A Classwise Supervised Ordering Approach for Morphology Based Hyperspectral Image Classification

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Abstract

We present a new method for the spectral-spatial classification of hyperspectral images, by means of morphological features and manifold learning. In particular, mathematical morphology has proved to be an invaluable tool for the description of remote sensing images. However, its application to hyperspectral data is problematic, due to the absence of a complete lattice structure at higher dimensions. We address this issue by following up previous experimental indications on the interest of classwise orderings. The practical interest of the proposed approach is shown through comparison on the Pavia dataset with Extended Morphological Profiles, against which it achieves superior results.

1. Introduction

The increased spatial and frequential resolutions of hyperspectral images render them a rich source of information for the remote sensing community, while their data volume makes their processing a considerable challenge. Fortunately, given that adjacent pixels are often correlated, integrating spatial information into the classification process is known to improve classification performance [7]. Hence it is no suprise, that a considerable number of approaches are available for this purpose, among which we focus specifically on those based on mathematical morphology (MM).

In particular, MM excels at the geometrical shape based processing of images and thus is particularly suitable for this task [10]. However, despite a significant number of performant morphological solutions for the description of panchromatic images, their extension to hyperspectral images has been particularly problematic. To explain, the problem stems from the need for a complete lattice structure on the set of pixel values; in other words, a vector ordering is needed, which is obviously missing at higher dimensions [1].

In this regard, this paper's contribution is a complete hyperspectral image classification method that combines the strength of the PerTurbo classifier [4], with the capacity of MM for spatial information extraction, thus leading effectively to *spectral-spatial* pixel descriptions. In particular, motivated by the experimental results in Ref. [1], concerning the effect of vector ordering choice on the performance of morphological profiles, we introduce a novel classwise ordering optimization approach in order to overcome the need for a universal vector ordering, thus leading to marginal classification maps that are subsequently merged.

The rest of the paper is organized as follows. Section 2 provides background information on morphological hyperspectral image description and its associated obstacles. Then, in Section 3, the proposed approach is introduced, while Section 4 presents the results of the conducted experiments and elaborates on them.

2. Morphological description of hyperspectral images

MM is a non-linear image processing framework mostly known for its capacity to study geometric shapes. As such, it is inherently suitable for exploiting spatial pixel relationships; which in turn renders it an invaluable tool w.r.t. the need for spectral-spatial description of remote sensing images. The effectiveness of morphological solutions such as *differential morphological profiles* (DMP) [8], along with the consistently increasing availability of hyperspectral data, has rendered the need for its extension to hyperspectral images more emphasized than ever. Yet, the application of MM to multivariate images is not straightforward.

To explain, MM is based on complete lattice theory, meaning that it can be applied on any type of data, as long as a complete lattice structure is imposed on the set of pixel values. Therefore, a way of ordering pixel values is required. Although this requirement can be trivially satisfied with grayscale images, when it comes to multivariate data it becomes far less obvious, since pixels are now vectorial in nature and unfortunately there is no universal way of ordering multivariate data. As a result, in the last 15 years several ordering approaches have been explored with this end, for a detailed survey of which the reader is referred to Ref. [1].

Faced with this obstacle, the initial attempts at morphological description of hyperspectral data focused on reducing the number of image channels by means of Principal Component Analysis (PCA), followed by the grayscale application of DMP on the principal image component [5]. While Benediktsson et al. [2] introduced *Extended Morphological Profiles* (EMP), where the morphological profiles are computed on more than one principal components by means of a marginal ordering. Plaza et al. [9] on the other hand have investigated spectral angle distance based orderings. More recently, Fauvel et al. [6] have employed the concatenation of spectral pixel signatures with EMP vectors. And finally, Velasco and Angulo [11] have explored machine learning techniques in order to define a supervised vector ordering.

Moreover, the main motivation for this paper have been the experiments at Ref. [1], where multiple vector orderings have been compared for hyperspectral image decsription by means of morphological methods. And the main result has been that while no single vector ordering is perfect for this task, certain vector orderings are relatively superior to others when describing certain pixel classes. For instance vector orderings that prioritize channels corresponding to blue frequencies, tend to describe water bodies at images more effectively. That is why, we propose a method using morphologically extracted features that capture both spatial and spectral information, based on classwise optimization of various vector orderings, each specializing on one pixel class. Its details are presented in the next section.

