Single Tree Detection in Millimeterwave SAR Data by Morphological Attribute Filters

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Abstract: This paper presents an approach for single tree detection in millimeterwave SAR intensity data. Due to the low canopy penetration of millimeterwave SAR trees are imaged with a high level of detail. Nevertheless, the appearance of trees in the image is manifold and rather nondescript which imposes some challenges to automatic detection schemes. Starting with an explanation of the appearance of trees in SAR data it is shown how models can help to understand the imaging process of trees and their properties. Then a new approach is presented to detect single trees, based on the insights of the previous discussion.

Zusammenfassung: Diese Arbeit stellt einen Ansatz vor, um einzelne Bäume in Millimeterwellen-Radar zu detektieren. Dabei werden ausschließlich hochaufgelöste SAR Intensitätsdaten verwendet. Aufgrund der geringen Eindringtiefe des Millimeterwellen-Radar in die Baumkronen werden diese deutlich abgebildet. Dennoch stellt die Erscheinung von Bäumen in SAR Daten eine Herausforderung an Detektionsalgorithmen dar. Es wird daher zunächst erörtert, wie Bäume durch die Sensorik abgebildet werden und inwiefern Modelle helfen können diesen Prozess nachzubilden. Anschließend wird ein Verfahren präsentiert was, aufbauend auf diesen Erkenntnissen, eine Detektion durchführt.

1 Introduction

The automatic recognition of individual trees in remote sensing data is a highly investigated research topic. While most hitherto published corresponding work is based on an exploitation of airborne or spaceborne optical imagery or airborne LiDAR data, the utilization of synthetic aperture radar (SAR) in this field is mostly restricted to large-scale forest classification (PERKO et al., 2010), biomass and forest volume estimation (NEUMANN et al., 2010; MERCER et al., 2010) or canopy height model reconstruction (IZZAWATI et al., 2006). However, the feasibility of single tree recognition in millimeterwave SAR data was demonstrated in (SCHMITT et al., 2013) by proposing a tree model reflecting the intensity signature of a tree in the SAR imagery. While mainly discussing the potentials – and more so challenges – of this kind of sensor configuration for the task, the proposed tree recognition strategies relied on the use of interferometric phase measurements in order to achieve height information as additional input to the detection and reconstruction procedures.
In contrast, the approach proposed in this paper utilizes the insights gained from this ongoing work, but focuses on the detection of single trees solely in SAR intensity data while fully ignoring the interferometric phase. This way, it enables a much wider application range, e.g. for cases where no InSAR data is available or where the interferometric phase measurements suffer from temporal decorrelation or volume penetration.

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The methodology of this work is based on morphology, which has been proven to be a very powerful image analysis tool especially in remote sensing. Recently, for example, MAKSYMIUK et al. (2013) already used Morphological Attribute Filters for vehicle detection in SAR intensity data.

2 Tree Representation in SAR intensity data

Trees have a manifold and rather nondescript appearance in SAR intensity data making it challenging to develop rules for their automatic detection. In particular, they do not exhibit strong backscattering nor do they have a simple and discriminative shape or geometry. The rich diversity of trees in terms of species but also in terms of variations of trees within the same species would be best addressed by supervised learning algorithms. Unfortunately, supervised learning requires large amounts of training data. Furthermore, additional difficulties arise by the grouping property of trees. In general, even in urban areas, trees seldom appear isolated, but mostly in small groups or even as small groves. In order to tackle this, one needs to understand the imaging of trees in radar imagery. Hence a model is required to reproduce the imaging process and investigate the effects of variations. Figure 1 shows a small group of trees in an optical image and correspondingly in a SAR image, taken from the MEMPHIS sensor of the Fraunhofer FHR. The sensor operates in the Ka band and offers a physical resolution of 16 cm in

