SUPER-RESOLUTION: AN EFFICIENT METHOD TO IMPROVE SPATIAL RESOLUTION OF HYPERSPECTRAL IMAGES

A. Villa$^{\star,\diamond}$*, J. Chanussot***, J. A. Benediktsson*$^{\diamond}$*, M. Ulfarsson*$^{\diamond}$ *and C. Jutten***.*

*GIPSA-lab, Signal & Image Dept., Grenoble Institute of Technology - INPG, France.

$^{\diamond}$Dept. of Electrical and Computer Engineering, University of Iceland, Iceland.

1. INTRODUCTION

Hyperspectral imaging is a continuously growing area of remote sensing application. The wide spectral range, providing a very high spectral resolution, allows to detect and classify surfaces and chemical elements of the observed image. The main problem of hyperspectral data is that the high spectral resolution is usually complementary to the spatial one, which can vary from a few to tens of meters. Many factors, such as imperfect imaging optics, atmospheric scattering, secondary illumination effects and sensor noise cause a degradation of the acquired image quality, making the spatial resolution one of the most expensive and hardest to improve in imaging systems. Several techniques have been proposed during the last few years in order to improve the spatial resolution of hypersepctral images [1, 2]. The main drawback of all these approaches is that they fuse information from a high resolution image with the hyperspectral one to enhance the spatial resolution, thus needing an additional source of information. Super-resolution mapping, that is the possibility to enhance spatial resolution of hyperspectral images using both spatial and spectral information, is a recently born concept [3]. In this work, a novel method, based on the use of source separation technique and a spatial regularization step by simulated annealing which doesn't require any *a priori* knowledge or further information is proposed to improve the spatial resolution of cover classification maps.

2. METHODOLOGY

2.1. Spectral Unmixing

In hyperspectral images with a low spatial resolution, several different materials can be found in the same pixel. In this case, a common hard classification process, where each pixel is assigned to a class, fails. A solution consists in using source separation, in order to retrieve the mixed endmembers lying within each pixel [4]. Spectral unmixing is the first step of the proposed approach, due to its ability to provide a complete description of each pixel. In the last years, several algorithms have been developed for automatic or semi-automatic extraction of spectral endmembers directly from the image data [5].
In this work, the Vertex Component Analysis (VCA) has been chosen due to its good performances with respect to several source separation algorithms both for the accuracy of retrieved endmembers and from a computational point of view [6]. Once the endmembers are extracted from the image, the abundance fraction of the elements within each pixel should be determined. Several algorithms have been developed to handle the linear mixing model according to the required constraint of abundances fractions, which are nonnegativity and full additivity. Due to the efficiency from a computational point of view, we have chosen

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a fully constrained least squares (FCLS) algorithm, which satisfies both abundance constraints and is optimal in terms of least squares error [7].

2.2. Improving Spatial Resolution

Spectral unmixing is useful to describe the scene at a sub-pixel level, but can only provide information about proportions of the endmembers within each pixel. Since the spatial location remains unknown, spectral unmixing does not perform any resolution enhancement. In this paper, we propose a super-resolution mapping technique, which takes advantage of the information given by the spectral mixing analysis and uses it to enhance the spatial resolution of thematic maps. Our proposed approach is as follows: In a first step, each pixel is divided in a fixed number of sub-pixel, according to the desired resolution enhancement. Every sub-pixel is assigned to an endmember, in conformity with its fractional abundance within the pixel. A Simulated Annealing (SA) mapping function is then used, to create random permutation of these sub-pixels, in order to minimize a chosen cost function. Relying on the spatial correlation tendency of landcovers, we assume that each endmember within a pixel should be spatially close to the same endmembers in the surrounding pixels. Therefore, the cost function to be minimized is chosen as the perimeter of the areas belonging to the same endmember.
Simulated annealing is a well established stochastic technique originally developed to model the natural process of crystalization [8]. This process is based on an analogy from thermodynamics where a system is slowly cooled in order to reach its lowest energy state. More recently, SA has been proposed to solve global optimization problems [9], and it has been used in various fields. The basic idea of the method is that, in order to avoid to be trapped in local minima, uphill movements, *i.e.*, the points corresponding to worse objective function values could, sometimes, be accepted for the following iteration. As with a greedy search, it accepts all the changes that improve the solution. Changes degrading the solution can be accepted, but with a probability that is inversely proportional to the size of the degradation (small degradations are accepted with a higher probability). This probability also decreases as the search continues, or as the system cools, allowing eventual convergence to the optimal solution.

