Hierarchical Analysis of Remote Sensing Data: Morphological Attribute Profiles and Binary Partition Trees

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Abstract. The new generation of very high resolution sensors in airborne or satellite remote sensing open the door to countless new applications with a high societal impact. In order to bridge the gap between the potential offered by these new sensors and the needs of the end-users to actually face tomorrow's challenges, advanced image processing methods need to be designed. In this paper we discuss two of the most promising strategies aiming at a hierarchical description and analysis of remote sensing data, namely the Extended Attribute Profiles (EAP) and the Binary Partition Trees (BPT). The EAP computes for each pixel a vector of attributes providing a local multiscale representation of the information and hence leading to a fine description of the local structures of the image. Using different attributes allows to address different contexts or applications. The BPTs provide a complete hierarchical description of the image, from the pixels (the leaves) to larger regions as the merging process goes on. The pruning of the tree provides a partition of the image and can address various goals (segmentation, object extraction, classification). The EAP and BPT approaches are used in experiments and the obtained results demonstrate their importance.

1 Introduction

Satellite and airborne remote sensing is currently undergoing a technical revolution with the appearance and blooming development of very high resolution sensors, the term *resolution* having the following three meanings:

P. Soille, M. Pesaresi, and G.K. Ouzounis (Eds.): ISMM 2011, LNCS 6671, pp. 306–319, 2011.

- *Spatial resolution*: Metric and sub-metric resolutions are now currently available for satellite remote sensing. A high spatial resolution opens the door for very accurate geometrical analysis of objects present in scenes of study.
- *Spectral resolution*: After decades of use of multispectral remote sensing, most of the major space agencies now have new programs to launch hyperspectral sensors, recording the reflectance information of each point on the ground in hundreds of narrow and contiguous spectral bands. The spectral information is instrumental for the accurate analysis of the physical component present in one scene.
- *Temporal resolution*: Due to the launch of constellations of satellites and the increasing number of operating systems, the temporal resolution between two acquisitions over a given scene of interest has dramatically decreased. This opens the door to the accurate monitoring of abrupt changes and to efficient response in case of major disasters. Temporal phenomena with longer scales may also be monitored.

The accurate analysis of remote sensing images is an important task for many practical applications with high societal impact, such as precision agriculture, monitoring and management of the environment, urban planning, natural hazards and disasters management, security and defense issues. However, in order to fully exploit the potential offered by the new generations of sensors and to actually face all the emerging applications, advanced image processing methods are required. As a matter of fact, most of the traditional processing algorithms fail when the resolution increases significantly. For instance, statistical learning becomes intractable with hyperspectral data because of the dimensionality of the data. Similarly, while it was easy to classify urban versus non urban areas with medium resolution data, very high resolution data enable the accurate classification at the building scale, but this requires to completely redesign the whole processing chain.

While the spectral information is usually used to perform a pixel-wise classification of the data based on the physical properties of the sensed materials, extracting meaningful *spatial information*, characterizing the sensed landscape in a complementary way with respect to the spectral signatures of the land covers, is a challenging task for an accurate analysis of the structures in the image. Recently, Daya Sagar and Serra [1] underlined how the retrieval and characterization of the spatial information is a current challenge for geoscience scientists. Due to the wide range of features related to the spatial domain, there are several ways of characterizing this source of information. From a general survey of techniques modeling the spatial information in remote sensing, one can notice that there are different approaches for extracting the spatial information and correspondent ways (with different levels of abstraction) for including the extracted information in the processing chain aiming at the understanding of the image. Roughly, it is possible to group the techniques in three approaches (ordered increasingly according to the level of semantic introduced in the representation of the scene):

1. techniques aiming at modeling the spatial context at a pixel-level by looking at the neighborhood of each pixel [2, Chap. 8],[3, Chap. 6],[4,5,6,7];
2. techniques based on segmentation that exploits the partition of the image into regions by extracting spatial features that can describe the structures in the scene [8, Chap. 5][9,10,11,12,13,14,15];
3. techniques working at the object level where also the thematic characteristics and the relations between structures are taken into account [16,17,18,19,20].

It this scenario, Mathematical Morphology (MM) [21,22,23,24] holds a fundamental role since it provides a set of powerful tools for analyzing the spatial domain.