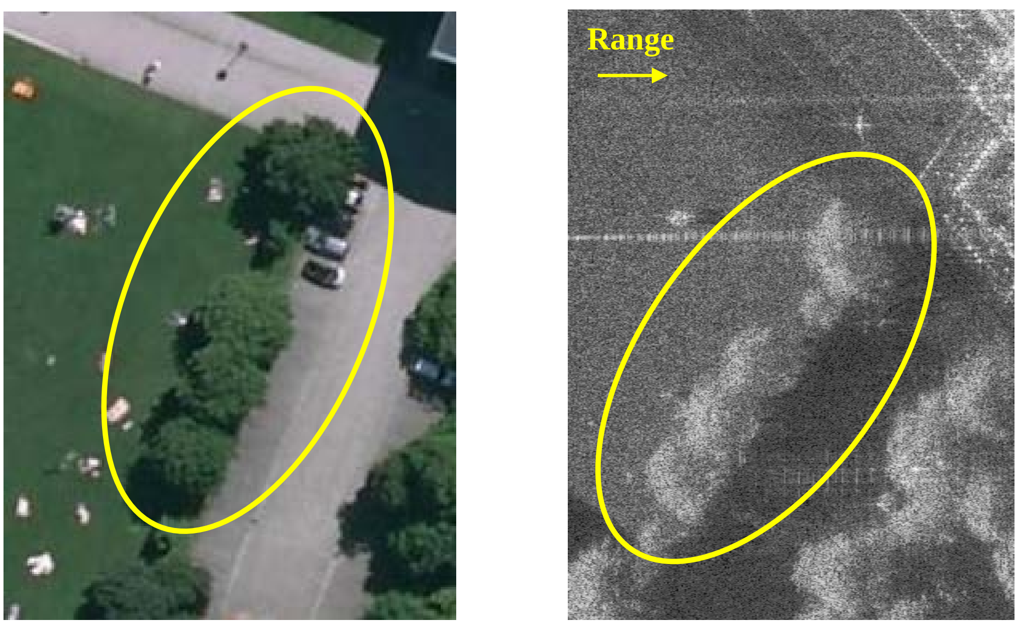

Figure 1: Small group of trees in optical orthoimage (left) and in a SAR image (right). The foreshortening is clearly visible as well as the sickle-shaped mapping of the trees.

range and 5 cm in azimuth. As SCHMITT et al. (2013) have shown, the ellipsoid can be considered as a reasonable geometrical model for average deciduous trees. Although this model is rather simple, it enables to make assumptions about the intensity profile of a tree. Unfortunately, while being a good and generalized approximation in terms of the shape of the trees, it is not suitable as input for simulating tree signatures in SAR images, e.g. using the RaySAR simulation environment (AUER, 2011). Even if the surface is assumed to possess only diffuse reflectivity, the resulting simulated intensity profile is not comparable to real SAR data. This is obvious in the simulation result shown in Fig. 2 which has been generated by RaySAR using an ellipsoid with diffuse reflectivity and a depression angle of 30°. Obviously, the simulated appearance of the tree is not representative for tree signatures as shown in Fig. 1. Detailed object models are required for obtaining a more realistic result. In this context, it turns out that the geometrical structure of the surface is far more important than the material properties. We used an automatic approach for generating random trees (WEBER & PENN, 1995). The resulting model, as shown in Fig. 2 (right), is very detailed with a trunk, branches and leaves. Apart from the surface and material properties it reproduces the geometry of a tree very realistically. The employed tree generation method is quite versatile and offers a good source for artificial trees which can be used to analyze the imaging of trees. Even more importantly, it offers the possibility to generate an arbitrary large database for supervised learning procedures.