3. Proposed approach

An overview of the proposed method is shown in Fig. 2. In short, we propose using a PerTurbo based classwise classification scheme that enables the computation of a pixel measure that can be associated with the notion of belonging to a class. This measure leads to the derivation of class specific vector orderings, that are subsequently used for morphological smoothing through multivariate alternating sequential filters, employing optimal structuring element (SE) sizes. As a result, classification errors due to acquisition noise or spectral variability are lowered, while the smoothing enables the topological preservation of the significant image features.

In particular, PerTurbo is a classification algorithm where each class is identified by its corresponding manifold in the input space, thanks to an approximation of the Laplace-Beltrami operator [4]. When a new sample needs to be classified, a perturbation of each class manifold is measured and then the sample is associated to the class which undergoes the least perturbation. This scheme can be re-interpreted in the kernel machine learning setting [4] and this perturbation measure appears to correspond to the reconstruction error in Kernel-PCA with a classical Gaussian kernel. Its performance has been shown to be comparable to Support Vector Machines [3, 4].

Although the output of PerTurbo could be used directly for spectral pixel classification, we propose to use the corresponding measure to derive a classwise vector ordering. More precisely, let τ_i be the perturbation measure associated to pixel class i, and $\mathbf{x_a}$ and $\mathbf{x_b}$ be two different vectors associated to the spectral coordinates of two pixels a and b. The induced vector ordering simply states that:

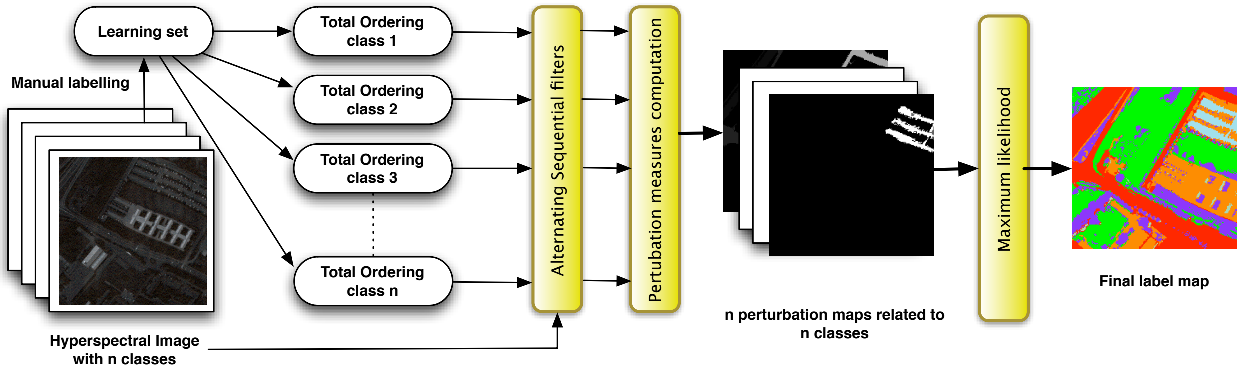
$$\mathbf{x_a} >_\mathbf{i} \mathbf{x_b} \Rightarrow \tau_\mathbf{i}(\mathbf{x_a}) > \tau_\mathbf{i}(\mathbf{x_b}) \tag{1}$$

Since distinct vectors can result in identical τ values, the relation of Eq. (1) is in fact a pre-ordering, lacking the anti-symmetry property. It can be transformed into a total ordering for instance by following it with a lexicographical comparison of vectors $\mathbf{x_a}$ and $\mathbf{x_b}$ [1].

Given n pixel classes, the derived n orderings are then employed for smoothing the input by means of multivariate alternating sequential filters [10]. This operation leads to n smoothed hyperspectral images. From which, we finally compute n perturbation maps, each related to a pixel class using τ_i on the image i. The final label per pixel is the one possessing the least perturbation in these maps, exactly as in the Perturbo algorithm. Figure 2 gives an illustration of this smoothing for the class Asphalt in the following experiment.

