A NEW UAV LASER SCANNING BENCHMARK DATASET FOR CHARACTERIZATION OF SINGLE-TREE AND FOREST BIOPHYSICAL PROPERTIES

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1. Introduction

High resolution unmanned aerial vehicle laser based scanning (UAV-LS) data allows the identification of individual trees and has shown promising results in providing accurate key forestry variables comparable to in-situ observations. New and improved approaches for analyzing UAV-LS point clouds have to be developed to transform the vast and growing amounts of data from UAV-LS into actionable insights for decision making also advancing the derivation of essential biodiversity variables (e.g. Pereira et al. 2013).

The use of UAV-LS data for deriving single-tree measurements is a rapidly increasing field of research, and several studies investigated the possibility to obtain measurements of tree biophysical properties such as height (Brede et al. 2017, Hartley et al. 2020), crown dimensions (Wallace, Lucieer, and Watson, 2014), tree density (Sankey et al. 2017), diameter at breast height (Jaakkola et al. 2017, Wieser et al. 2017, Dalla Corte et al. 2020) and above ground biomass (AGB) or volume (Brede et al. 2019, Liang et al. 2019, Wang et al. 2019, Puliti, Breidenbach, and Astrup 2020). Despite the considerable efforts dedicated to developing automated ways to process UAV-LS data into useful data, current methods tend to be tailored to small datasets, and it remains challenging to evaluate the performance of different algorithms based on a consistent validation dataset. Furthermore, with the increased availability of deep-learning methods to segment and parse forest point clouds (Windrim and Bryson 2020, Krisanski et al 2021), there is an increasing need to develop large databases of annotated trees in dense point clouds. To fill this knowledge gap and to further advance our ability to measure forests from UAV-LS data, we present a new benchmarking dataset.

2. Data

2.1 Input data

This benchmark is designed to provide the best quality aerial laser scanning data on the use of surveygrade UAV-LS data collected using RIEGL scanners of the VUX and mini-VUX series. Amongst the various UAV-LS sensors available today, the RIEGLones, when combined with high precision Inertial Measurement Units (IMUs), represent the state-of-the-art as they allow scanning at high frequency and the laser pulses are characterized by narrow beam divergence (i.e. small footprints) enabling the acquisition of very dense point clouds $(1 - 10 \text{ k pts/m}^2)$ with larger canopy penetration rates and larger measurement accuracy compared to consumer-grade sensors (e.g. Velodyne VLP16). To date, the available UAV-LS data for this benchmark covers different forest types across the world, including boreal coniferous forests, temperate deciduous and coniferous forests, savanna type of vegetation, and production forest plantations.



Figure 1. Geographical overview of the currently available drone laser scanning data

2.2. Manual annotation

A sample of the available point clouds were manually annotated into single-trees and in different components of the tree, namely stems, branches, and leaves/needles (see Figure 2). The point clouds were annotated with particular attention to segmenting all tree size classes including co-dominant and suppressed trees.



Figure 2. Structure of the annotation in the benchmark data with information regarding single trees, different tree parts, and tree species.

2.3 Field data

Field measurements were conducted in each of the sites included in the benchmark. The diameter at breast height (DBH) was measured for all the annotated trees. In addition, when available, other measurements such as tree species, height, and volume are included.



Figure 3. Workflow for benchmarking tree detection, segmentation and parsing algorithms.

References

3. Scope of the benchmark

The main aim of this benchmark is to provide a solid base for further advancing our ability to characterize forest structures and obtain in-situ measurements from very dense airborne laser scanning data. Future possibilities to utilize these data consist of:

• *Benchmarking* of algorithms for tree detection, segmentation, and parsing (Figure 3). By providing a consistent and independent validation data source this benchmark will allow ranking of different algorithms based on their performance across various forest types.

• Development of deep-learning models to automatically segment single trees and tree parts. The annotated data is particularly suitable for training deep learning models for semantic and instance segmentation of forest point clouds.

• Development of methods for direct measurement of tree (DBH, volume, tree species) and forest biophysical properties (DBH distributions, volume, stem density).

4. Open data

The UAV-LS data annotated as part of this benchmark will be publicly released for scientific purposes.

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