a kernel-based spatial-spectral classification method that exploits the structural and texture properties of objects within images using a Guided Image Filter. The Guided Image Filter is an edge-preserving filter that enhances and denoises the image while maintaining the edges of objects within an image. The method consists of first reducing the dimensions of the feature vector of the HSI using PCA. Then, the reduced feature set is fed into an SVM classifier to generate a classification map based on spectral characteristics. Finally, the Guide Image Filter is applied onto the classification map by using the first component of PCA as the guided image. Although this method removes spatial irregularities of the classification map, it disregards the accuracy of regression in the spectral domain and may not be ideal of applications where certain objects can be encompassed by others.

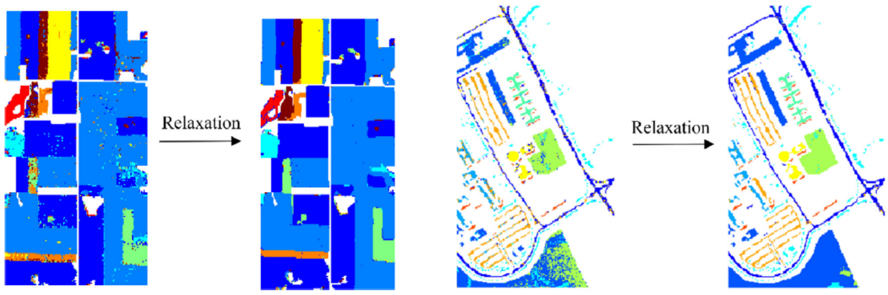

Figure 3: Examples of classification map relaxation

The use of Sparse Representation methods, such as dictionary learning and compressive sensing, has been started to become prevalent in spatio-spectral classification. The idea behind using sparse representation for classification stems with the fact that HSI pixels that belong to the same class can be represented by a few training samples, or atoms, from the same class. Atoms from different classes are compiled within a training dictionary that is then used for classifying test pixels [10].To further enhance the performance of sparse-based classifiers, Chen et al. [11] proposed the use of a Joint Sparse Representation Model (JSRM) for classification that combines sparse modelling with the concept of exploiting spatio-spectral contextual information that was discussed above. According to experimental results, JSRM has shown far better performance in classifying HS images compared to pixel-wise methods.The procedure for such classification consists of first defining a fixed-size local region for each test pixel and grouping neighbouring pixels within regions of similar pixels. Pixels within these regions are then represented by common atoms within the sparse dictionary. Finally, the sparse dictionary is used for building a classifier model that is used to assign labels to test pixels [11]

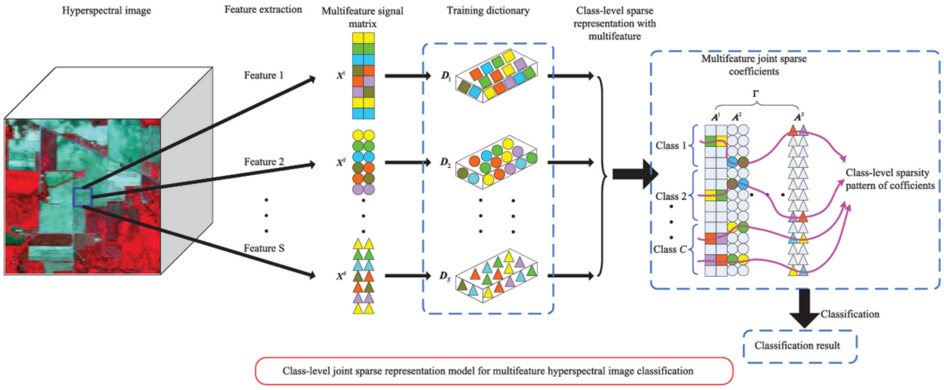

Figure 4: The Joint Spatial Representation Model Process []

In addition to feature stacking, and morphological feature fusion, there exists segmentation-based methods that apply segmentation algorithms onto HSI for extracting segments based on object detection. One of the earliest works that employed such a method was by Ghassemian et al. who proposed the segmentation of objects within HSI using their gradient vectors of image pixels. Then, segmented objects are classified based on their spectral characteristics as represented by the object feature vector. Classifying the detected object rather than pixels removed data redundancy and simplifies the computation. However, the disadvantage of this method is that spectral information of pixels that are spatially independent are disregarded within the classification process.

3 Experiment

To explore the impact of incorporating spatial feature using fusion within HSI classification, this paper implements spectral and spatial-spectral methods through experimentation and discussed their performance based on the results.

One of the method implemented is that proposed by Han et al [5], which employs a semisupervised learing method for classification based on Spatial Majority Voting. The idea is based on the assumption that a pixel belongs to the same class as the majority of pixels within a spatial window. This method would roughly represent postprocessing classifiers within this experiment. Data is reduced using PCA on the spectral bands and then is fed into an SVM classifier. The resulting classification map is filtered using the spatial majority voting filter and classication metrics are computed.