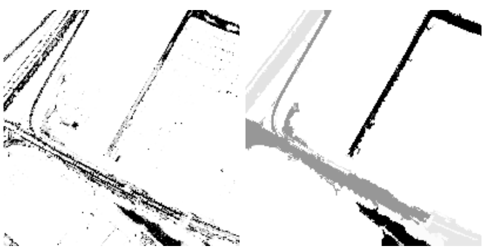
Furthermore, as far as the sizes of the SE used in morphological filtering are concerned, we have adapted them to each class. Assuming that the learning samples are approximately evenly sampled spatially, one can devise a simple strategy to determine optimal SE sizes. We simply start filtering the image with a small size. And then, at the filtered image, we check that the pixels associated with the learning samples still yield a minimal perturbation measure (i. e. they have not been eliminated by filtering). If not, we increase the size and repeat. The final optimal size is the largest one that pre-

Figure 1. Overview of the proposed method



serves the correctness of all learning samples. Hence this step is fully automatic and does not require any user participation.

Figure 2. The normalized measure (black is high) of belonging to the class is illustrated in the following example (left) before smoothing (right) after



4. Experiments & Discussion

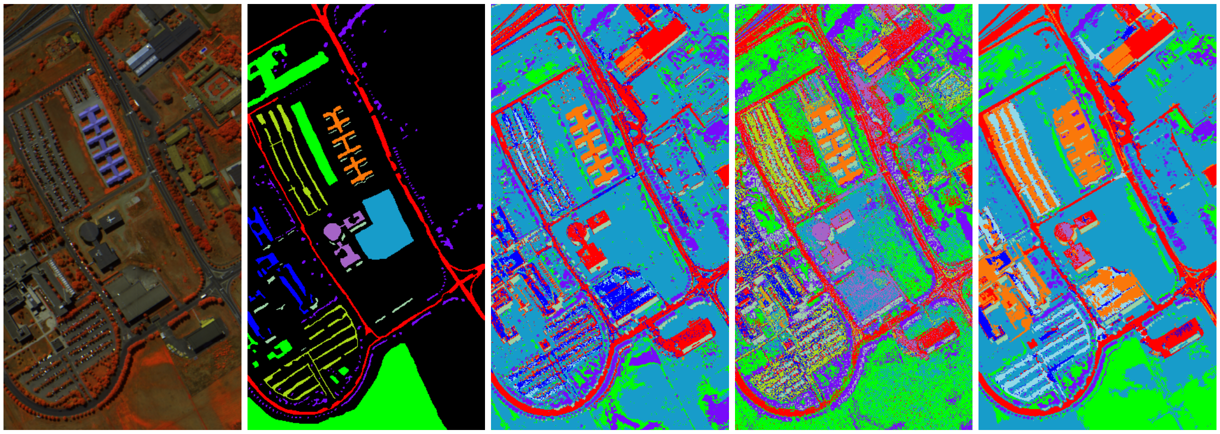
In order to test its validity, our approach has been tested using the Pavia University dataset. This hyperspectral image has been captured thanks to a ROSIS sensor during a flight campaign over Pavia, Northern Italy. The image size is 610×340 pixels, with 103 spectral bands.The geometric resolution is 1.3 meters. The available ground truth differentiates 9 classes which are presented in Fig. 3.

Three series of experiments have been conducted for this purpose. In each experiment, only 30 random samples of each class were drawn from the ground truth and used as a learning set. The experiments were repeated 20 times each so as to lower the importance of the random selection of learning samples. This is why in the performance table a mean accuracy is given, along with its standard deviation. In a first series of experiments, the image was directly processed without alternating sequential filters. This amounts to consider directly the spectral pixel signatures along with a Perturbo classification. In the second time, the EMP approach was used. Only the three first principal components were retained (more than 97% of total image variance), and circular SE of 3, 5 and 9 pixels radius have been used [2]. These choices were done with regards to the literature, but of course it is clear that the induced parameter variability will certainly require more extensive comparisons. On the other hand, our approach does not involve parameter tuning and is thus automatic. In all experiments, data has been centered and normalized so that each dimension presents unitary variance. The same σ value associated to the Gaussian Kernel has been used ($\sigma = 10$).

Results are presented in Table 1. Classification examples for each method are also presented in Fig. 3. Visually, it can be seen that our method enforces a better spatial smoothing of the different classes. Regarding the statistics, EMP and our method enforce the same average accuracy, while our method performs better at overall classification. The most represented classes (1,2 and 9) are better estimated. It is also noticeable that most of the time our method enhances the simple spectral classification performed by Perturbo.

