

Effect of Hyperspectral image denoising with PCA and total variation on tree species mapping using Apex Data

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Abstract: In this paper, the impact of image denoising on feature selection and tree species mapping accuracy is assessed. We apply a novel algorithm for hyperspectral (HS) image denoising using principal component analysis (PCA) and total variation (TV). The method is embedded in an object-based classification framework and tested for complex forests with closed canopies and scarce reference data. Results show that, under the given conditions, HS image denoising is beneficial yielding stable mapping results with acceptable accuracy levels. Denoising also affected feature selection processing time with a time gain of 41.6%.

Keywords: Hyperspectral data, denoising, object-based tree species classification, broadleaved forest.

1. Introduction

The development of HS remote sensing technology makes it possible to provide a large amount of spatial and spectral information for forest applications such as tree species classification and forest attributes estimation (Lucas et al., 2008; Dalponte et al., 2013; Cho et al., 2007). Despite advances in sensor technology, HS images are inevitably degraded by noise, which not only degrades the visual quality of the HS data but also limits the precision of the subsequent image interpretation and analysis (Matteoli et al., 2011; Liao et al., 2013). Therefore, it is critical to remove the noise and retain the signal component prior to subsequent image processing. Many researchers and specialists who deal with HS data classification prefer to simply remove such noisy bands from consideration (Lukin et al., 2013) using feature selection and feature reduction techniques (Borges et al., 2007). However, recent studies (Backer et al., 2008; Zhong and Wang, 2013) have indicated that denoising can lead to expedience of their further use in classification tasks (Lukin et al., 2013). We therefore suggest denoising the HS data prior to feature selection.

2. Study site and data

The study area with central point coordinates 51° 4'3.51"N – 3° 2'21.35"E is located in the forest reserve Wijnendale in the western part of Belgium. This forest reserve belongs to a 280 ha large forest area and covers approximately 66 ha. The forest is characterized by a high crown closure, non-existence of a pre-ordered spatial tree distribution, growth stage diversity and multi-layering of the canopy. Hyperspectral data was acquired in cloud-free conditions on the 21th of June 2010 with the Airborne Prism Experiment (APEX, 286 spectral bands). Radiance values were atmospherically corrected to top of canopy reflectance, based on the radiative transfer model MODTRAN4. Geometric correction was based on direct georeferencing. Field reference data were collected in 121 sample plots that are located on

alternate grid points in a systematic grid of 50 m by 50 m. One plot covers an area of 0.1 ha. Within each sample plot, tree species, diameter at breast height (DBH) and tree coordinates were recorded for all trees with DBH \geq 5 cm. In total, 1543 trees were recorded. Tree distribution in the upper canopy was 27.6 % common beech, 5.5 % copper beech, 20.6 % pedunculate oak, 4.6 % common ash, 8.2 % european larch, 28.6 % poplar and 4.6 % sweet chestnut.

3. Workflow and proposed denoising technique

In this experiment, a novel denoising technique is applied on the HS APEX image data. The goal of this work is to evaluate to what extent noise in HS data had an impact on tree species mapping. The specific site conditions were complex given the closed forest canopy and scarce reference data. We tested the effect of the HS denoising technique from the viewpoint of classification accuracy characterized by a confusion matrix. The classification was performed within an OBIA framework where trees are associated with segments consisting of collections of adjacent pixels with similar values. Compared to pixels, the resulting segments presented more realistic processing units for classification. As a classifier, we used a support vector machine (SVM). Fig. 1 shows the methodological workflow.

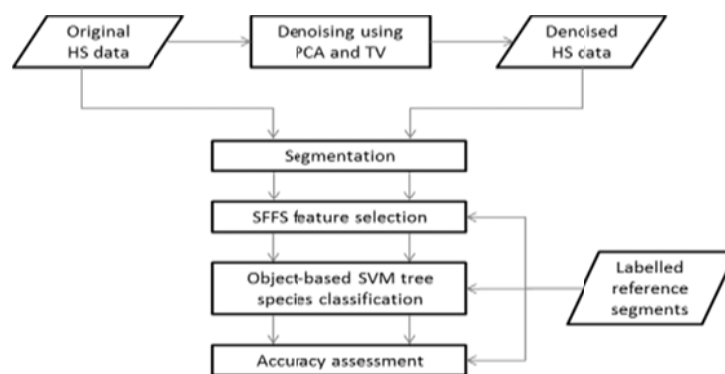


Figure 1. Methodological framework.

The novel denoising method (Liao et al., 2013) first used principal component analysis (PCA) to decorrelate the HS image bands and to separate information content from noise. The first few PCA channels contained most of the total variance (i.e. most information of the HS image), while the remaining large number of PCA channels mainly contained noise. Restoration of these noisy and high-dimensional PCA channels would cause high computational cost in processing the data, while removal of these channels would result in information loss. Therefore, we applied a fast total variation (TV) method with group sparsity to restore only the first few PCA channels. We removed the noise in the remaining PCA channels using a soft-thresholding scheme. After segmentation, Sequential Floating Forward feature Selection (SFFS) was performed selecting the most appropriate HS band subset in terms of overall accuracy, for both the original and denoised datasets. Next, object-based species mapping was performed using a multiclass SVM with Gaussian RBF kernel function. To train the classifier, only 10% of the labelled segments were used. The resulting 90% of labelled segments were applied to test the accuracy of the classifications. We applied a grid search strategy in a range between 10^{-1} and 10^3 for C, and between 10^{-2} and 10^3 for γ , and performed a tenfold cross-validation on the training data set. Accuracy

was determined using confusion matrices. The classification results are shown in terms of overall accuracy (OA), average class accuracy (AA) and Kappa. The average class accuracy is the average of the producer's accuracy of the classes analyzed.

