MORPHOLOGICAL ATTRIBUTE FILTERS FOR THE ANALYSIS OF VERY HIGH RESOLUTION REMOTE SENSING IMAGES

Mauro Dalla Mura[(a,b)], Jon Atli Benediktsson[(b)], Björn Waske[(b)] and Lorenzo Bruzzone[(a)]

[(a)] Department of Information Engineering and Computer Science, University of Trento
Via Sommarive, 14 I-38050, Povo, Trento, Italy, E-mail: {dallamura@disi.unitn.it, lorenzo.bruzzone@ing.unitn.it}
[(b)] Faculty of Electrical and Computer Engineering, University of Iceland,
Hjardarhaga 2-6, 101 Reykjavik, Iceland, E-mail: {benedikt@hi.is, waske@hi.is}

1. INTRODUCTION

It is well known that spatial information is meaningful for the analysis of remote sensing images, especially when dealing with very high resolution (VHR) images. The importance of geometrical features increases even more in the analysis of structured land covers (e.g., in urban areas), where they can be more descriptive than the spectral ones. One of the most investigated geometrical features is the size of the objects present in the image. An approach commonly used in remote sensing for extracting information on the size is based on the computation of a morphological profile, MP, a sequence of morphological openings and closings by reconstruction [1]. Filters by reconstruction, in contrast with standard morphological operators, first transform the input image by erasing those regions that do not enclose a set of pixels of a certain shape and size, called structuring element, SE; and after reconstruct the filtered image with an iterative process [2]. The amount of simplification obtained in the initial filtering is mostly due to the size of the SE. The reconstruction phase aims at fully retrieve the regions not completely removed. By filtering the image with a SE of progressively increased size, larger regions are erased from the image. Since a MP is a concatenation of an anti-granulometry and a granulometry, respectively a sequence of closings and openings of increasing size [1], the analysis of its derivative (differential MP, DMP), gives information on the scale of the structures. For example, in [1] this information was used in classification for discriminate small buildings from the large ones. Although MPs have proven their capabilities, they are on the other hand computationally demanding. In fact, in practical situations only a restricted range of sizes of the SE is considered (in general less than 10 for both openings and closings). In scenarios where the objects in the image can assume a wide range of scales (e.g., heterogeneous urban areas), a limited number of sizes might be not sufficient for representing all the structure scales exhaustively and/or for discriminating among objects of similar size (if the size step of the SEs is too wide). Moreover, if other geometrical features rather than size need to be extracted, an approach based on filters by reconstruction might not be the best choice. For example, very recently, the issue of extracting geometrical features from VHR images able to discriminate between roads and buildings was addressed by computing two MPs [3]. One MP is built by disk-shaped SEs for extracting the smallest size of the structures, while the other employs linear SEs for characterizing their maximum size (along the orientation of the SE). This is of help in discriminating between the two classes because the maximal length is different in the two cases, but, unfortunately, such analysis is not complete because not all the possible lengths and orientations can be practically investigated.
In this paper we introduce morphological attribute filters in the remote sensing community, as an effective and flexible methodological tool for the analysis of VHR remote sensing images. Morphological attribute filters, under an efficient implementation, have the following important advantages with respect to traditional morphological filters by reconstruction: i) significantly smaller computational complexity in building granulometries (i.e., MPs); ii) better characterization of the size feature; and iii) greater potentialities and flexibility in extracting other features rather than size.

2. MORPHOLOGICAL ATTRIBUTE FILTERS

In this section operators by reconstruction and attribute filters are introduced. The founding methodological basis are presented, allowing their analysis and comparison. Due to space constraints we only focus on openings, but all the results can be easily adapted to closings.
Openings by reconstruction can be seen as a subset of attribute openings (both belonging to the class of connected filters) [4], and they lead, in general, to similar results. The similarity increases when the attribute and the SE are sensitive to the same geometrical feature (e.g., considering the length of the regions as an attribute and the SE a line). Moreover, the results obtained by an attribute opening carried out by removing all the regions in which a given SE cannot fit (i.e., the attribute computed would be "the SE must fit in the region") are exactly the same of those of an opening by reconstruction using the same SE. Since the computation of such attributes is demanding with respect to simpler increasing attributes (e.g., the area), which lead closely to similar results, this approach is not diffused.

