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Tree species classification using within crown localization of waveform LiDAR attributes

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ABSTRACT

Since forest planning is increasingly taking an ecological, diversity-oriented perspective into account, remote sensing technologies are becoming ever more important in assessing existing resources with reduced manual effort. While the light detection and ranging (LiDAR) technology provides a good basis for predictions of tree height and biomass, tree species identification based on this type of data is particularly challenging in structurally heterogeneous forests. In this paper, we analyse existing approaches with respect to the geometrical scale of feature extraction (whole tree, within crown partitions or within laser footprint) and conclude that currently features are always extracted separately from the different scales. Since multi-scale approaches however have proven successful in other applications, we aim to utilize the within-tree-crown distribution of within-footprint signal characteristics as additional features. To do so, a spin image algorithm, originally devised for the extraction of 3D surface features in object recognition, is adapted. This algorithm relies on spinning an image plane around a defined axis, e.g. the tree stem, collecting the number of LiDAR returns or mean values of returns attributes per pixel as respective values. Based on this representation, spin image features are extracted that comprise only those components of highest variability among a given set of library trees. The relative performance and the combined improvement of these spin image features with respect to non-spatial statistical metrics of the waveform (WF) attributes are evaluated for the tree species classification of Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) Karst.) and Silver/Downy birch (*Betula pendula* Roth/*Betula pubescens* Ehrh.) in a boreal forest environment. This evaluation is performed for two WF LiDAR datasets that differ in footprint size, pulse density at ground, laser wavelength and pulse width. Furthermore, we evaluate the robustness of the proposed method with respect to internal parameters and tree size. The results reveal, that the consideration of the crown-internal distribution of within-footprint signal characteristics captured in spin image features improves the classification results in nearly all test cases.

1. Introduction

Airborne small-footprint pulsed LiDAR is an important measurement tool for forest canopies with good estimation of biomass and height (Vauhkonen et al., 2014a). However, in operational LiDAR-based forest inventories, tree species identification is important since different species have different allometric dependencies, which influence the accuracy of timber volume estimation (Packalén and Maltamo, 2008). Accurate tree species identification however is very challenging. It is to some degree possible from structural and intensity features calculated from discrete-return LiDAR data (Ørka et al., 2009), but is more accurate in combination with aerial imagery (Holmgren et al., 2008; Ørka et al., 2012), hyperspectral data (Kandare et al., 2017) or with attributes derived from waveform(WF)-recording LiDAR data (Yao et al., 2012; Hovi et al., 2016). If LiDAR data alone could provide a reliable species discrimination, acquisition costs would be reduced and economic feasibility stimulated. Prospectively, precision forestry could be stimulated, whereby forestry decisions are made and valuable timber is collected at demand based on precise inventory data from remote sensing surveys.

With tree species classification of individual tree segments in airborne LiDAR data, most approaches so far have focused on the

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analysis of large-scale geometric properties and distributions within the point clouds of individual tree segments, on the medium-scale distribution within parts of the tree segments, *or* on the statistical analysis of the WF attributes. Meanwhile, it is long-standingly known that both in cases with texture scales larger than the given resolution (*H-resolution*, e.g. large- and medium-scale structures within the tree crown) and texture scales smaller than the resolution (*L-resolution*, e.g. small-scale within footprint structures), a characteristic spatial autocorrelation can be found in the signal (Strahler et al., 1986). In this paper, we aim to combine information from both the *L*- and *H-resolution* signal.

Therefore we pose the following research questions (*RQs*) to be answered in this paper:

- *RQ1: Feature Design*
  Is it possible to design a feature type, which can be used to capture the geometric distribution of WF attribute values within the tree crown?
- *RQ2: Species Classification Improvement*
  Given the recent advances in species classification by detailed WF analysis (Hovi et al., 2016), can the accuracy be improved even further by considering the localization of the WF attributes within the tree crown? If so, how big is the gain?
- *RQ3: Failure Cases*
  How are the failure cases distributed among tree sizes? Trends would be of practical relevance.

After providing a review of related work in Section 2, we explain our methodology in Section 3. Subsequently, the data used to test the new feature type's performance is presented in Section 4, while the results on our three main research questions are presented in Section 5 and discussed in Section 6. Section 7 gives a conclusion and outlook for future research.