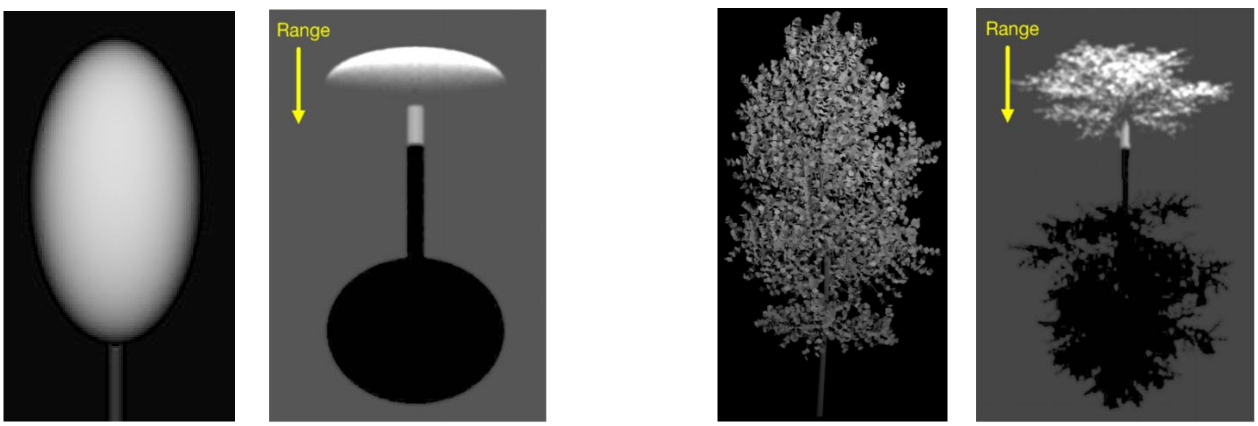

Figure 2: Tree models and their corresponding appearance in SAR in intensity images with the simple ellipsoid (left) and the synthetically generated tree (right) according to (WEBER & PENN, 1995). The simulation is conducted with RaySAR (AUER, 2011) with a spatial resolution of 5 cm in azimuth and 15 cm in range (depression angle: 30°).

Compared to the simple ellipsoid model, the simulated image of the tree model is by far more realistic and, hence, supports the interpretation of tree signatures in Fig. 1. The signal contributions from leaves and branches are condensed in a bright frayed area facing the line-of-sight of the SAR sensor. The lower end of the trunk is followed by a shadow zone which is much larger than the tree layover area. It should be noted that the simulation result shown in Fig. 2 has much smaller pixel spacing than the real data presented in Fig. 1, whereas the spatial resolution is the same. Intensity peaks are clipped in order to emphasize the tree layover and shadow extent in the image (8-bit gray value).

3 Tree Detection by Morphological Attribute Filters

The use of morphological approaches has great potential in remote sensing. Techniques like Morphological Attribute Filters (AF) and Morphological Attribute Profiles (MAP) as presented in (DALLA MURA et al., 2010) allow for a comprehensive multiscale analysis and filtering of the image in terms of shape and other more general attributes. It was already demonstrated in (MAKSYMIUK et al., 2013) that Attribute Filters are an appropriate method to perform object detection in SAR intensity data.

3.1 Hierarchical image representations and Morphological Attribute Filters

The major concern of Morphological Attribute Filters (AF) is the removal of certain objects from the image. All filtering approaches aim to preserve objects which are not subject to removal as best as possible and simultaneously avoid the introduction of artificial structures (e.g. smoothing at edges). Morphological reconstruction methods are able to perform this kind of task while removing all objects which do not satisfy a given criterion T. One of the first methods is the well-known operation *opening by reconstruction* which uses the size as an attribute for the criterion: *the given structure element must fit inside the region*. Based on the increasingness of the property one has to distinguish between attribute opening and thinning or closing and thickening (BREEN & JONES, 1996). In order to apply this kind of filtering it is necessary to define the data structures involved. First of all, the criteria are applied to connected components of an image, which are just sets of pairwise connected pixels from a cross section of an image f at a gray level t. The motivation to utilize them is the assumption that connected components are related to an object and thus define a membership between single pixels and objects. The left part of Fig. 3 shows several connected components on different gray levels.