4. Experimental results

Table 1 demonstrates the potential of the proposed method. At first glance, the impact of image denoising on species classification could be designated negligible, given only marginal increases in OA, AA and Kappa.

Table 1. General and species-specific classification accuracies using original and denoised HS datasets (average results from tenfold cross-validation).

HS image	nof bands selected (SFFS)	OA (%)	AA (%)	Kappa	Producer's accuracies (%)						
					Beech	Ash	Larch	Poplar	Copper beech	Chestnut	Oak
Original	225	69.85	60.78	60.65	71.80	28.60	76.90	89.10	92.70	12.60	53.80
Denoised	141	70.06	62.13	61.12	68.80	35.30	77.30	90.00	93.20	15.10	55.30

Table 2. standard deviation of the general classification accuracy measures.

HS image	nof bands selected (SFFS)	Stdev OA (%)	Stdev AA (%)	Stdev Kappa
Original	225	4.34	7.48	6.17
Denoised	141	1.51	2.48	1.97

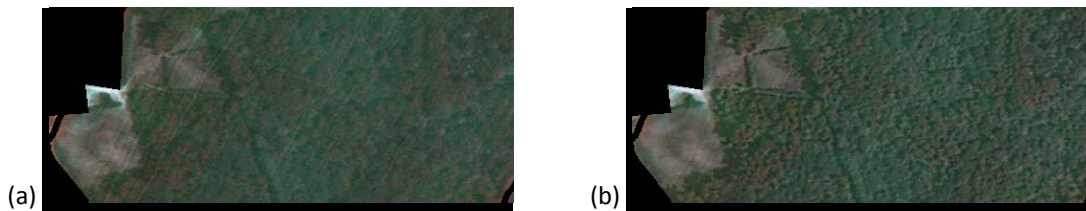


Figure 2. (a) Original versus (b) denoised image subset. RGB composition by band 1, 280 and 286.

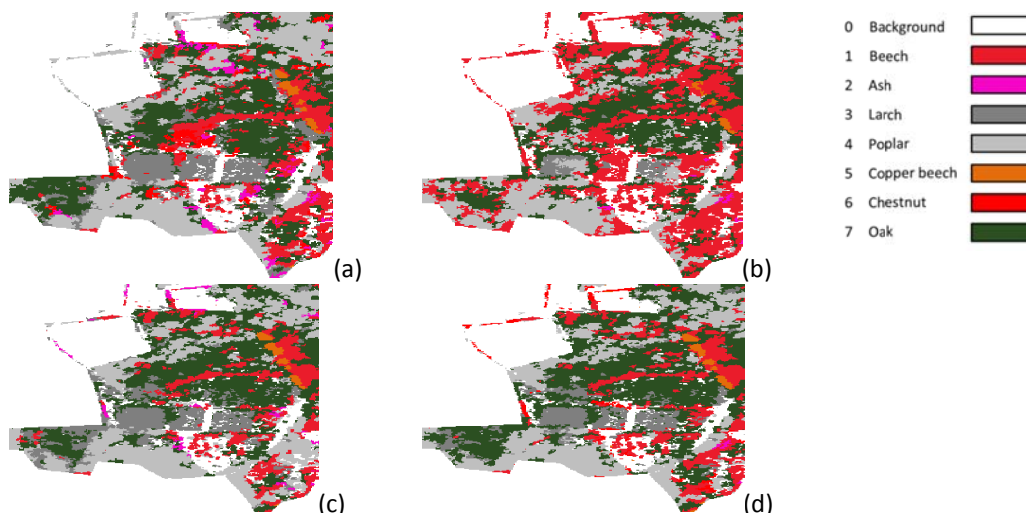


Figure 3. Classification maps using the (a, b) original and (c, d) denoised HS data: (left) best and (right) worse runs.

However, there is more: standard deviations on the three accuracy measures (Tab. 2) were approximately three times smaller for the denoised dataset compared to the original HS data, suggesting that image denoising yielded more stable classification results. In the case of complex, densely closed forest canopies, a robust and stable classification approach is undoubtedly an added value. The denoising algorithm induced an image quality increase such that more stable classification results could be obtained. Figure 2 shows the effect of denoising on image quality for an image subset. The denoised data were clearly smoother, without loss of detail. Moreover, the algorithm succeeded at destriping the original noisy HS data. This quality enhancement effect could also be detected in the final classification maps, where denoised HS data yielded more stable tree species maps (Fig. 3). Finally, denoising yielded a gain in SFFS processing time of 41.6%.

5. Conclusions

We tested the effect of HS image denoising on tree species mapping accuracy within the close-to-nature forest reserve Wijnendale (Belgium). PCA was used to decorrelate the HS images and the first PCs were restored applying a total variation method. Subsequently, noise in the remaining PCs was suppressed using a soft-thresholding scheme. The integrated denoising/OBIA mapping approach proved to yield acceptable and consistent mapping results.

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