

# Towards Forest Structure Characteristics Retrieval from SAR Tomographic Profiles

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## Abstract

SAR Tomography has proven to be a unique tool for the retrieval of 3D structure information from forest scenarios: it can reveal different scattering mechanisms at different heights. However, the translation of these measurements into relevant forest structure information is not straightforward and research is still ongoing. In this direction, this paper suggests a framework for the estimation of forest structure from a SAR tomography scheme based on a low number of single pass coherences. Vertical reflectivity profiles are estimated by means of Compressive Sensing Imaging techniques. Two complementary descriptors are then suggested accounting for the simultaneous vertical and horizontal spatial variability of the scene. Their ability to reflect a characteristic structure behavior for the different types of forest considered is analyzed in simulated and real scenarios.

## 1 Introduction

In the context of forest observation, in the last years, attention is shifting from 2D to 3D information by adding vertical structure observables, since it has been demonstrated that the horizontal distribution is not sufficient for an appropriate assessment of several physical parameters of interest. For example, information of 3D forest structure instead of 2D height distribution leads to far more accurate and robust allometric estimators of forest biomass and provides a key insight on the processes driving its evolution [1]. In front of this need, recent advances in Synthetic Aperture Radars (SAR) offer unique and unprecedented opportunities both in terms of new acquisition configurations and 3D imaging. It has been shown that SAR signals at low frequencies can penetrate to a certain extent forest bodies. This capability can reveal, through advanced imaging techniques, such as PolInSAR and SAR tomography (TomoSAR in the following), different scattering mechanisms at different heights ([2] [3]).

However, research is still ongoing on how to translate these measurements into relevant information related to 3D structural parameters of the observed scene. There are two fundamental drawbacks when addressing forest structure assessment by means of TomoSAR. On the one hand, the usual ecological parameters commonly employed to characterize forest structure rely on measures based on individual trees: basal area, diameter

of the crown, diameter of the stem, density of trees... Since in a TomoSAR scheme, the measured signal in a given resolution cell results from the combination of an undefined number of trees, these parameters are not possible to be recovered in a direct way. On the other hand, forest structure, related to morphological characteristics is assumed to be stationary up to a certain level, i.e., natural changes in a forest morphology occur at temporal scales in the range of at least several months. However, since the retrieved reflectivity profiles are sensitive to the dielectric properties of the trees and, therefore, to their water content, their variability is much faster. They may even be sensitive to daily cycles of moisture content variation and to meteorological conditions [4]. This means that reflectivity profiles can be changing even if forest structure remains constant. Aiming to circumvent these discrepancies, this paper proposes a new framework of descriptors to estimate 3D forest structure from the reflectivity TomoSAR profiles.

The remainder of the paper is structured as follows. Section 2 summarizes the technical details of the method proposed. Results are presented in Section 3 and some conclusions and discussion are drawn in Section 4.

## 2 Forest structure estimation from TomoSAR vertical profiles: methodology description

### 2.1 TomoSAR by means of single pass coherences

TomoSAR relies on the exploitation of angular diversity that allows the discrimination of multiple scattering centres at different heights by combining single-look complex data through spectral estimation. In order to have angular diversity, one solution is to combine contributions acquired at different spatially displaced passes of the sensor. In spaceborne schemes, usually a certain period of time elapses between two consecutive acquisitions, so that the scene conditions are often slightly different and these differences can affect the phase difference between the acquisitions. This leads to the temporal decorrelation problems that cause misinterpretations of the relative position of the scatterers in the vertical profiles retrieved. Furthermore, the combination of different passes goes at the expenses of temporal resolution: processes varying at scales faster than the time span required for the tomographic acquisition consisting of a sufficient number of baselines cannot be monitored. In order to overcome temporal decorrelation, the option considered in this paper is to perform the inversion with a set of single pass coherences denoted by  $\gamma(k_z)$ , where  $k_z$  is the baseline for a given acquisition [5] [6]. Since the pairs of measurements are acquired simultaneously in time (or at slightly different times), they are less affected by temporal decorrelation. For each baseline, we then have:

$$\gamma(kz) = \int f(z) e^{-ikzz} dz \quad (1)$$

where  $f(z)$  is the vertical normalized reflectivity profile. For a given finite set of  $N$  baselines (we assume that each single pass acquisition provides a different baseline), we define the vector of baselines such as  $\underline{\mathbf{k}} = [k_{z1}, k_{z2}, \dots, k_{zN}]$  and the corresponding vector of coherences  $\underline{\boldsymbol{\gamma}} = [\gamma(k_{z1}), \gamma(k_{z2}), \dots, \gamma(k_{zN})]$ . With this:

$$\underline{\boldsymbol{\gamma}} = \sum_z f(z) e^{-i\underline{\mathbf{k}}z} \quad (2)$$

$\underline{\boldsymbol{\gamma}}$  can be considered as a partial Fourier Transform of  $f(z)$ . The linear system in (2) is usually expressed as:

$$\underline{\boldsymbol{\gamma}} = \Phi \underline{\mathbf{f}} \quad (3)$$

where  $\Phi$  is the so-called steering matrix, constructed from the elements  $e^{-i\underline{\mathbf{k}}z}$ .

