FUSION OF HYPERSPECTRAL AND LIDAR DATA USING MORPHOLOGICAL COMPONENT ANALYSIS

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ABSTRACT

This paper presents a new classification framework for the fusion of hyperspectral and LiDAR data. The proposed approach aims at exploiting the complementarity of the features, i.e., textural features in the hyperspectral data and the height features in the LiDAR data, respectively. In this work, we use a morphological component analysis (MCA) method for textural feature extraction. The classification is then executed by a multinomial logistic regression classifier (MLR). Our obtained experimental results reveal that the proposed feature fusion method can lead to very good classification results.

Index Terms—Remote sensing image classification, morphological component analysis (MCA), feature fusion, LiDAR, Hyperspectral classification.

1. INTRODUCTION

In recent years, fusion of hyperspectral and LiDAR data has been a very active research line in the remote sensing community [1]. On the one hand, hyperspectral sensors provide detailed spectral information, as they record hundreds of images corresponding to different spectral channels. On the other hand, LiDAR data can provide information about height. Consequently, it has been proved that hyperspectral and LiDAR data exhibit complementary information that generally allows for more accurate classification results.

In the literature, several techniques have been specifically developed for complementary exploitation of hyperspectral and LiDAR data for classification purposes. For instance, the methodology in [2] jointly considered the features extracted by morphological attribute profiles [3] computed on both the hyperspectral and LiDAR data, and then concatenated the extracted features into one stacked vector. The authors used the random forest (RF) [4] and the support vector machines (SVM) [5] as nonparametric classifiers. The multinomial logistic regression (MLR) is another technique that is widely applied for hyperspectral image classification. In [6], the authors proposed a new method to integrate multiple types of features extracted from hyperspectral and LiDAR data in an MLR framework. In [7], an ensemble multiple kernel active learning framework was proposed for classification of hyperspectral and LiDAR data using a limited number of training samples. A multiple classifier system has also been proposed for fusion of hyperspectral and LiDAR data in which different classifiers are first applied and then a specific fusion method is used to combine the classification results.

In this paper, we present a new classification framework for the fusion of hyperspectral and LiDAR data. The proposed approach aims at exploiting the complementarity of the features by extracting textural features from the hyperspectral data and height features from the LiDAR data. In order to extract the textural information, we use a multiple morphological component analysis (MMCA) framework for image separation that is able to extract different kinds of textural features from the image. Hyperspectral images generally show significant contrast and intensity regions and edges, and therefore it is essential to represent each object by using multiple texture features. For the LiDAR data, we use the height feature as a complementary source of information to the ones derived from the hyperspectral data. For classification, we use a multinomial logistic regression (MLR) based classifier [8]. Specifically, we adopt an MLR-based framework [9] of generalized composite kernel machines for spectral-spatial hyperspectral image classification, which equally balances the spectral and the spatial information contained in the hyperspectral data without any weight parameters. The hyperspectral and LiDAR data used in our experiments were collected over the same area in Extremadura, Spain. Our experimental results show that the proposed approach, by means of fusing hyperspectral and LiDAR data, can lead to very good results.

2. PROPOSED METHOD

The proposed method comprises two main steps. Firstly, we use MMCA to extract the textural features from hyperspectral data set. Then, we adopt a composite kernel learning framework to combine the extracted textural features from hyperspectral data with the ones from the LiDAR data.
2.1. MMCA

For a given image \( y \) with \( N \) pixels, the objective of MMCA is to separate it into two components: a smoothness component \( y_s \) and a texture component \( y_t \), respectively. These components represent the original image under a linear combination as follows:

\[
y = y_s + y_t + n,
\]

where \( n \) is the residual in the approximation of the image.

In general, the MMCA framework includes three main steps. In the first step, we randomly choose several partitions from image \( y \) for the initialization of the two dictionaries. In the second step, for the two components (i.e., the smoothness \( y_s \) and its texture \( y_t \)) we build two corresponding dictionaries based on certain transformations on the chosen image partitions. Finally, in the last step, sparse coding is performed to learn the MC coefficients. At the same time, following [10], the associated dictionaries are iteratively updated by adopting total variation and hard threshold regularization. After separation, it is observable that different textural features lead to specific components. Following our previous work [11], we use the following features.

- **Content feature.** This feature represents the traditional texture feature used for MCA decomposition, resulting in the standard cartoon and texture MCs. Following [10], for the content component we use a local curvelet transform to generate the dictionary from the randomly chosen image partitions. For the texture component, a local Gabor wavelet transform (GWT) is adopted to build the dictionary from the same image partitions.

- **Coarseness feature.** This is a relevant textural feature in an image. As the bilateral filter is a non-linear, edge-preserving and noise-reducing smoothing filter for images [12], we use it to build a coarseness dictionary.

- **Contrast feature.** This feature measures the variance of the grey scale distribution, where high and low contrast means fast and slow intensity changes. In this work, we adopt the anisotropic diffusion (AD) [13] and its modification to build high contrast and low contrast dictionaries.