In 2002, Soille and Pesaresi [25] identified the main applications in the context of remote sensing image analysis that could be addressed by MM: i) image filtering; ii) image segmentation and iii) image measurements. Thus, MM tools permit to enrich the image analysis by including spatial information mainly at pixel- and region-level, and, in the decade following this milestone paper, numerous techniques involving MM for the analysis of remote sensing images have been proposed. In particular, focusing the attention on very high resolution (VHR) images, we highlight the consolidation of the role of *connected operators* [26,27] as efficient filters for achieving a simplification of the image obtained by only merging flat zones (i.e., avoiding the detriment of the geometrical features of the regions unaffected by the transformation). Connected operators have gained popularity also due to the successful diffusion of Morphological Profiles (MPs) [9,28]. MPs are a multiscale decomposition of a grayscale image in a stack of filtered images obtained by transforming the input scene with a sequence of opening and closing by reconstruction filters (i.e., connected operators) based on structuring elements (SEs) with fixed shape and increasing size. In [25] it was also fostered that multiscale and multidirectional segmentation methods based on the concept of MP were promising approaches since they could lead to a further exploitation of MM tools in the remote sensing field. Accordingly, not only the multiscale or multidirectional approaches have confirmed their suitability to the extraction of the spatial information but furthermore, techniques performing more general *multilevel analyses* have been proposed.

Moreover, with a further step forward on the path leading to the semantical understanding of the scene, *hierarchical representations* of structures in the image have started to be successfully exploited[29,30]. In particular, the use of Binary Partition Trees (BPT) [31] has been recently investigated in remote sensing for various applications (segmentation, classification, object detection) [32,33,34,35].

This paper is organized as follows. General considerations on the multilevel and hierarchical approaches are given in the next section. Sec. 3 is devoted to the presentation of the Attribute Profiles, a generalization of MPs based on attribute connected filters. Sec. 4 is devoted to the presentation of Binary Partition Trees and their use for the analysis of hyperspectral data. Finally, concluding remarks are presented in Sec. 5.

2 Multilevel Analyses and Hierarchical Representations of the Scene

The intrinsic mixture of land covers in natural landscapes can lead to a very complex imaged scene especially when dealing with dense urban areas and VHR images. Multiscale approaches have proved to be suitable for extracting the components relevant for the application, crawling the overwhelming information given by the huge amount of details [36,10]. The MP leads to a multiscale decomposition of the image (in bright and dark components) since it can be seen as a sequential configuration of the scene with a progressively decreasing amount of either bright or dark details [9]. Thus, by considering the behavior of the grayscale value of each pixel as the size of the SE varies, it is possible to extract information on the scale (i.e., size) of the objects in the image. Using linear SEs with different directions (i.e., morphological directional profiles [25]) enables the characterization of the structures on the basis of their orientation and length. Another recent development dealing with advanced morphological directional operators applied to remote sensing data is the use of path operators for the detection of the road network on VHR remote sensing images [37]. With the presence of heterogeneous structures in the image, a multiscale or multidirectional approach is compulsory since an analysis carried out at a single scale/direction would lead to a partial extraction of the spatial characteristic of interest. However, apart from the scale and direction, other parameters can be used for a more complete characterization of the objects in the scene (e.g., for modeling the shape or texture). Extending the multiscale idea, if the image is progressively simplified by performing a sequence of transformations with a varying parameter, it is possible to obtain a more general multilevel decomposition of the image. Attribute filters [38] proved to be suitable for implementing this idea. If applied in a sequence with fixed attribute and varying reference used in the definition of the predicate we obtain Attribute Profiles (APs) [39,40], which can be considered as a generalization of the MPs. By exploiting the use of attribute filters in the AP structure, it is possible to perform a multilevel analysis (i.e., decomposition) of the image according to many possible characteristics (e.g., geometric, textural, spectral, etc.) due to the freedom in the definition of the predicate. Moreover, according to the attribute, it is possible to extract features on the scene whose significance is closer to the conceptual information that is sought (e.g., the attribute area can better fit the general concept of size than might the width of a SE).

In the framework of mathematical morphology, representations of an image as a hierarchical tree structure of connected components have been proposed. Examples of hierarchical structures are min- and max-trees [41], inclusion-trees (or tree of shapes) [42] and binary partition trees (BPTs) [31].