### 2.2 Reflectivity profiles inversion by means of Compressive Sensing

Since in a TomoSAR scheme, the number of baselines is usually low and the baselines are not spatially uniformly distributed, the retrieval of the vertical profiles from the set of coherence measurements is not straightforward. Spectral estimators (Fourier, Capon, MUSIC) are widely employed for this purpose. Recently, the application of Compressive Sensing (CS) techniques to the estimation of forest profiles has been proposed [7]. In the scope of this paper, inversion is also carried out through a procedure based on CS. We will then briefly review its basic principles.

Essentially, the theory of CS assumes that the unknown signal  $f$  in (3) can be recovered with a high probability by solving an  $l_1$  minimization problem, provided that it is sparse or compressible in a certain projection space  $\Psi$  and that  $\Phi$  satisfies the Restricted Isometry Property [8]. If we assume that  $f$  is not sparse, but compressible, we have that  $\alpha = \Psi f$  is sparse. Conversely, if  $\Psi$  is a wavelet projection,  $f = \Psi^* \alpha$  (where  $\Psi^*$  is the complex conjugate of  $\Psi$ ). Then, we have [8]:

$$\boldsymbol{\gamma} = \Phi \Psi^* \alpha \quad (4)$$

Let's consider  $\Theta = \Phi \Psi^*$ , then (4) can be expressed as:

$$\boldsymbol{\gamma} = \Theta \alpha \quad (5)$$

With this, the  $l_1$  minimization problem to be solved can be expressed as:

$$\min_{\alpha} \|\alpha\|_{l_1} \text{ s.t. } \boldsymbol{\gamma} = \Theta \alpha \quad (6)$$

It should be noted that, when dealing with distributed scatterers, generalized distributed CS (DCS) schemes can be considered [9]. Further research should explore this option.

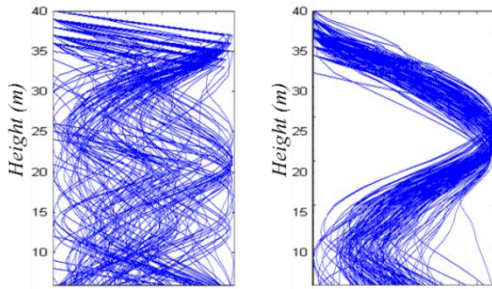
### 2.3 3D structure descriptors proposed

It is widely assumed that any measure of structure in a forest at a given time should account for the simultaneous spatial variability both in the horizontal and in the vertical dimension. In this section, two descriptors estimated from reflectivity profiles are proposed, aiming to translate the notions usually employed in ecology to evaluate horizontal and vertical forest structure.

- **Horizontal structure**

In ecology, the variable usually employed to describe horizontal structure is forest density. As already mentioned in the introduction, since the reflectivity profile

in a resolution cell results from the nonlinear combination of the contributions of an undefined number of trees, it is not possible to robustly estimate density with a TomoSAR system. However, it has been observed that the similarity of the vertical reflectivity profiles in a given neighborhood provides information about the homogeneity of the spatial distribution of the different types of trees and, hence, about forest type. For instance, **Figure 1** shows, for 2 different forest types, 50 vertical reflectivity profiles superimposed, corresponding to neighbouring pixels. In the first area, there is a great diversity of profiles (which might correspond to an older forest), whereas in the second area, the curves in a given neighbourhood are very similar to each other (which rather corresponds to a younger stand). Therefore, we propose to define in TomoSAR data a descriptor of horizontal structure for each pixel as the mean cross-correlation of the vertical profiles in a given neighbourhood of this pixel. It should be noted that the size of the area considered can be adjusted (also taking into account the resolution of the data), resulting thus in a multiscale analysis.



**Figure 1:** Example of 50 superimposed vertical reflectivity profiles for two different forested scenarios.

- **Vertical structure**

The number and distribution of the different layers is commonly taken as a measure of vertical forest structure in ecology. We propose to translate this notion into the reflectivity profiles domain as the number of significant local maxima. In further studies, we could also consider complementary information such as the distance between the different layers.