- **Directionality feature.** This is a global property which describes the orientation of the local texture. In this work, two directional features, i.e., horizontal and vertical, are considered. Again, for each feature, two dictionaries, one for the smoothness component and another one for the texture component, are constructed. Here, we use wavelet thresholding filter based on the stationary wavelet transform (SWT) [14] to build the dictionaries.

2.2. Composite kernel learning

Following [9], we use the generalized composite kernel (GCK) method to integrate multiple types of features extracted from hyperspectral and LiDAR data. The proposed method is based on combining the MLR algorithm and multiple features, without any regularization parameter. This provides a flexible scheme for multiple feature fusion.

3. EXPERIMENTAL RESULTS

The considered data sets were collected over the same area in Extremadura, Spain. The data is available online\(^1\). The hyperspectral data set is collected by a CASI 1500i Sensor operated by Instituto Nacional de Técnica Aeroespacial (INTA) with the size of samples is 300 x 497 and the number of spectral bands is 144, which is covered the visible and near infra-red regions between 0.4 and 2.5 microns. Fig. 1(a) shows the three-band false color image of the Extremadura area, while Fig. 1(c) shows the ground-truth map available for the study area, displayed in the form of a class assignment for each labeled pixel, with 6 mutually exclusive ground-truth classes comprising, in total 12103 samples. In order to add the LiDAR information to the hyperspectral data cube, we converted the LiDAR data into a raster format, finally the obtained LiDAR data contains the same resolution as the hyperspectral data, and presents only a single value per pixel which was calculated as the highest value of all sets of values whose coordinates coincided with the one of the pixel under test. Fig. 1(b) shows the LiDAR intensity image.

3.1. Experimental setting

In order to evaluate the classification capacity of the extracted features, we use the MLR classifier (implemented via the LORSAL algorithm [8]), which has been shown to be effective with limited training samples. In our experiments, we use the Gaussian Radial Basis Function (RBF) kernel [15]. It should be noted that, in our experiments, the overall accuracies (OAs), individual classification accuracies, and \( \kappa \) statistics, along with the standard deviations, are obtained from ten conducted Monte Carlo runs and the average classification accuracies are reported.

- In order to simplify the computational procedure, we use the minimum noise fraction (MNF) [16] to reduce the dimensionality of the input data, retaining 99% of the spectral information in the original data, and then perform MMCA feature extraction on the MNF features. Therefore, in this experiment, \( raw \) denotes the results obtained from the MNF features.

- We use \( "S_{Hi}" \) to denote the results obtained by using the MCA components, \( "S_{HiL}" \) to denote the results

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\(^1\)www.umbc.edu/rssipl/people/apalaza/HyperspectralLidarExtremadura.zip
it is hard to extract valuable attribute features by using MCA approach, for instance, the classification accuracy of class 'Alfalfa' is 98.23\%, which is better than the other method. From Table 1 we also found that class 'Buildings' has poor classification accuracy in all methods, this is because of the diversity of buildings in the study area.

4. CONCLUSIONS AND FUTURE LINES

We have developed a new technique for fusion of hyperspectral and LiDAR data. The proposed method extracts different kinds of textural features from the hyperspectral and then uses the height feature as a complementary source of information obtained from the LiDAR data. The final classification is performed by a generalized composite kernel machine to equally balance the spectral and the spatial information contained in the fused data. Our experimental results show promising results with a hyperspectral/LiDAR data set in Extremadura, Spain. Results with additional data sets will be shown in the final paper.

5. REFERENCES


Table 1. Overall (OA) [%], individual classification accuracies and $k$ [%] (along with the standard deviation after ten Monte Carlo runs) obtained after fusing the hyperspectral and LiDAR data sets using 0.5% of the samples for training and the rest for testing.

<table>
<thead>
<tr>
<th>Class</th>
<th>Samples</th>
<th>Classification Methods</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Train (61)</td>
<td>Test (12042)</td>
</tr>
<tr>
<td>Alfalfa</td>
<td>3</td>
<td>379</td>
</tr>
<tr>
<td>Soil</td>
<td>27</td>
<td>5520</td>
</tr>
<tr>
<td>Water</td>
<td>3</td>
<td>342</td>
</tr>
<tr>
<td>Pathway</td>
<td>12</td>
<td>2438</td>
</tr>
<tr>
<td>Trees</td>
<td>11</td>
<td>2138</td>
</tr>
<tr>
<td>Buildings</td>
<td>5</td>
<td>1045</td>
</tr>
</tbody>
</table>

- Average accuracy: - - 89.57±2.15 90.47±2.25 91.05±2.41 90.39±2.25 90.97±1.75
- Overall accuracy: - - 91.13±1.45 92.67±0.87 93.11±0.95 92.72±0.97 92.85±1.08
- $\kappa$ statistic: - - 87.23±2.04 89.48±1.27 90.15±1.41 89.55±1.39 89.76±1.55