Min- and max-trees are based on the region inclusion obtained by performing a threshold decomposition [43] of the image. Inclusion tree relies on the saturation operator, which basically fills the holes in the regions. BPTs store a hierarchical region-based representation in a tree structure. This provides a hierarchy of regions at different levels of resolution to cover a wide range of applications. This generic representation, independently from its construction, can be used in many different applications such as segmentation, classification, indexing, filtering, compression or object recognition [31,35]. Depending on the definitions of the used region model and the distance used to determine the order of merging of regions, different BPTs can be constructed. Once a BPT is constructed, providing a full hierarchical representation of the information, the pruning step must be defined in order to either segment simplify the image or to select one given node (object detection).

Recently, such structures have started to be exploited also in remote sensing, mainly for image classification and segmentation [39,40,44,32,33,34,35,45,46]. The hierarchical representation of the images is not only useful for computing efficient algorithmic implementations of some MM operators [47] but can give important information on the relations between the regions in the image, since the nodes in the tree can refer to salient objects in the image.

3 Attribute Profiles and Extended Attribute Profiles

In this section we review the definition of a generalization of the concept of the MP, *i.e* the Attribute Profile [40] and its extension for multichannel data, the Extended Attribute Profile [44]. For a review of ten years of developments of the MP, the reader is referred to [48].

3.1 Attribute Profiles

Attribute profiles were proposed in [40] for overcoming the limitation of the MP to model other feature than the size of the objects. APs are based on attribute filters [38] and thus, can process the image according to features such as the contrast, texture, geometry, etc. Analogously to the MP, the AP operates either on bright or dark component with attribute thinning and attribute thickening as operators, respectively. The AP can be defined as a concatenation of a thickening attribute profile, $\Pi_{\phi^{T'}}$, and an thinning attribute profile, $\Pi_{\gamma^{T'}}$ computed with a generic ordered criterion T':

$$AP(f) = \left\{ \begin{array}{lll} \Pi_{\phi^{T'_\lambda}}, & \lambda = (n-1+i), & \forall\lambda \in [1,n]; \\ \Pi_{\gamma^{T'_\lambda}}, & \lambda = (i-n-1), & \forall\lambda \in [n+1, 2n+1]. \end{array} \right\}. \tag{1}$$

With $T' = \{T_1, T_2, \ldots, T_n\}$ the set of ordered criteria, for $T_i, T_j \in T'$ and $j \geq i$, the relation $T_i \subseteq T_j$ holds. The family of criteria needs to be ordered for guaranteeing that the absorption property is fulfilled by the AP (condition that might not be verified for non increasing predicates). The fulfillment of the absorption property ensures the consistency of the derivative of the AP (DAP). Different information can be extracted from the structures in the scene according to the attribute and criterion considered in the filtering leading to different multilevel decompositions of the image. Moreover, the computation of the APs, when based on the min- and max-tree representation of the image, leads to an efficient implementation of the multilevel filtering. In particular, an AP can be obtained by building up only once a max- and a min-tree for the thinning and thickening transformations, respectively, and by performing each filtering of the sequence as a different pruning of the tree.

3.2 Extended Attribute Profiles (EAP)

In [44] the AP was extended to multichannel images as proposed in [49]. Thus the EAP is obtained by computing an AP on each of the c principal components extracted from the original multichannel data (e.g., hyperspectral image):

$$EAP(f) = \{AP(PC_1), AP(PC_2), \ldots, AP(PC_c)\}. \tag{2}$$

When considering different attributes, it is possible to stack in the same data structure the EAP computed with each attribute, leading to the definition of Extended Multi-Attribute Profile (EMAP) [44]:

$$EMAP(f) = \{EAP_{a_1}(f), EAP'_{a_2}(f), \ldots, EAP'_{a_m}(f)\} \tag{3}$$

with a_i a generic attribute and $EAP' = EAP \backslash \{PC_1, \ldots, PC_c\}$ for avoiding the multiple presence of the c principal components.

APs and EAPs were used for the thematic classification of panchromatic VHR images [40] and hyperspectral images [44] proving that the extraction of different spatial features can lead to greater accuracies in comparison with those obtained by considering MPs and EMPs, respectively. In [50], the APs were considered for change detection on VHR images showing promising results in providing a characterization of the changes complementary to the one given by the classical spectral analysis.

4 Binary Partition Trees for the Analysis of Hyperspectral Data

Hyperspectral sensors collect multivariate discrete images in series of narrow and contiguous wavelength bands. The resulting data sets enable the characterization of regions based on their spectral properties. Conventional analysis techniques have traditionally considered these images as an unordered array of spectral measurements. In the last few years, the importance of the spatial information considering, in particular, spatial correlation and connectivity in the image has been proved. As previously mentioned, this information turns out to be essential to interpret objects in natural scenes. Hence, hyperspectral analysis tools should take into account both the spatial and spectral spaces. However, the number of wavelengths per spectrum and pixel per image as well as the complexity of handling spatial and spectral correlation explain why this approach is still a largely open research issue.

