INTERACTIVE SEGMENTATION OF HIGH RESOLUTION SYNTHETIC APERTURE RADAR DATA BY TREE-STRUCTURED MRF

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ABSTRACT

Reliable segmentation of SAR images requires some forms of user supervision: we resort here to the interactive version of the Tree-Structured Markov Random Field (TS-MRF) segmentation suite. The TS-MRF model, and the associated segmentation tool, provide a flexible and spatially adaptive description of the data. In the interactive version, the user can drive the process based on the inspection of the current result, deciding step-by-step which direction to take, and switching from one segmentation modality to another. Experiments with the segmentation and classification of multitemporal SAR images prove the potential of the interactive approach and of the TS-MRF tool.

Index Terms— SAR, segmentation, classification, MRF, interactive, supervised.

1. INTRODUCTION

The analysis of remote sensing imagery is more and more heavily supported by computer programs, which carry out important intermediate tasks such as image segmentation and classification. In the absence of supervision, however, such tools provide often disappointing and even misleading results. This is not surprising, given the large variety of unpredictable sceneries which can occur in remote sensing images, hardly captured by compact models. Classical supervision requires the user to single out some suitable regions of the image, and to use the selected data to properly train the algorithms of interest, a painstaking process over which the user has little control and that could require several iterations.

Here, we follow a different approach for data analysis, already analyzed in [1, 2], based on a tight interaction between the user and the computer. Indeed, while number-crunching tools are necessary to compute data statistics and synthetic features, the user should be constantly given the opportunity to drive the process towards the desired results, based on a wider vision of the problem and the accumulated expertise. Research is focusing recently on this approach, both for optical [3, 4] and SAR [5] data. In more detail, we propose here an innovative user-driven approach for the exploration of multitemporal high resolution Synthetic Aperture Radar (SAR) data. After appropriate registration, calibration and filtering, SAR images are processed by an interactive and powerful image classification/segmentation tool based on the tree-structured Markov random field (TS-MRF) model [6, 7]. The user participates actively in the processing chain making the key high-level decisions and modifying the processing flow if necessary. This interaction is particularly useful with SAR images, which require a deep understanding of many relevant physical phenomena a solid expertise and to reach a correct interpretation of data. In next Section we provide the necessary background on the TS-MRF model and segmentation tool, then in Section 3 demonstrate the potential of this approach on a 15-image multitemporal stack of SAR images. Finally, Section 4 draws conclusions.

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2. THE TS-MRF MODEL AND TOOL

In the TS-MRF model, the image is described by a binary unbalanced tree (see Fig.2 and Fig.3(b) for an example). Each node is associated with a region (not necessarily connected) and the corresponding data, with the root corresponding to the whole image. A label map is also associated with each internal node pointing at two children nodes. Each node/region is partitioned, proceeding recursively, until the K leaves of the tree are reached, segmenting the whole image in K disjoint regions. Both the label maps and the data are described by appropriate statistical models. Label maps are modeled as a binary Markov random fields (MRF), with given distribution, and the observable at the leaves are modeled as multivariate Gaussian variables. As a consequence, the observables in the internal nodes are mixtures of Gaussian, or they can be approximated as Gaussian if detailed information on the nodes is lacking (unsupervised case). In this tree-structured model, a dedicated binary MRF is associated locally with each node/region, which allows to adapt accurately to the non-stationary behavior typical of images. Indeed, non-stationarity is the major issue in image modeling, and TS-MRF addresses effectively this problem.

The basic actions of TS-MRF segmentation are node splitting, merge-split refinement, and topological split.

1. *Node splitting:* for each node, a binary MRF segmentation is carried out according to the MAP criterion. The split can be accepted, in which case the tree keeps growing recursively from the node, or rejected, stopping the growth at the selected node. In [6] a split-gain indicator is computed locally for each node, which drives the growth of the tree by indicating whether a node must be split and in which order. All other parameters are also estimated locally for each node, including class statistics.