3. EXPERIMENTS

In this section, results obtained on real data sets are presented. We consider ROSIS data acquired over the University of Pavia, Italy, with 103 bands, ranging from 0.43 to 0.86 μm, with a 1.3 m spatial resolution. The high value of the spatial resolution is due to fact that ROSIS is an airborne sensor. Here, we consider a small segment (110x75 pixels) of the image, which contains several elements of interest, namely meadows, asphalt, metal sheet and shadows. Figures 1 (a) and (b) show a gray scale image of the 30th band of the scene and the available reference data. The original image was processed with a 5x5 low pass filter, so that each pixel in the new image represents a square of 8.5 meter (Figure 1c), which is a realistic assumption when dealing with hypersepectral data. We performed two experiments on the obtained data set: assuming that no ground truth is available to train a classifier, we first performed an unsupervised classification of the low resolution image, with a k-means classifier. In a second test, we applied the proposed method to enhance the spatial resolution of the thematic map. Results are presented in Figure 1 (d) and (e). When mixed pixels belong to the scene, as in the case here, an unsupervised classifier inevitably leads to poor results. The class shadow, represented in dark brown, which is only in a small portion of the image, was not detected, and also the metal sheet (color green) was not well retrieved. Based on a visually comparison, results obtained with the proposed method were much closer to the reference data. In order to have a quantitative assessment of the results we have compared the reference data with the obtained map. The overall accuracy was 87.46%

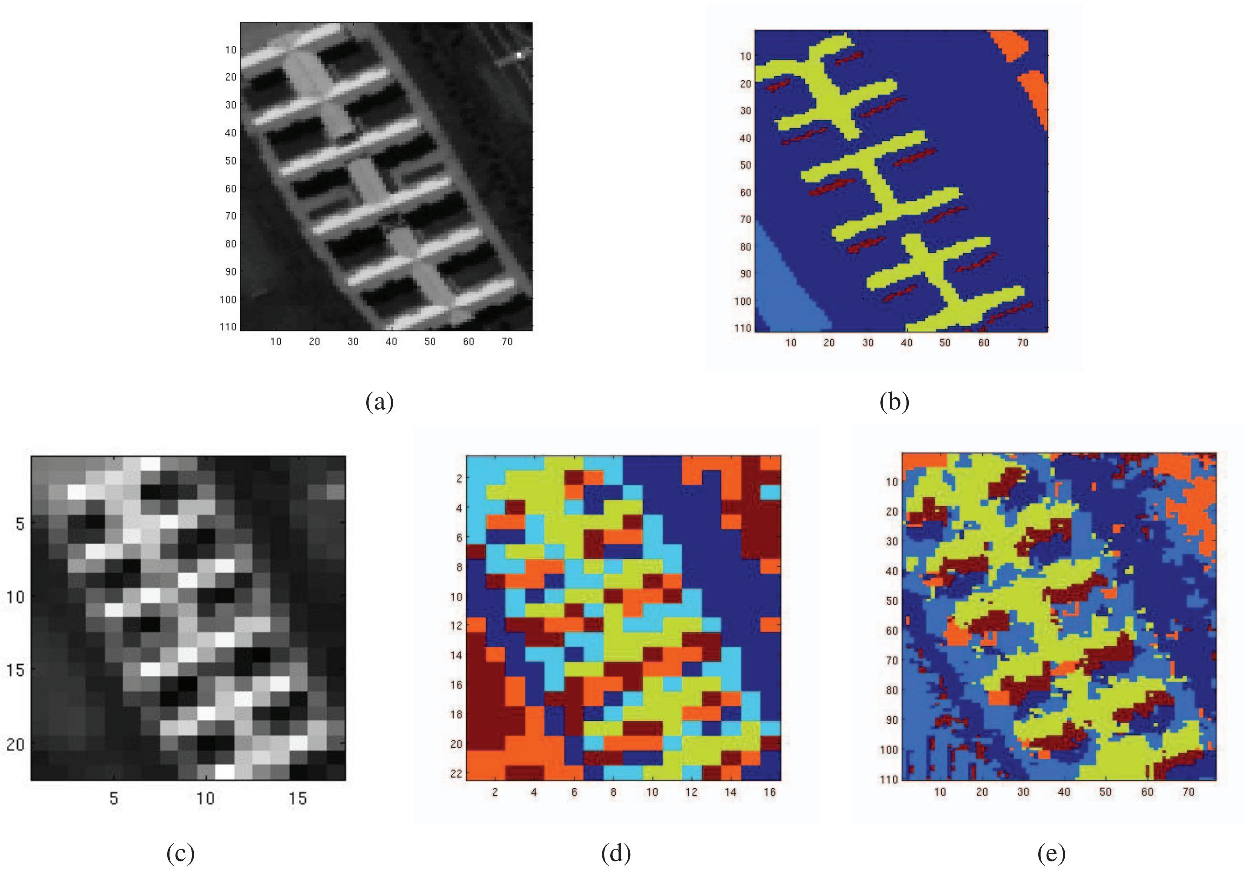

Fig. 1. (a) Original high resolution data, band 30 (b) Ground truth of HR image (c) Low resolution image obtained after filtering (d) Classification map obtained with a k-means classifier (e) Classification map obtained with the proposed method

4. REFERENCES

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