Over the past decade, Binary Partition Trees have been used for various purposes in various contexts for grey scale and color images. Due to the high dimensionality of the data, extending the use of BPTs to hyperspectral images is a very challenging issue. This has been recently investigated, as a way to provide an abstraction from the pixel-spectrum-based representation[32]. Note that the use of BPTs has also recently been investigated in the frame of polarimetric SAR images filtering and segmentation [51]. This representation [31] hierarchically stores a region-based representation in a tree structure, as illustrated on Fig. 1, and provides a hierarchy of regions at different levels of resolution to cover a wide range of applications. This generic representation can be based on an iterative region merging algorithm but requires a region similarity metric and a region model. The *region model* M_R specifies how regions are represented and how to model the union of two regions. The *merging criterion* $O(R_i, R_j)$ defines the similarity between neighboring regions and hence determines the order in which regions are merged. Working with hyperspectral data, the definition of both concepts is not straightforward. Regarding the region model, a non parametric statistical model (a multi-dimensional histogram) is used [52]. This leads to the definition of a robust distance between histograms taking into account the correlation between bands. Different hyperspectral region models and similarity metrics are presented and analyzed in [33] and a new merging strategy using a new association measure depending on canonical correlations relating principal coordinates is proposed in [35].

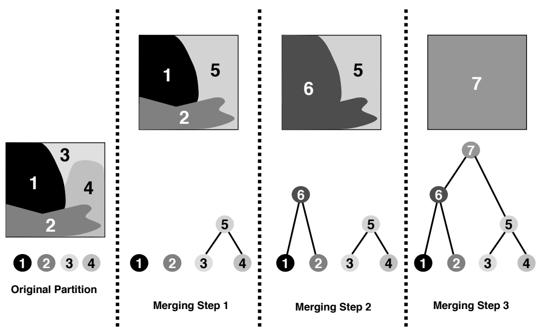


Fig. 1. Example of BPT construction using a region merging algorithm

Once the BPT is constructed, a second step consists in designing a pruning strategy meeting the goal of the addressed application. These two steps (construction and pruning of the BPT) are separate: the construction is based on the intrinsic information of the image, while the pruning should be related to the application. A new pruning strategy aiming at the segmentation of hyperspectral images is proposed in [34]: the regions contained in the BPT branches are studied by recursive spectral graph partitioning. The goal is to remove subtrees composed of nodes which are considered to be similar. To this end, affinity matrices on the tree branches are computed using a new distance-based measure depending on canonical correlations relating principal coordinates.

4.1 Experimental Analysis

4.2 Experiments Based on APs and EAPs

In [40] the APs were used for extracting spatial features considered for the classification of two Quickbird panchromatic images acquired on the city of Trento (Italy). The APs were computed with three attributes: i) area; ii) moment of inertia [53]; and iii) standard deviation. The area attribute was chosen for modeling the size of the structures in the image, the moment of inertia for extracting information on the shape of the regions and the standard deviation was considered as a descriptor of the spectral homogeneity of the objects. In the experiments, each AP was firstly classified by a Random Forest (RF) classifier [54] separately and then all the APs stacked together were considered. The use of different attributes led to the extraction of complementary information from the scene leading to increasing accuracies when considered in classification. In terms of classification errors, a decrease in the kappa error up to 38% and 17% with respect to the original panchromatic image and the MP, respectively was experienced when considering the APs.

The EAPs were used in [44] for the classification of two hyperspectral images acquired on Pavia. Four attributes were considered in the analysis by building the four correspondent EAPs: i) area of the regions; ii) diagonal of the box bounding the region; iii) moment of inertia; iv) standard deviation of the gray-level values of the pixels in the regions. All the EAPs computed were also considered together in the EMAP structure. A RF classifier was employed for classifying the features extracted by the profiles. The inclusion of the spatial information led to an increase in accuracy of up to 21.9% with respect to considering only the PCs (spectral information only). In the experiments the use of the proposed EAPs and EMAP led to an increase of overall accuracy up to about 12% over the results obtained by considering the EMP. Particulars of the classification maps obtained are shown in Fig. 2.

