Drone LiDAR for mistletoe recognition and monitoring

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1. Introduction

Within the last decade the rapidly developing technologies such as laser scanning, so called Light Detection and Ranging (LiDAR), remote sensing, and machine learning have tremendously changed the face of forest ecology. Laser scanning provides the spatial overview and the precise three-dimensional object description (Wehr et al., 1999), while remote sensing collects large volumes of environmental data, including those from the inaccessible habitats (Pajares et al., 2015). Finally, machine learning allows the data to be processed at a deeper level (Jordan et al., 2015).

The recognition and monitoring of small- and medium-size tree-related microhabitats (TrMs) inhabited by fungi, mosses, ivies, mistletoes, etc. (Frey et al., 2020) are important, since they are well-recognized indicators of tree and whole-forest health. Moreover, TrMs supports the diversity of insects, birds, animals and plants, including mistletoes, in forest ecosystems. Mistletoes are taxonomically diverse group of aerial hemiparasitic plants from the Loranthaceae, Viscaceae, Santalaceae, Amphorogynaceae, and Misodendraceae families (order Santalales), attaching to their hosts by root-like structure called the haustorium and being largely dependent on water and nutrient supply from the hosts (Nickrent et al., 2010). There are two main mistletoe species in the Czech Republic – deciduous yellow-berried mistletoe (*Loranthus europaeus* Jacq.; Loranthaceae) parasitizing mostly European oak (*Quercus robur* L.) hosts and rarely other trees (Danihelka et al., 2012; Krasylenko et al., 2019), and the ever-green European mistletoe (*Viscum album* L.; Santalaceae) with three subspecies – *V. album* sbsp. *album* with the broad host preferences, *V. album* sbsp. *austriacum* specialized on *Pinus*, and *V. album* sbsp. *abietis* parazitizing *Abies* (Wild et al., 2019).

The early forest remote studies were based on the terrestrial lidar scanning (TLS)-produced data, which are presented as dense and precise point clouds with the mm accuracy (Rehush et al., 2018). On the other hand, TLS requires a labor-intensive data acquisition and could be used only on the relatively small areas. The accuracy and density of TLS data decrease from bottom to the top (Dassot et al., 2011). Other approach, an unmanned laser scanning (ULS), as compared to TLS, is significantly more sparse and less accurate, but the maximum density and accuracy ULS achieves at the canopy level. The biggest advantage, however, is that ULS can provide the data sufficient for the detailed observations from the larger territory (Kellner at al., 2019; Krůček et al., 2020). In our studies we focus on misteltoe recognition.The population structure and spatial distribution of mistletoes on the host trees make them suitable objects for ULS. Furthermore, these parasitic plants are perennial, slowly growing and long-living (some *Viscum* specimens can exist for more than 30 years), being clearly visible by the naked year in all seasons, and especially well-resolved in fall, winter and early spring.

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2. Materials and Methods

2.1 Data collection and study sites

The data was collected using RiCOPTER, a remotely piloted airborne laser scanning system equipped with Riegel VUX1 UAV scanner (RIEGL, USA) at the altitude about 60 m above the ground. In March 2019 two flights with criss-cross flight directions were performed. The remote scanning covered the area of circa 20 ha located in the floodplain of the Morava and the Dyje Rivers. In its subsoil are the sediments of the Vienna Basin; above them are deposited fluvial gravels, on which sandy flood clays lie. The bottomland hardwood forest covers the largest area of the protected area. Dominant species are narrow-leaved ash (*Fraxinus angustifolia* Vahl.), field maple (*Acer campestre* L.), hornbeam (*Carpinus betulus* L), small-leaved linden (*Tilia cordata* Mill.), and European oak (*Q. robur*) (Janik et al., 2008).

More than twenty *Viscum* and *Loranthus*-colonized trees of different species were recorded during a field survey on the well-studied and documented part of Ranšpurk National Nature Reserve in South Moravian Region characterized by the predominance of *T.cordata* with a few *Q. robur* and *C. betulus* individuals. The precise GPS coordinates of each tree in the forest plots parasitized by mistletoes were juxtaposed with the point cloud.

2.2 Data processing

In the machine learning terms, the mistletoe detection belongs to the object classification issue. The whole plot space were divided by the big voxels (2 m*2 m*2 m) using the CloudCompare software (https://www.danielgm.net/cc/). Each voxel was classified as “with mistletoe” or “without mistletoe”. A key limitation for the machine learning methods efficiency is the training dataset range, since a larger dataset obviously means the higher accuracy of the prediction. To make is large enough, the data augmentation technique was used by adding the slightly modified copies of already existing data or newly created synthetic data based on the primary sample (Bohak et al., 2020). Point cloud segments with the mistletoes were cut into numerous voxels of the required sizes at various angles allowing them to intercept. The mistletoe-containing areas were cut in the way that the different training voxels had different spatial distribution of mistletoe inside different voxels. Moreover, noise, artificial branches and twigs were added to increase the training sample range to several hundreds items.

A few machine and deep learning models will be tested and compared basing on the mistletoe as the key organism in these studies. The conventional machine and deep learning approaches require different algorithms of the data pre-processing. The deep learning effectively uses the raw data, though Random Forest (RF) and Support Vector Machine (SVM) methods need more compact feature vectors (Breiman 2001). The large voxels will be divided into 125 smaller voxels, and for each of the sub-voxels the point density will be computed. Altogether, 125 values will form the feature vector. As part of the deep learning approach, two extra approaches will be tested: 2D- and 3D-trained convolutional neural networks (CNNs). For the volumetric pre-trained networks, the whole point cloud inscribed in the big voxel (Maturana et al., 2015) will be used, while for the flat pre-trained networks the rasterized multiview orthographic projections (MVOPs) (Carlbom et al., 1978) are suitable.

3. Results and Discussion

Based on general information, we expect that the deep learning approach will be more efficient. All methods have hypothetical pros and cons, but the experiment will show the most effective solution for a recent case. It is reasonable to assume that the deep learning approach will be the most beneficial for the recognition of mistletoes in our experimental plot. However, it is significantly more computationally intense (Le Cun et al., 2015). In case the results of classical machine learning models will show relatively similar accuracy of prediction, it is worth preferring it for further practical applications. The obvious advantage of three-dimensional meshes is that we are exploring 3D objects. However, the development of 3D networks lags far behind the development of two-dimensional ones. This means that the pre-trained 2D networks were trained on significantly larger sample, which makes them more accurate “on average“ (Le Cun et al., 2015).

4. Conclusions

The proposed method can be employed both in the forest management by arborists and dendrologists as well and in the forest ecology research. For example, the accurate spatial distribution maps of mistletoes are very helpful for the evaluation of the degree of the mistletoe infection rate as well as for the host tree health and performance. Also, this methodology can be extended to the task of the detection of other types of TrMs, such as hollows or bird nests.

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