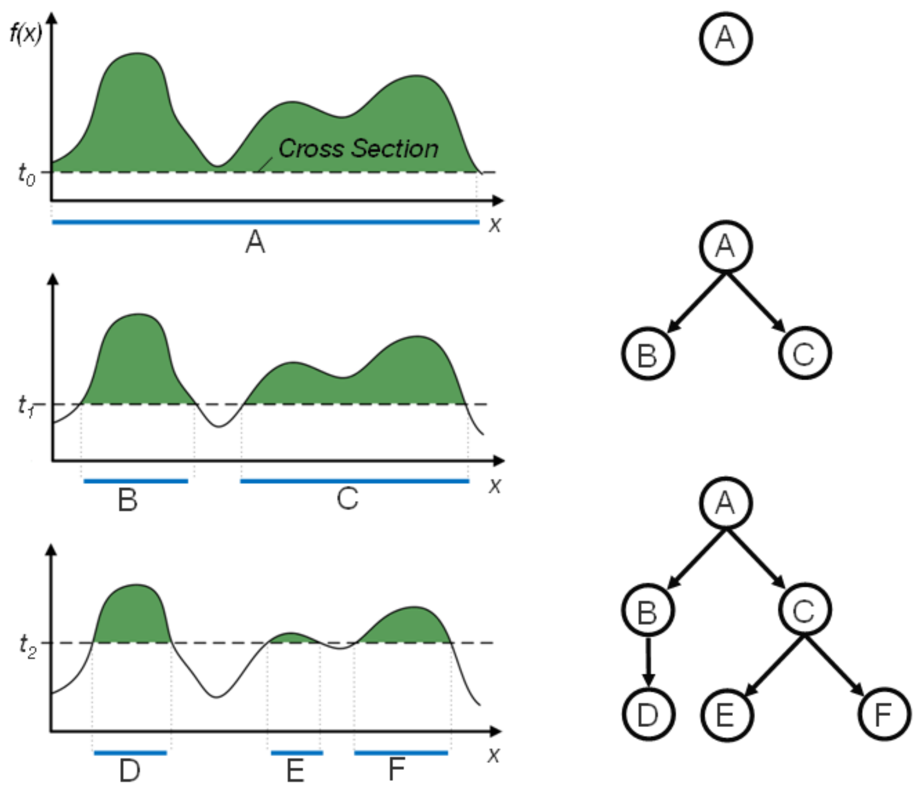

Figure 3: Exemplary generation of a Max-Tree. On the left side a one-dimensional graylevel profile is depicted with several cross sections at various graylevels. On the right is the corresponding Max-Tree with the connected components as nodes.

Since the image can be represented as a hierarchy of connected components (CC) they are usually arranged in a graph data structures or more specific as tree structures, also called Max-Trees in the context of AFs (there are also Min-Trees). The right side of Fig. 3 shows the Max-Tree for the given example. One important property of Max-Trees is that the set of pixels related to a node is a superset of all pixels of its successors. For example, the set of pixels at node *C* contains all pixels of node *E* and *F* as subsets.

In the Max-Tree data structure every node represents a connected component at a specific gray level. Furthermore it is possible to attach many more attributes to the nodes describing them in more abstract ways. A filtering process then consists of a graph traversal with the evaluation of the criterion on every node. If the criterion is not satisfied, the corresponding node is removed from the graph. There are several strategies how the removal affects the graph and its nodes (DALLA MURA et al., 2010). But common to all strategies is the preservation of shape for all remaining nodes or more specific their corresponding CCs. This procedure is known as Morphological Attribute Filtering (AF). We want to urge readers not to get confused between Max-Tree as abstract data structure and the trees subject to our detection method.

3.2 Single tree detection

As mentioned above, the major benefit of AFs and the image representation via Max-Trees is the ability to perform a filtering based on diverse attributes without affecting the shapes of the objects itself. This property allows removing content from the image without loss of information necessary to perform a specific detection task. This is especially important for tree detection with the aforementioned difficulties considering the tree appearance in SAR data.

The main workflow of our detection method consists of two major parts. First we apply an attribute filtering to simplify the image, and then we analyze the remaining objects in terms of their relation to trees. The attribute filtering is just the removal of CCs whose sizes are too big to belong to a tree. The concrete size depends on the assumption of general tree sizes and the image resolution. Additionally we remove e.g. elongated objects by using the roundness and moment of inertia as criteria. Taking a look at Fig. 2 with the exemplary Max-Tree this filtering step would remove the nodes towards the root node transforming the Max-Tree into a forest of smaller Max-Trees containing only CCs at higher gray levels. Notice that this is a property of *increasing* criteria: If a CC satisfies a criterion, then all its supersets (its predecessors in the Max-Tree) also satisfy the criterion. Besides the size there are many other attributes:

- *Statistical attributes*: Mean, standard deviation, skewness, kurtosis, entropy, contrast, and homogeneity of the corresponding gray values within a CC
- *Shape descriptors*: orientation of the main axes, moment of inertia, length of diagonal, bounding box, and isotropy/roundness
- *Topological properties*: Euler number or the number of child nodes.