4.3 Experiments Based on BPTs

We present here some results dealing with segmentation, object detection and recognition as these are important challenges in remote sensing images. The automated selection of results in hierarchical segmentations combining spectral/spatial information has been previously studied [30]. Despite of some interesting results, problems regarding under and over-segmentation remained. Adequately pruning BPT representations combining spectral and spatial features can overcome some of these limitations.

We first provide an evaluation of the BPT pruning proposed in [34]. The experiments have been performed using a portion of Pavia Center image from hyperspectral ROSIS sensor. The data contain 102 spectral bands. Fig. 3(a) shows a RGB combination of three of them. The BPT is computed by the procedure described in [34]. To evaluate the quality of the BPT pruning, we compare the results obtained with a Min cut applied on the BPT against a trivial pruning

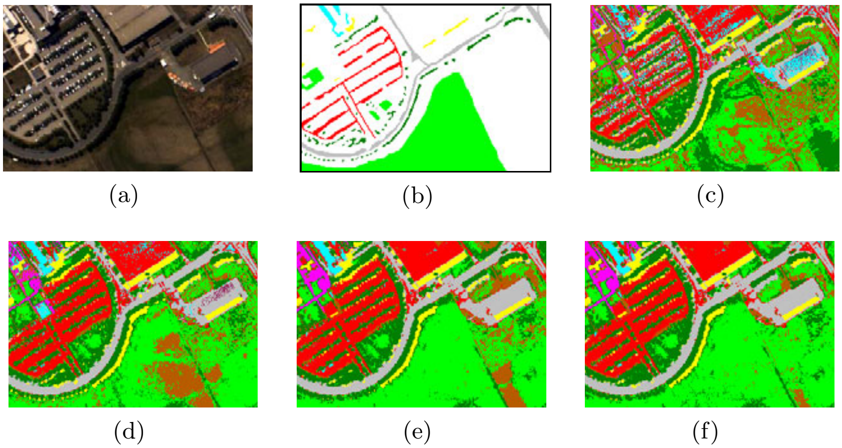
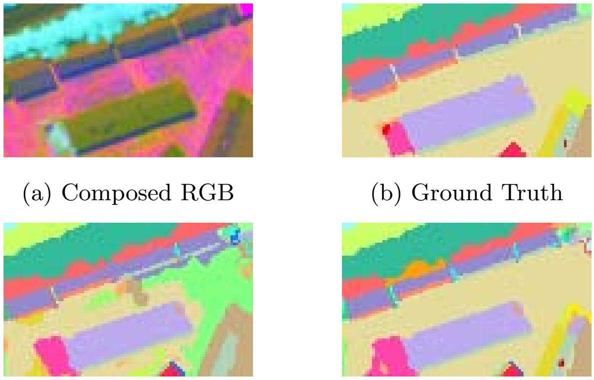


Fig. 2. Pavia data set. (a) True color composition; (b) Reference map. Details of the classification maps obtained with a RF classifier and: (c) the PCs, (d) the EMP, (e) the EAP with area attribute, and (f) the EMAP.
Thematic classes: trees, asphalt, bitumen, gravel, metal sheets, shadows, meadows, self-blocking bricks, bare soil.

criterion based on the number of regions in the BPT following the merging sequence [33]. To evaluate the resulting partitions, the symmetric distance d_{sym} [55] is computed with the manually set ground truth (GT) shown in Fig. 3(b). Fig. 3(c)(d) show the segmentation results obtained with the trivial and the Mincut BPT pruning, respectively. In both cases, the partitions have 54 regions. Comparing both results, the quantitative d_{sym} and the visual evaluation corroborate that the partition obtained by the advanced pruning is much closer to the ground truth than the one computed with a simple stopping of the region merging algorithm.

The second set of experiments is performed using a portion of a publicly available HYDICE hyperspectral image. After removing water absorption and noisy bands, the data contain 167 spectral bands. Fig. 4(a) shows a RGB combination of three of them. To evaluate the quality of the BPT construction (and not the pruning strategy), we extract a segmentation result involving a given number N_R of regions by undoing the last $N_R - 1$ mergings over the initial partition. The result is compared with the classical Recursive Hierarchical Segmentation algorithm (RHSEG), the similarity criterion used for RHSEG being SAM with spectral clustering weight 0.1 [29,11]). The manually created GT is shown in Fig. 4(b). Fig. 4(c)(d) show the segmentation results obtained with BPT and RHSEG, respectively. In both cases, the resulting partitions involve 63 regions. Again, the qualitative visual inspection and the quantitative evaluation assess the interest of the BPT representation.