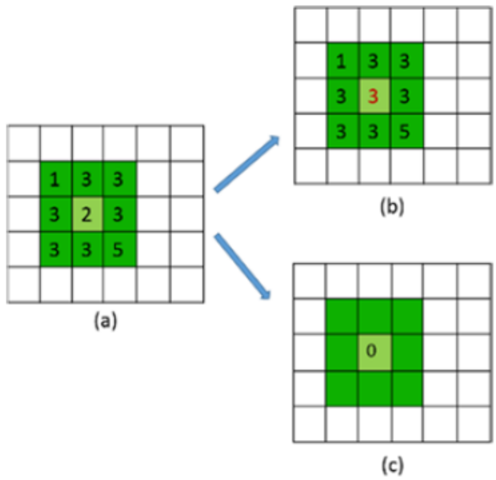

Figure 5: Spatial Majority Voting a) 3x3 Majority Filter; b) center pixel changes to most frequent value; c) confidence level of value

Another spatial-spectral fusion method implemented was that of Kang et al. who proposed the use of Edge-Preserving Filters within the classification process [6]. Edge-preserving features provide good characterization of spectral features within the object while preserving the significant spatial features within the feature vector. Their method advances on this idea by proposing a PCA-based EPFs method that applies the dimensionality reduction PCA algorithm on stacked EPFs prior to classification. This way, the spectral complexity of the data is reduced while highlighting the separability of the pixels within the EPFs. This method would roughly represent preprocessing classifiers within this experiment. EPFs are extracted using the EPFs algorithm which are then reduced using PCA. The reduced data is fed into an SVM classifier and the classification metrics are computed.

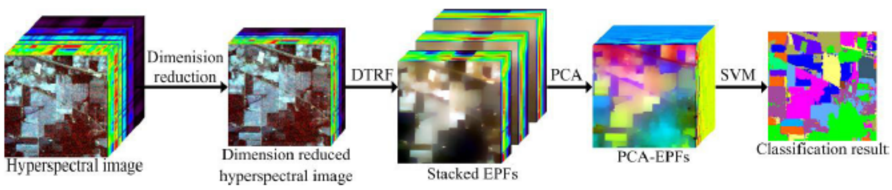

Figure 6: The outline of the PCA-based EPFs method

Implementation of the experiment is done within MATLAB with the use of image analysis and classification libraries. Evaluation of the classification is done by acquiring the overall accuracy, kappa coefficient metrics, and total time taken.

3.1 Dataset

The AVIRIS Indian Pines dataset was used as part of the experiment. It consists of an HSI image of 145 by 145 pixels and 224 different spectral bands. The scene consists of agricultural, forest, and vegetation objects with other structures such as highways, rail lines, and housing. Objects within the scene are distributed into 16 different class labels of crops such as corn and soybeans. The data is filtered by removing water absorption bands which reduced the data into 200 totals spectral bands.

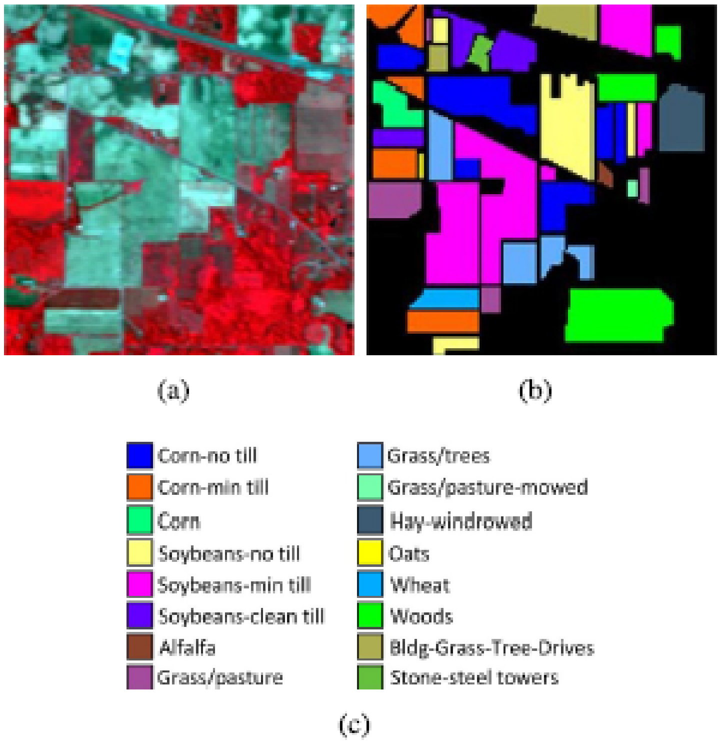

Figure 7: a) 3-band composite of Indian Pines dataset b) Ground Truth class map c) Class labels with respect to colour

3.2 Experimental Results

	Spectral-Only Classifier	SMV Classifier	PCA-Based EPFs Classifier
Overall Accuracy (%)	70.8	77.1	83.6
Kappa Coefficient	0.667	0.739	0.814
Total Time Taken (s)	2.73	4.00	25.8

Figure 8: Ground Truth Map of Indian Pine Image

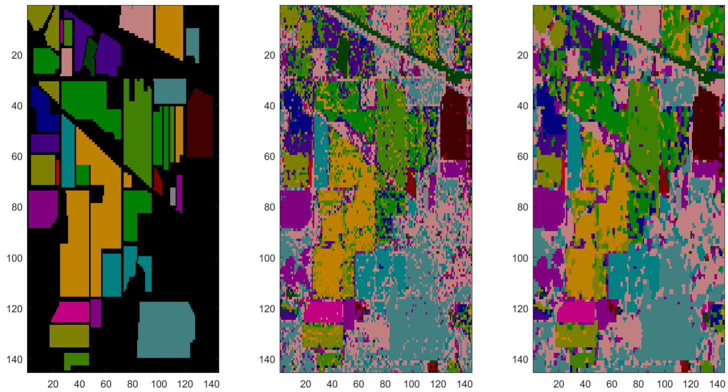

Figure 9: Classification Output of Spatial Majority Voting. The first image is the ground truth, second is the output of the spectral classifier, and third the output after spatial majority voting

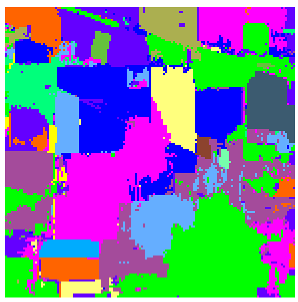

Figure 10: Classification Output of PCA-based EPFs classifier

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