RECURSIVE TEXTURE FRAGMENTATION AND RECONSTRUCTION SEGMENTATION ALGORITHM APPLIED TO VHR IMAGES

Raffaele Gaetano, Giuseppe Scarpa, Giovanni Poggi

University "Federico II" of Naples, Italy
Department of Biomedical, Electronic and Telecommunication Engineering
Via Claudio 21, 80125, Naples, Italy
{firstname.lastname}@unina.it

1. EXTENDED ABSTRACT

Texture-based segmentation is drawing an ever increasing attention, both because of its applicative importance, more and more obvious with the high resolutions available nowadays, and because of the technical challenges it presents. As a matter of fact, a large variety of segmentation tools have been proposed for textured images, from the seminal work of Haralick [1], to more recent well-known contributions [2, 3], but such tools focus mainly on *micro*-textures, described by means of local properties, while they have a hard time modeling, identifying, and eventually segmenting *macro*-textures. The importance of macro-textures, on the other hand, cannot be overemphasized, especially when dealing with very high resolution (VHR) remote sensing images whose resolution goes well below the meter. In such a case, in fact, what we can appreciate in a scene (think of urban areas) are mostly macro-textured items, like road *networks*, building *blocks*, parking *lots*, *lines* of trees, and so on, which are certainly quite difficult to model with micro-textural features.

We recently proposed a new segmentation technique, the Texture Fragmentation and Reconstruction (TFR) algorithm [4, 5, 6], which deals quite effectively with macro-textures. TFR is based on the Hierarchical Multiple Markov Chain (H-MMC) model [5] for texture representation, and provides a hierarchical output, that is, a sequence of nested segmentation maps varying for the number of segments and their intrinsic scale. Without dwelling into fine details we can attribute much of H-MMC description power to its region-wise (as opposed to pixel-wise) approach for texture modeling, which allows one to represent long-range spatial interactions in a rather straightforward way. As a consequence, the TFR algorithm succeeds in identifying large-scale textures, in an unsupervised setting, even if composed by just a few instances of their basic structures [5, 6]. In addition, thanks to the region-wise approach, TFR has a much smaller complexity than comparable techniques, since it escapes the curse of pixel-wise texture feature extraction. Such an advantage may well become crucial with the huge amount of data involved with high resolution imagery.

On the down side, one of the main feature of TFR observed in [5, 6] was that the finer the scale (larger n) the worse the segmentation S_n. In other words the segmentation quality is generally decreasing towards finer scales in the final output.

To understand this phenomenon we must take a deeper look at the processing flow of the algorithm as outlined in the block diagram of Fig. 1 (a). The first step is the color-based classification, where the image is partitioned in color classes by means of a MRF-based segmentation algorithm [7]. In this step each color class is also decomposed into the set of its elementary connected regions, referred to here as *fragments*. Then, the spatial-based clustering creates the elementary texture components by collecting together all fragments of the same color which also have similar shape and contextual features. The output of this block is therefore a first texture segmentation map S_N with N texture classes. S_N is the finest-scale map of the whole hierarchical segmentation $H = \{S_n\}_{n=2,\dots,N}$ provided by TFR. Coarser and coarser maps, $S_{N-1}, \dots, S_2$, are then obtained in the third (merging) step through the pairwise fusion of texture classes.

It can be now understood that, in presence of a particularly heterogeneous textural content, in both the color classification and contextual clustering steps the variability of image data increases the dimensionality of the involved feature spaces, making the statistics less reliable and consequently reducing the accuracy of these blocks. As a result, texture mixing phenomena are more likely to appear at finer scale segmentations, while at coarser scales they can partially be solved thanks to some proper mergings.

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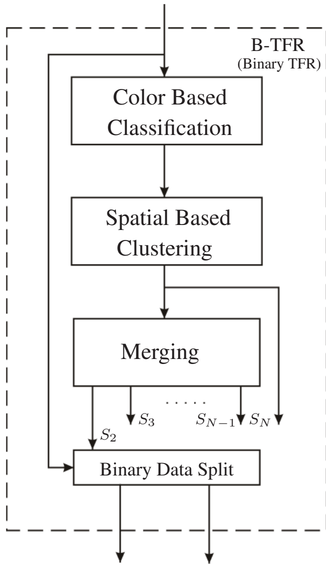
(a) 

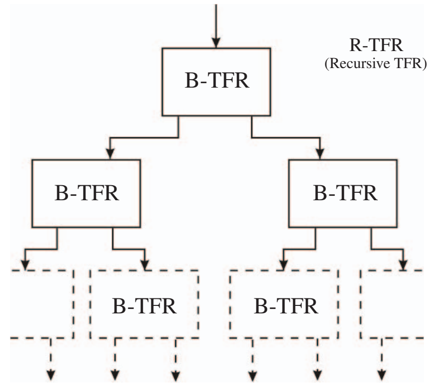
(b) 

Fig. 1. Flow chart of the binary restriction of TFR (B-TFR) on the left and the proposed R-TFR algorithmon on the right.

This observation originates the variation of TFR proposed here, and called *Recursive* TFR (R-TFR). The idea is very simple: since TFR is able to accurately segment the image in a few large regions, each characterized by (more) homogeneous textural properties, we use it in cascade, by first identifying such macro-regions, and then operating within each of them. For example, we can first divide an image in urban and vegetation regions by means of a binary TFR (B-TFR) map, and then use again TFR within each region, thus avoiding the the class overfitting problem outlined above. Then, the obvious generalization, described pictorially in Fig.1 (right), is to use B-TFR as the basic step to build top-down, recursively, a complete segmentation map. The final output of this new algorithm is again a hierarchical segmentation, as one can stop the procedure at different steps, or prune back the tree of segments as desired. Of course, computational complexity increases, but this should not be much of a problem given the lightness of TFR.

In order to test the effectiveness of the proposed method we experimented with optical remote sensing images, with spatial resolution below the meter, and the first results are definitely promising.

2. REFERENCES

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