2. *Merge-split refinement:* the exclusive use of binary splits might impair the segmentation performance, because of the inability of the algorithm to deal with non-binary structures. To address this problem, in [6] a merge-split action was added. Each newly created children node is tentatively merged with each of the other nodes, except the sibling, and then split again based on a local binary MRF. A merge gain is computed locally to accept or reject the action. The overall effect is a refinement of the boundary between the two interested nodes.

3. *Topological split:* if the user is interested in segmentation in a more strict sense, rather than classification, keeping a single class-wise data description is only a constraint which can impair local accuracy. Therefore, in order to build an object-level description of the image, after each binary split a topological split of the children classes follows, in which disjoint segments are assigned different labels. In this view, each MRF split is followed by a topological split, which usually generates a large number of children, increasing the computational burden but also the accuracy of local description.

3. INTERACTIVE TS-MRF BASED SEGMENTATION

To test the effectiveness of interactive TS-MRF segmentation we carry out experiments on a multitemporal stack of Cosmo-SkyMed Strip-Map images taken near Caserta, Italy. The stack comprises 15-images of size 5200×4600 pixels, with a spatial resolution of 3 meters, for an overall coverage of about 195 km2. Data are HH polarized, acquired with ascending orbit and a look angle of approximately 33^o. Fig.3(a) shows one of the available single-look SAR images. In order to fully exploit this wealth of information through the TS-MRF suite, the input data must be appropriately pre-processed. First of all, the images are co-registered via the three-step procedure proposed in [8]. Then, a radiometric calibration is performed based on ancillary data. To improve data quality, we perform

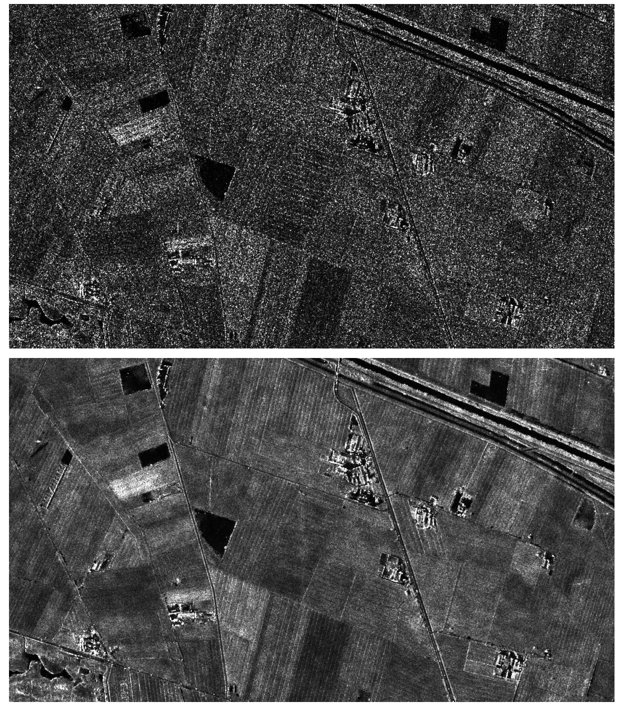

Fig. 1. A detail of one of the SAR images before and after despeckling.

a multitemporal despeckling by means of the De Grandi filter [9] which provides a speckle reduction in the order of 12 equivalent number of looks (see Fig.1) without loss in spatial resolution. Eventually, we perform a point-wise homomorphic transform of the data, which provides class-wise statistics of the scene close to Gaussian distributions, allowing us to use the TS-MRF suite without any structural modification w.r.t. the case of multi-spectral optical data.

