

Introduction

In the provided papers, the core issue identified is that standard methods often fail to capture the complex geometric details of objects like roads or buildings, as they rely on fixed window sizes . The "tree-based paradigm" offers a solution by structuring images as hierarchies of regions (nodes) rather than simple grids .

Pros of tree-based Paradigm:

- **Superior Spatial Modeling:** Dalla Mura et al. explain that unlike standard morphological filters which use a fixed structuring element (SE), tree-based Attribute Filters process connected components based on adaptive attributes like area or moment of inertia. This allows for a "more complete description of the scene" [1-1] and better modeling of structural information compared to conventional filters .
- **Computational Scalability:** Constructing the tree (e.g., a Max-Tree) happens once, subsequent filtering is very fast & scalable. Dalla Mura et al. note that this implementation "strongly reduces the computational load" [1-1] compared to conventional profiles, potentially by an order of magnitude .
- **Multiscale Hierarchy:** Bosilj et al. highlight that these trees naturally organize image content from fine details (leaves) to coarse regions (root) . This vertical inclusion information enriches the analysis beyond simple flat partitions, allowing us to handle objects that exist at different scales simultaneously . [2-46]

Cons and Limitations :

- **Parameter Sensitivity:** A significant drawback is the difficulty in selecting the right attributes and thresholds. Santana Maia et al. explicitly state that APs are criticized for their "sensitivity to parameter selection" [3-47] particularly the threshold values used to prune the tree . If these are chosen poorly, the description of the scene may fail, or lead to redundant information .
- **Complexity with Multivariate Data:** Extending these methods to multi-band images (like hyperspectral data) is mathematically challenging. Bosilj et al. explain that inclusion trees require a total ordering of pixel values, which is difficult for vector data (multivariate images) [2-19]. This often forces us to use marginal strategies (processing bands individually) or reduced size which might be sensitive to translation , rotation and scaling [2-1]

- **Generalization Issues:** A critical "con" raised by Santana Maia et al. is the potential for poor generalization if not handled properly. They argue that standard validation methods often involve "malpractice" where the tree is built on the entire image, mixing training and testing structures. [3- 50]. When they tested on spatially disjoint splits (separate trees for training and testing), performance was different.

Toolings :

- **Attribute Profiles (APs):** This is the flagship tool. Dalla Mura et al. introduced APs to generalize Morphological Profiles (MPs). By using Attribute Filters, APs can characterize regions by parameters like geometry or texture, not just size. This effectively creates a multi-level signature for every pixel .
- **Pattern Spectra:** While APs are used for local features, Bosilj et al. discuss how these hierarchies can be used to generate global descriptors (granulometries or pattern spectra). These summarize the distribution of shapes and sizes in an image, which is useful for classifying overall texture or land cover types .

Evolutions :

- SEs to Attributes (2010): The innovation in Dalla Mura et al. was replacing the rigid Structuring Element (SE) of mathematical morphology with flexible Attribute Filters. This shifted the focus from "does this shape fit?" to "does this region have these properties?" .
- Inclusion to Partitioning (2018): Bosilj et al. provided a crucial taxonomy, distinguishing between Inclusion Trees (like Min/Max-Trees) and Partitioning Trees (like α -trees). This evolution is important because Partitioning Trees are better at segmentation tasks and avoiding the loss of the information where regions merge incorrectly .
- Self-Duality and Deep Learning (2021): Santana Maia et al. document the shift toward Self-Dual Attribute Profiles (SDAPs) using the Tree of Shapes (ToS), which handles dark and bright objects in a single tree . They also highlight the modern trend of feeding AP features into Convolutional Neural Networks (CNNs) but kinda indicated that it led to better classification but increase in test time.

References:

- [1] M. Dalla Mura, J. A. Benediktsson, B. Waske, and L. Bruzzone, "Morphological Attribute Profiles for the Analysis of Very High Resolution Images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 48, no. 10, pp. 3747–3762, 2010.
- [2] P. Bosilj, E. Kijak, and S. Lefèvre, "Partition and Inclusion Hierarchies of Images: A Comprehensive Survey," *Journal of Imaging*, vol. 4, no. 2, pp. 2018
- [3] D. Santana Maia, M.-T. Pham, E. Aptoula, F. Guiotte, and S. Lefèvre, "Classification of Remote Sensing Data With Morphological Attribute Profiles: A decade of advances," *IEEE Geoscience and Remote Sensing Magazine*, vol. 9, no. 3, pp. 43–71, 2021.