2.1. Opening by Reconstruction

Openings by reconstruction based on the geodesic reconstruction require a marker, *mrk*, and a mask, *msk*, image [1]. They perform the transformation in two operations: i) the generation of the marker image from the input image, *f*; and ii) the geodesic reconstruction of the marker by the mask image (*msk* = *f*). In general, the marker is computed by eroding the input image with a structuring element *B*, $mrk = \varepsilon_B(f)$, reducing the complexity of the input image. The following reconstruction is then performed by iterative applications of $\delta_g^{(1)}$, the geodesic dilation with an SE of elementary size on the eroded image. This leads to $R_f^{\delta}(mrk) = \delta_f^{(n)}(mrk) = \delta_f^{(1)} \cdot \delta_f^{(1)} \cdot \ldots \cdot \delta_f^{(1)}(mrk)$, performed *n* times, until the stability is reached ($\delta_g^{(n)}(mrk) = \delta_g^{(n-1)}(mrk)$). The reconstruction phase entirely retrieves all the regions not completely suppressed by the erosion (i.e., those where *B* was not fitting completely in). The application of an opening by increasing the size of the SE yields to a granulometry by reconstruction. It is important to notice that, this algorithm performs a complete filtering (i.e., one erosion and several dilations until the stability is reached) of the image for each of the levels (i.e., a SE size) of the granulometry.

2.2. Attribute Opening and Thinning

Attribute openings are based on the operators of connected opening and trivial opening [4]. For simplicity, we introduce the operators for the binary case and than we extend the concepts to the grayscale. Binary connected opening, Γ_x, transforms an input image *f* by removing all those regions that do not contain the pixel *x* while keeping all those pixels connected to *x* according to a connectivity rule (i.e., the region, or connected component, enclosing *x*). Binary trivial opening, Γ_T, requires an increasing criterion *T* (i.e., if *T* is satisfied for a region, than it is also satisfied by all the connected components enclosing the region), and it preserves a given connected component if satisfies the criterion *T*. By applying a binary trivial opening on all the connected components of *f* (results of connected openings) we obtain a binary attribute opening Γ^T, as $\Gamma^T(f) = \bigcup_{x \in f} \Gamma_T(\Gamma_x(f))$. If the attribute selected is not increasing, the transformation is not an opening but a thinning [4]. Binary attribute opening can be easily generalized to the grayscale images through the threshold decomposition principle [2]. The grayscale attribute filter is defined as $\gamma^T(f)(x) = \max\{k : x \in \Gamma^T[Th_k(f)]\}$ where $Th_k(f)$ is the binary image obtained by thresolding *f* at graylevel *k*. The great flexibility of these filters is given by the attribute component; its choice is the key point of the transformation because it tunes the filter behavior. Different attributes may lead to completely different results, as in the case of an attribute sensitive to geometrical features (e.g., size, shape, etc.) and one related to the graylevels of the pixels (e.g., uniformity, contrast, etc.). By filtering with a progressively relaxed criterion *T*, a granulometry is created. The attribute thinnings do not lead to a granulometry because the absorption law is not fulfilled (the attributes are not increasing [4]), but to a pattern spectra. In [5] a fast algorithm for computing attribute filtering based on Max-tree, an efficient data representation, is presented. The input image is converted in a tree structure, where each node of the tree refers to each flat zone generated in the threshold decomposition of the image. The attributes are then computed on the regions represented by the nodes. Finally, the filtering is performed by pruning the tree, deleting those nodes that do not satisfy the criterion and by restituting the filtered image.

3. ANALYSIS AND RESULTS

The advantages of using attribute filters are particularly evident if we analyze granulometries. In terms of computational complexity, an opening by reconstruction, implemented as in Section 2.1, in the worst case has time complexity of $O(N^2)$, with *N* the number of pixels in the image. Thus, for a granulometry composed by *L* levels, the worst-case computational complexity has an order of LN^2. Instead, when considering a granulometry based on attribute openings, computed by an efficient algorithm based on Max-tree [5], the worst-case time complexity of a granulometry is of $O(LN(C+G+1))$, where *G* is the number of gray-levels of the input image and *C* the connectivity rule. A granulometry built by filtering the Max-tree is efficient because the tree is computed only once (this is the most demanding stage, having maximum complexity of $N(C+G)$) and sequential filtering of the image are just given by different prunes of the tree, which require only *N* operations for each level. This is particularly relevant for feature extraction tasks where a feature can be well characterized by investigating the attribute on fine steps and for a wide range of values. An additional benefit given by the algorithm based on Max-tree is the computation of some attributes during the construction of the tree, which further speeds up the process. Moreover, if the image needs to be filtered on the base of features not related to the size of the structures (e.g., shapes), this can be performed by only one attribute filtering with an appropriate attribute. Instead, by approaching the problem with filters by reconstruction, several MPs based on different SEs would be required, performing unnecessary multiscale analyses. The detailed results obtained by the application of attribute filters to a pansharpened QuickBird VHR image are reported in the full paper. The experimental results confirm the analysis above and demonstrate that morphological attribute filters are attractive for the analysis of very-high resolution images.

4. REFERENCES

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