The elementary actions described in Section 2 were proposed originally for automatic segmentation, driven by suitable numerical indicators, like the split gain, the merge gain, and other node statistics. Here, they are given to the user as basic tools, to be used interactively on the basis of a continuous inspection of results. In interactive TS-MRF the user assesses by visual inspection the meaningfulness of any split to decide whether to proceed, validating the split, or stop. Moreover, after each class split, the newly created classes can be compared with the others to check whether a merging is needed to redefine over-segmented classes. In our case study, we obtained fairly naturally the six-class segmentation tree shown in Fig.2 (stopping at the colored nodes) using only visual information on class homogeneity and region compactness. At this stage, all connected segments have a label attached, corresponding to one of the colored nodes of the tree[1]. This is the product shown in Fig.3(b). A large part of the

[1]Note that labels have been attached only after the process, based on an available ground truth.

image is now satisfactorily segmented and ready for further processing.

However, regions corresponding to human settlements and man-made structures are fragmented in a myriad small segments, which clearly do not allow a simple analysis. To extract a further *urban* class, we split all classes (colored nodes in Fig.2) through the topological split action, obtaining thus a detailed object layer. Then, from the original SAR stack we compute a coherence map, shown in Fig.3(c), as the average of the pair-wise coherences of the oldest with all the others images. Finally, we use the coherence map to classify each individual segment as either urban or not, obtaining a new class, shown in lilac in the final map of Fig.3(d). Note that the new class has the same (high) resolution of the object layer, definitely superior to the coherence map resolution.

The interactive use of TS-MRF provides eventually a thematic map much more meaningful than those provided by fully unsupervised methods, e.g. [6, 10], and also superior to maps obtained through conventional supervised approaches [7].

4. CONCLUSIONS

An appropriate human-machine interaction can significantly improve the performance of fundamental tasks such as segmentation and classification. This approach, however, requires powerful, fast, and easy-to-use segmentation tools. The TS-MRF algorithmic suite, thanks to its hierarchical image model which adapts to local class statistics, fits well this approach and provides the required flexibility of use to deal with non-standard problems. We validated the potential of this approach, and the effectiveness of the TS-MRF tools, by segmenting SAR images, a very challenging task due to the intense speckle noise. Early results, judged by visual inspection, were very encouraging. In [11] we present a more thorough analysis of performance including objective measures of classification accuracy, further confirming the validity of the proposed approach.

In future work we will improve the data preprocessing, resorting to nonlocal filtering [12], and consider data models more specific of high-resolution SAR images.

5. REFERENCES

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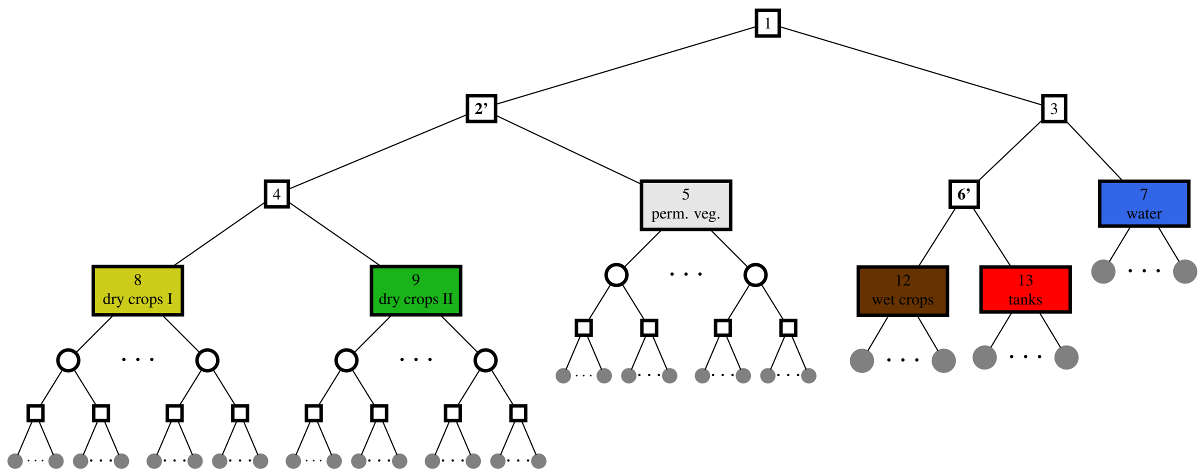

Fig. 2. Segmentation tree for the test image of Fig.3. Nodes associated with squares are obtained through split and merge. Nodes associated with circles are obtained through topological split. Leaves correspond to individual connected segments.