2. Related work

Different approaches have been taken in tree species identification so far, yet the comparison between different studies is intricate. Different feature types may be more or less descriptive, depending on the context such as the local biome (boreal, temperate), the species composition, the number of species and the classification depth (a limitation on the number of classes to be distinguished, e.g. classifying tree genera rather than species or classifying deciduous vs. coniferous trees) (Heinzel and Koch, 2011), the season (Kim et al., 2009; Hovi et al., 2016), age distribution, site fertility, sensor characteristics and settings and stand type (homogeneous or mixed) (Korpela et al., 2010b). The final results in classification performance may furthermore depend on the amount of and the variability within the validation data as well as on the validation scheme, and are therefore usually case-specific. Furthermore, many algorithms require parameter selections that may have to be optimized. Thus, generic methods are eligible.

In the following, the current state of the art is assessed. Sections 2.1, 2.2 & 2.3 cover the general topics of segmentation, classification and feature design for LiDAR point clouds, while different approaches in tree species classification are summarized according to their scale of operation in Sections 2.4, 2.5 & 2.6. Finally, multi-scale approaches are reviewed in Section 2.7.

2.1. Segmentation

Despite the fact, that there are area-based approaches for species-specific timber volume estimation (Räty et al., 2016), we focus on single-tree species classification in order to obtain reliable evaluation metrics. Thus, crown segmentation is a crucial prerequisite, and failures of the single-tree extraction reduce the quality of the species classification result (Vauhkonen et al., 2014b). Solutions include, but are not limited to crown surface based approaches (Persson et al., 2002), *k*-means clustering (Morsdorf et al., 2004), algorithms using both the crown surface and volumetric normalized cuts (Reitberger et al., 2009) and graph-based solutions (Strîmbu and Strîmbu, 2015). Vauhkonen et al. (2012) compared different single-tree detection algorithms on different testing sites, showing that the stand density and spatial complexity (clustering or regular patterns) affect the quality of the segmentation more than differences among the algorithms and that most algorithms perform better in the environment they were developed in.

2.2. Classification

In single-tree species classification, the different methods of discrimination include both statistical classifiers and machine learning systems. Since one cannot usually assume linear separability or an easy-to-model distribution of features, non-linear and non-parametric classification algorithms are especially popular (Vauhkonen et al., 2014b). Highly efficient algorithms such as support vector machines (Schölkopf, 1997) and random forest classifiers (Breiman, 2001) are available in a variety of software packages. With these classifiers, the most important prerequisite for a successful classification is a good feature design that condenses all class-specific signal in the data into discriminant features, so that the different classes are represented differently in the feature space. Lately, deep learning techniques such as Convolutional Neural Networks (CNNs) are becoming more and more popular, where the filtering for class-specific patterns in the data is autonomously learned via backpropagation. However, the task of fitting a CNN to any given data and classification problem remains intricate.

2.3. Feature design

Generally, feature design for point cloud classification is highly application-specific and depends on both the data and object properties. However, some general concepts are noteworthy. For objects with densely sampled surfaces, signatures of histograms of orientations (SHOT) (Tombari et al., 2010) and spin images (Johnson and Hebert, 1999) have been used as descriptors of local surface patches in object recognition (Velizhev et al., 2012). Since these descriptors require a surface to define a normal vector, more general descriptors such as 3D shape contexts (Frome et al., 2004) or point feature histograms (Rusu et al., 2009) have been designed. Furthermore, shape distributions (Osada et al., 2002) enable a parameterization of the overall object shape. Within dense and geometrically precise point clouds obtained for example by terrestrial laser scanning, a point-wise semantic labelling may be achieved using the eigenvalues of the 3D covariance matrix, which capture the local point distribution geometry (West et al., 2004; Weinmann et al., 2013). According to scale selection studies, those features perform best when the neighbourhood size is determined by optimization of the local dimensionality-based entropy (Demantké et al., 2011; Gressin et al., 2012), which favours a particularly homogeneous neighbourhood (purely linear, planar or scattered), or by optimization of the local eigenentropy (Weinmann et al., 2015), which favours minimal disorder. In airborne laser scanning (ALS), the sparsity of the data (usually 5–40 $\mathrm{pts/m^2}$), the geometric imprecision and object complexity limit the feature choice. Apart from WF attributes describing the shape of the recorded signal, geometric features such as point height