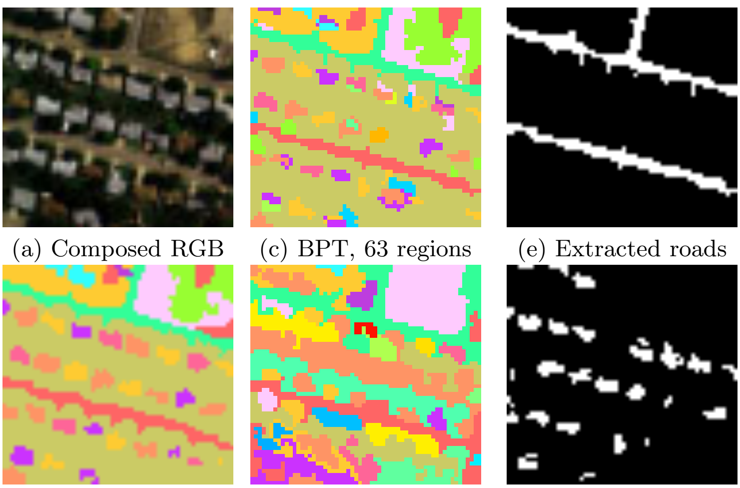
Finally, object detection and recognition is also considered. By combining simple shape descriptors (area, elongation of an oriented bounding box) with spectral information (typical spectrum for one given class), one can select



(a) Composed RGB (b) Ground Truth

(c) Pruning by number of regions (d) Min *Ncut* Pruning BPT

Fig. 3. (a) Pavia Center ROSIS RGB Composition, (b) Manually created Ground Truth, (c) Partition extracted from the trivial pruning leading to d_{sym}=40, (d) Partition computed with the proposed pruning leading to d_{sym}=20



(a) Composed RGB (c) BPT, 63 regions (e) Extracted roads

(b) Ground Truth (d) RHSEG, 63 regions (f) Extracted buildings

Fig. 4. a) Urban HYDICE RGB Composition, (b) Manually created Ground Truth, (c) Partition extracted from BPT leading to d_{sym} =25, (d) Partition computed with RHSEG [29] leading to d_{sym} =70, Roads (e) and Buildings (f) detection based on BPT representation

various nodes within the BPT [35]. Results of this object-oriented pruning are presented on Fig. 4(e)(f) for the detection of roads and buildings, respectively. These results are very promising and outperform standard pixel-wise spectral classification [35]. Gathering connected pixels belonging to meaningful structures into specific nodes, the BPT again turns out to be extremely well suited to the analysis of remote sensing data.

5 Concluding Remarks

Using airborne or satellite platforms, remote sensing is playing a key role in a growing number of applications. The acquired images are more and more complex: increased dimensionality in the case of hyperspectral data, increased complexity of details in the case of images with very high spatial resolution. The structures of interest in these images are of various scales and shapes. In order to tackle the induced issues, multi-scale and hierarchical processing methods are highly desirable. In this context, mathematical morphology provides a set of extremely powerful tools, such as the attribute filters and the binary partition trees. In this paper, we reviewed these strategies, pointing key features regarding their use and extension to remote sensing data. Excellent performances have been achieved on a variety of applications: segmentation, classification or object detection and recognition.

Some open issues remain. We can cite a few of them: when dealing with one specific application, how can one select the optimal set of attributes? Is there a way to achieve scale invariant processing - over what range of scales? - in order to increase the generality of the algorithms? Regarding the spectral dimension: while it is now widely recognized that spatial-spectral approaches dramatically increase the classification performances, the two dimensions (spectral and spatial, respectively) are considered either sequentially or in parallel with a data- or decision fusion step to merge them. Is there a way to take both dimensions into account in a more intricate way? Are the norms and distances designed for the case of hyperspectral data (typically with a few hundreds bands) robust when the dimension drastically increases, as in the case of the ultra-spectral images (typically a few thousands of bands)? Finally, we must underline that this paper was mostly focused on optical data. Images formed using radar sensors (synthetic aperture radar, polarimetric or interferometric data) are also increasingly used and also require new developments. A few papers are already available, but the problematic is quite different as the signal to noise ratio is significantly lower than for optical data and the information about the physical nature and geometry of the actual structures is much more difficult to access. There will undoubtedly be more developments dealing with these data in the coming years.

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