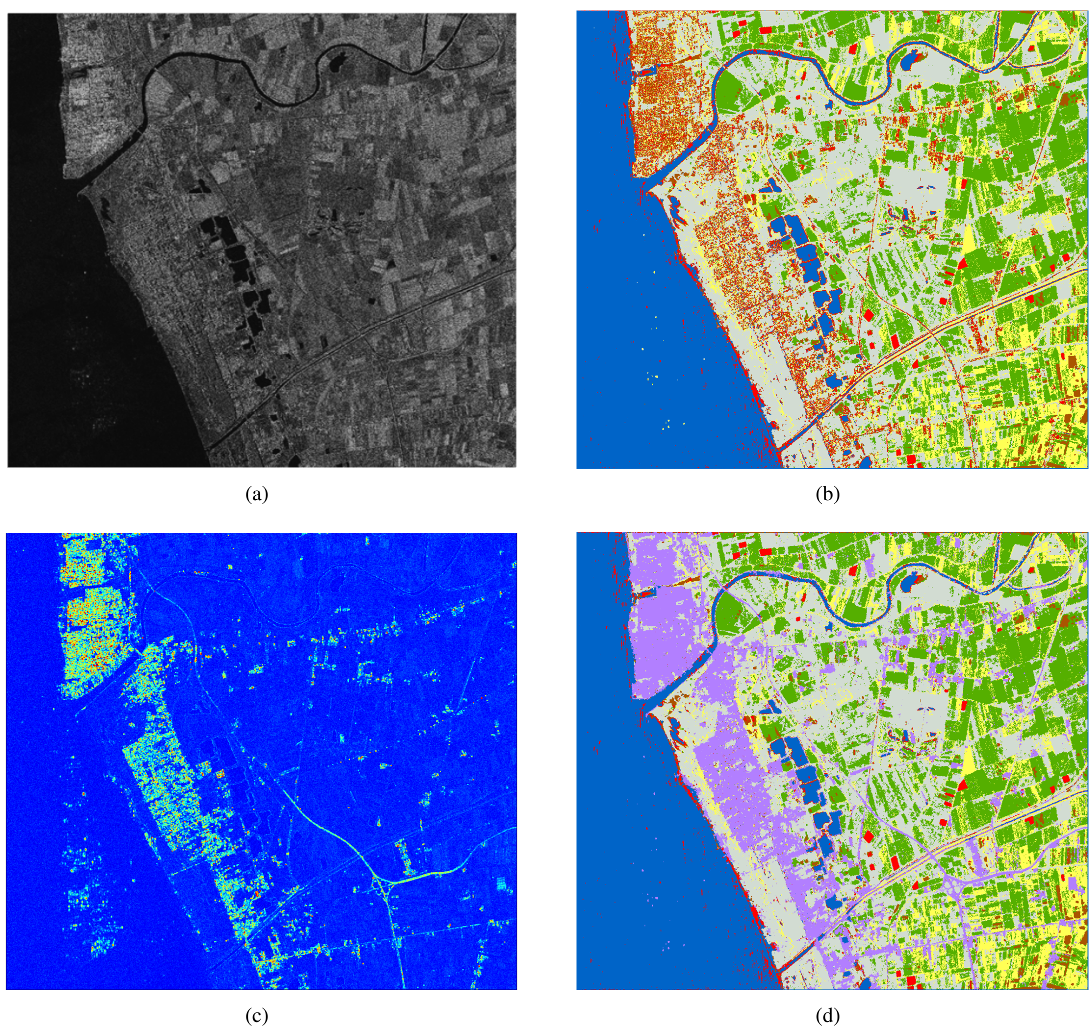

Fig. 3. Segmentation results: (a) original single-look SAR image, (b) 6-class segmentation, (c) coherence map, (d) 7-class segmentation including the “man-made” class.