After the filtering step the problem of detection still remains unsolved, since the image is simplified (see right part of Fig. 5) but in order to detect trees it is necessary to analyze the remaining CCs. As mentioned above, trees have a manifold and very nondescript appearance in SAR intensity images. The imaging of trees results in a kind of sickle-shaped objects but even this is not distinctive enough to allow for an explicit description and a reliable detection of them. Instead our approach is based on the observation that due to the foreshortening we expect that the maximum of the intensity of a mapped tree is shifted towards the sensor (SCHMITT et al., 2013), which can also be observed in Fig. 2 for both simulated models and also on the left of Fig. 4.

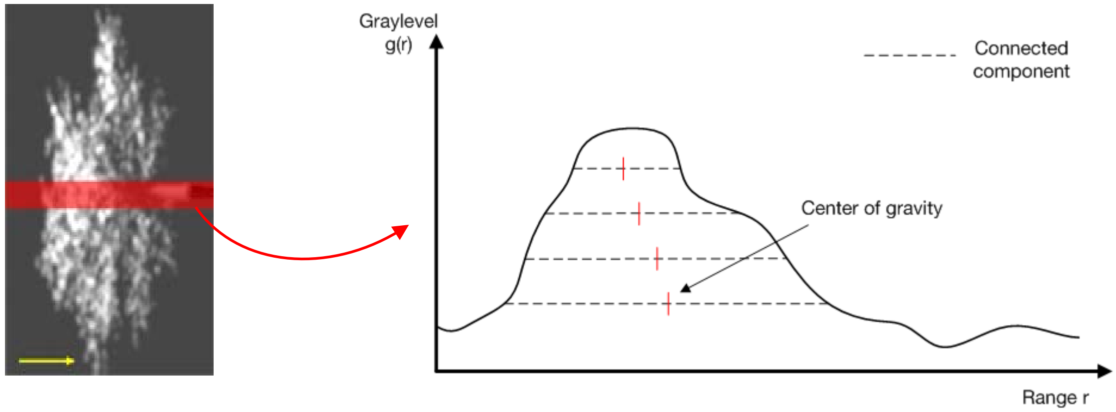

Figure 4: Exemplary slope of the gray values of a tree along range direction. Left side shows the simulated tree. The right side depicts the slope representative for most trees. The most important feature the displacement profile of the center of gravity (COG) with increasing gray level towards the sensor.

The shifting of the maximum is not a property of a single CC but it depends on pairs of them which belong to the same object. Fortunately this is exactly what is represented by the Max-Tree and the CCs as nodes. An object is composed of multiple CCs and their relationship is defined by the hierarchy of the Max-Tree. Furthermore, as a consequence of the previous attribute filtering, we can assume that all remaining CCs potentially belong to a tree in the image.

Concretely we generate a profile of local displacements of the center of gravity (COG) of the CCs by traversing the Max-Tree from the leaves to the roots. This is depicted in Fig. 4 on the right. It shows a slice of the image along the range axis. There are several CCs and it can be seen that the COG moves towards the sensor if we traverse from the root to the leaf (bottom to top). In our approach this displacements are weighted with the graylevel difference between the CCs and stored in a profile for further analysis. This profile is then used as main indicator for the detection of trees. The main feature for the tree is the aforementioned shift of the COG. But besides the sign of the displacement one could use the magnitude as well as further properties of the profile like the number of CCs or the minimum and maximum of the graylevels. These features may serve as a fitness or reliability measure for the detection. After the decision process is done by comparing the fitness value with a threshold, it may happen that a tree has multiple detections. This might occur if a tree has multiple local graylevel maxima in the image, which were not removed by the filtering. In order to suppress them a local merging is performed by an iterative merging of maxima whose distance is smaller than the diameter of an average tree. We use a simple merging rule by deleting the detection which has a smaller fitness value. An example of a detection result with this approach is shown in Fig. 5.

4 Experiments

The proposed method is evaluated on a dataset of the German MEMPHIS sensor from Fraunhofer FHR. This sensor operates at a center frequency of 35 GHz (Ka band) and a bandwidth of 900 MHz. The physical resolution is 16.5 cm in range and 5.1 cm in azimuth.

The flying altitude is 768m with a depression angle of 30°. Since the sensor operates in the Ka band we assume a low canopy penetration which is preferable for this task. The test scene shows the surroundings of the “Alte Pinakothek” in Munich containing more than 120 trees. Most of them reside in groves but there are also some largely isolated trees. It seems that all trees belong to the same deciduous species. The ground truth data is manually labeled from an orthoimage and laser scanning data providing additional height information.