In conclusion, the proposed method even if still at its initial stage, presents interesting results compared to the EMP approach. By using morphological filtering it accomplishes exploiting spatial information, while classwise ordering optimization enables it to process multivariate data by benefitting optimally from each ordering's class specific advantages. Future work will concentrate on adapting the classwise ordering optimization strategy directly to morphological profiles as well as on more extensive testing with more datasets and classifiers using a broader range of parameters.

Figure 3. Pavia University dataset. The color code for is the following: Asphalt, Meadows, Gravel, Trees, Painted metal sheets, Bare Soil, Bitumen, Self-Blocking Bricks, Shadows



(a) three-channel color composite (b) available reference data (c) Perturbo Classification results (d) EMP (3 PCs, 3 SE sizes=3,5,9) (e) Our new method

Table 1. Classification accuracy (%) for the proposed approach versus a spectral classification and an EMP-based classification.

Class	sample set size	Perturbo	EMP	New method
1	6631	86.7 (4.6)	72.3 (4.3)	94.2 (3.3)
2	18649	42.0 (13.4)	67.9 (4.0)	68.1 (10.7)
3	2099	70.4 (12.1)	74.2 (7.3)	62.8 (16.0)
4	3064	86.9 (13.2)	77.8 (3.1)	77.0 (16.0)
5	947	97.7 (2.7)	91.5 (1.6)	94.7 (2.7)
6	3682	43.5 (13.5)	75.3 (2.7)	73.6 (14.0)
7	1345	99.9 (0.1)	98.4 (0.4)	99.9 (0.1)
8	1330	26.2 (21.9)	95.3 (0.9)	57.2 (7.4)
9	5029	87.2 (5.8)	73.3 (5.0)	97.5 (2.4)
Average Accuracy		71.2 (9.7)	80.6 (3.3)	80.6 (8.1)
Overall Accuracy		**61.6 (4.8)**	**73.2 (1,3)**	**77.7 (4.4)**

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References

[1] E. Aptoula and S. Lefèvre. A comparative study on multivariate mathematical morphology. *Pattern Recognition*, 40(11):2914–2929, 2007.

[2] J. A. Benediktsson, J. Palmason, and K. Arnason. Classification of hyperspectral data from urban areas based on extended morphological profiles. *IEEE Trans. on Geosc. and Remote Sensing*, 43(3):480–491, 2005.

[3] L. Chapel, T. Burger, N. Courty, and S. Lefèvre. Classwise hyperspectral image classification with perturbo method. In *IGARSS*, page to be published, 2012.

[4] N. Courty, T. Burger, and J. Laurent. Perturbo: a new classification algorithm based on the spectrum perturbations of the laplace-beltrami operator. In *ECML-PKDD*, Athens, Greece, 2011.

[5] F. Dell'Acqua, P. Gamba, A. Ferrari, J. A. Palmason, J. A. Benediktsson, and K. Arnason. Exploiting spectral and spatial information in hyperspectral urban data with high resolution. *IEEE Geosc. and Remote Sensing Letters*, 1(4):322–326, 2004.

[6] M. Fauvel, J. A. Benediktsson, J. Chanussot, and J. R. Sveinsson. Spectral and spatial classification of hyperspectral data using svms and morphological profiles. *IEEE Trans. on Geosc. and Remote Sensing*, 46(11):3804–3814, 2008.

[7] D. A. Landgrebe. *Signal Theory Methods in Multispectral Remote Sensing*. Wiley, New York, 2003.

[8] M. Pesaresi and J. Benediktsson. A new approach for the morphological segmentation of high-resolution satellite imagery. *IEEE Trans. on Geosc. and Remote Sensing*, 39(2):309–320, 2001.

[9] A. Plaza, P. Martinez, J. Plaza, and R. Pérez. Dimensionality reduction and classification of hyperspectral image data using sequences of extended morphological transformations. *IEEE Trans. on Geosc. and Remote Sensing*, 43(3):466–479, 2005.

[10] P. Soille. *Morphological Image Analysis : Principles and Applications*. Springer-Verlag, Berlin, 2003.

[11] S. Velasco-Forero and J. Angulo. Supervised ordering in $\mathbb{R}^n$: Application to morphological processing of hyperspectral images. *IEEE Trans. on Image Processing*, 20(11):3301–3308, 2011.