## 3 Results

### 3.1 Tests on simulated data

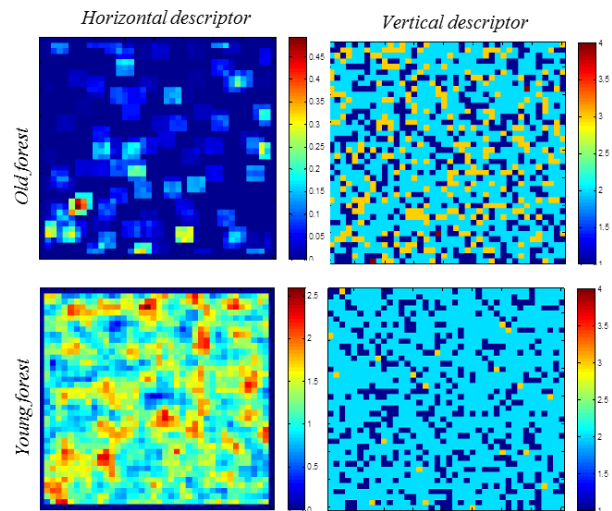
The methodology described in the previous section is tested on a series of simulated data produced from models provided by the Department of Ecological Modelling at the Helmholtz Centre for Environmental Research (UFZ). This dataset represents different types of tropical forest scenarios generated by an individual based model called FORMIND [10]. It simulates the growth of spe-

cies rich forests. For each tree, at a given time, its exact position, its height, its diameter and its crown radius are provided. In the scope of this paper, 2 different scenarios are considered: a 50 years old forest (young forest in the following) and a 500 years old forest (old forest in the following).

From these models, the reflectivity profiles are estimated for each tree. It is assumed that the reflectivity profiles are directly related to biomass content and therefore they are generated through allometric equations. These individual reflectivity profiles are combined to obtain a reflectivity profile for each spatial resolution cell, whose dimensions correspond to the spatial resolution of the simulated TomoSAR sensor. Results are shown here for spatial resolution cells of 25x25 m. SAR coherences can be then deduced from (2) for a selected set of baselines. In this experiment, we chose 5 baselines with not regularly distributed values of  $k_z$  ranging from 0.1 to 0.4.

Then, the vertical profiles are retrieved following an imaging approach based on CS, employing a Symlet wavelet decomposition with 5 coefficients for the projection space  $\Psi$  in (4). A Basis Pursuit scheme is selected for solving the minimization problem in (6).

Finally, the 3D structure descriptors, defined in Section 2 are estimated for the two scenarios considered. Results are shown in **Figure 2**.

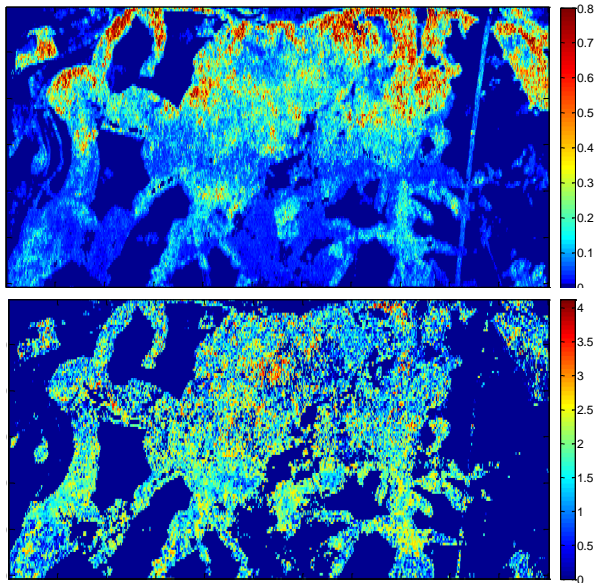


**Figure 2:** Horizontal (left column) and vertical (right column) forest structure descriptors estimated for two different forest types: old forest (top row) and young forest (bottom row).

It can be observed that the different forest structure of the young and the old forest is clearly reflected in the horizontal and vertical descriptors proposed. As expected, the old forest is more heterogeneous in the horizontal dimension (which produces low values in the horizontal structure descriptor) and there is also more diversity in heights, i.e. more layers.

### 3.2 Tests on real data

Structure analysis has also been carried out in a set of real TomoSAR full pol data acquired by DLR's E-SAR airborne sensor, over the area of Traunstein, in Germany. It is a scenario with different types of managed forests stands in typical temperate conditions. 5 baselines are available, with  $k_z$  ranging from 0.1 to 0.3 at L-band. The descriptors for horizontal and vertical forest structure characterization are estimated from the reflectivity profiles retrieved by means of CS. Results are shown in Figure 3.



**Figure 3:** 3D Forest structure estimation in Traunstein area. Horizontal structure descriptor map (top) and number of layers map (bottom).

## 4 Conclusions

In this paper, a framework for 3D forest structure estimation from TomoSAR reflectivity profiles is proposed. It accounts for the simultaneous vertical and horizontal variability of the observed scenario. Preliminary results on simulated and real data suggest its capability to distinguish between different types of forests. A thorough evaluation of these results is awkward in real scenarios due to the unavailability of extensive groundtruth data. Moreover, the sparseness of inventory plots compromises horizontal structure validation. However, by cross-checking with lidar height maps, it should be observed that the descriptors do not depend linearly on forest height. Thus, it can be deduced that they reflect effectively a different structure parameter. Further validation is currently being carried out. Besides evaluation of the performance of the method proposed, future work

will be to check the robustness of the structure descriptors in front of meteorological effects.

## Acknowledgments

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