Although a preprocessing of the SAR imagery it is not strictly necessary the proposed detection method gains from a proper preprocessing. Since the presented workflow is based on attribute filtering on Max-Trees, it is useful to remove spurious dark pixels to fill holes in the CCs. To affect the image as little as possible a multiscale *closing by reconstruction* is performed.

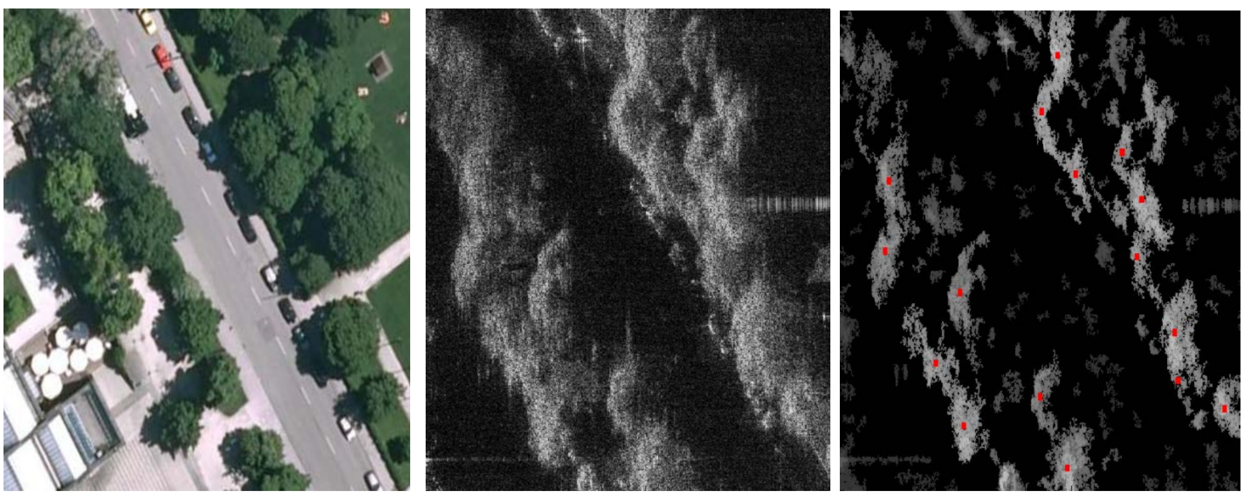

Figure 5: Detection result applying the presented approach. Left is the optical image showing a street with trees on both sides. The image in the middle is the original SAR intensity image. On the right is the detection result. The objects in the image are the remaining connected components after the Attribute Filtering. The red squares represent the detected trees and are placed at the center of the connected component with the highest graylevel. Therefore they are representatives for the local maxima.

The second step performs a graylevel transformation to emphasize the brightness interval where the trees expectedly reside. Because we want to suppress too dark as well as too bright pixels we use the sigmoid transformation function to stretch the interested graylevel interval without clipping. The detection result on the test scene as well as the ground truth data are shown in Fig. 6. It can be seen that most of the trees were detected, even if they are arranged in groves, in which case the detection is very difficult. Nevertheless there are some missing detections as well as false detections. Former occur mostly in groves, latter around buildings. Since our approach can only perform detection and no recognition, it is not possible yet to derive the tree height to achieve an accurate position determination. Furthermore the sizes of the tree crowns were not evaluated.

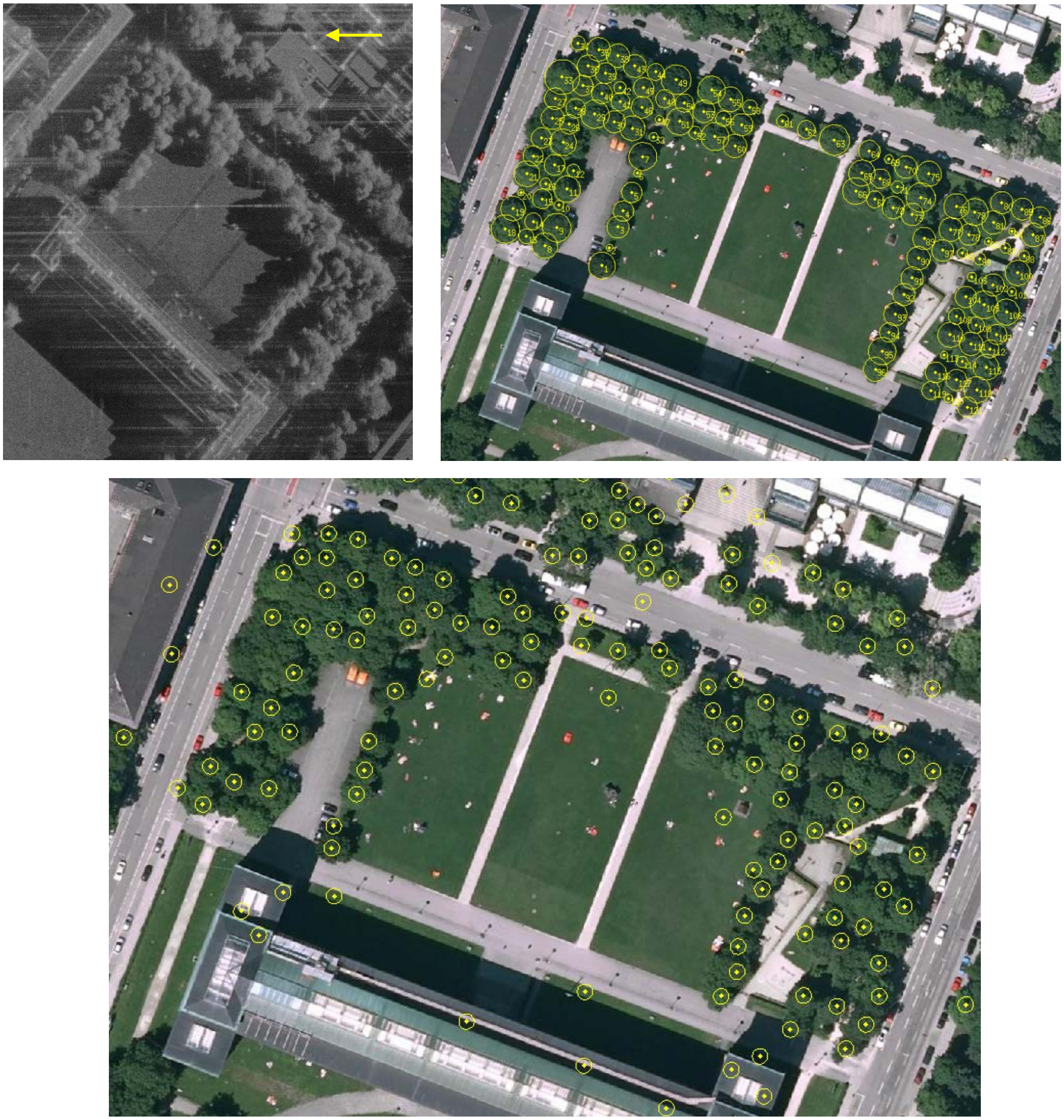

Figure 6: Input SAR image (upper left) for the single tree detection and the corresponding ground truth data (upper right). The bottom image presents the detection results. The tree positions on the ground were computed by assuming a constant tree height of 10 m.

5 Conclusions

The presented approach using Morphological Attribute Filters has demonstrated that single tree detection in millimeterwave high resolution SAR intensity data is feasible without the need to exploit interferometric phase measurements. Although the methods were kept simple many of the trees were detected. It seems a promising approach which might offer a better performance if further efforts are made towards a more sophisticated system. A direct continuation of this work involves the application of Morphological Attribute Profiles (DALLA MURA et al., 2010) for a detailed multiscale analysis of the attributes to derive even more information increasing the detection performance. But detection is only the very first step of a recognition system. To turn this into a fully comprehensive tree recognition system it would be necessary to derive further properties of the trees like crown diameter or tree height. The former can be addressed by analyzing the connected components involved into the detection of a single tree. One major topic for the future would be the integration of the simulation into a recognition system to generate a large number of training samples for a supervised classification scheme or to make simulations whenever it is required by the recognition system to evaluate a hypothesis. This would avoid the definition of manmade rules for the detection process. In addition, it might be promising to integrate the proposed methodology into approaches also using interferometric data in order to benefit from a joint exploitation of all available observations.

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