INVESTIGATING THE IMPACT OF POINT CLOUD DENSITY ON SEMANTIC SEGMENTATION PERFORMANCE USING VIRTUAL LIDAR IN BOREAL FOREST

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ABSTRACT

Virtual LiDAR Scan (VLS) serves as a powerful tool for the replication of real world conditions and can assist with the calibration of LiDAR systems. In this study, we utilize HELIOS++, a VLS software, to investigate the impact of point cloud density on the semantic segmentation performance of a well-established Deep Learning (DL) method for point clouds, KPConv. Our experiment is focused on a typical Quebec boreal forest composed of *Abies balsamea* and *Picea mariana*. We generated 10250 structurally diverse forest plots to train 10 DL models on a wide range point cloud densities to assess their effect on the semantic segmentation. Densities varied from 23 points/m^2 to 225 points/m^2, replicating point clouds output from classic airborne LiDAR scanning and high-density unmanned LiDAR scanning. Our results demonstrate that point cloud densification improves IoU score for both boreal tree species by an average of 0.3 percentage points per 10 points/m^2.

Index Terms— Boreal Forest, Simulation, LiDAR, Computer Vision, Deep Learning

1. INTRODUCTION

Boreal forests are fragile ecosystems that have undergone significant changes in recent decades due climate change, fires, illness, and anthropogenic activity. To better understand these changes and to create improved preservation regulations, active monitoring has been set up across these forest regions [1].

Airborne LiDAR Scanning (ALS) is a commonly used acquisition tool for monitoring forest ecosystems due to its ability to provide valuable geometric and radiometric information [2]. Yet, the data often require postprocessing before they can be used. Studies have shown the benefits of machine learning, or more specifically Deep Learning (DL), for the automation this step [3].

However, DL algorithms are data-driven and rely on very large amounts of manually labeled data to be efficient. Furthermore, forest environments present complex and irregular shapes, making manual labeling of 3D point clouds especially difficult. As a result, there is a shortage of open-access point cloud datasets focused on forest environments designed specifically for model training [4].

To solve this constraint, one of the proposed approaches is using Virtual LiDAR Scan (VLS): by modeling a 3D scene and using ray tracing technology, it is possible to simulate a complete LiDAR acquisition with its ground truth, regardless of the platform. Although studies using VLS for forest environments have mostly focused on radiometric sensor calibration [5] or validating models to extract vegetation attributes from LiDAR waveforms [6], to our knowledge, no studies have used VLS in order to evaluate the impact of the sensor calibration on semantic segmentation quality.

This paper introduces a complete VLS workflow, from forest modeling to DL testing, to assess the impact of point cloud density on semantic segmentation quality. We provide a comparison of model performance trained from an average point density of 23 points/m^2 to 225 points/m^2, allowing our evaluation to cover a wide range of calibration, from classic ALS to high-density Unmanned LiDAR Scanning (ULS).

2. RELATED WORKS

Since the development of LiDAR technology, there has been an increased focus in simulating the interaction of light beams with the environment. The state-of-the-art in LiDAR simulation for airborne platforms is currently held by the DART model [7] and HELIOS++ [8]. The former is an implementation of a Monte Carlo ray tracing method with optimized computation time while the latter is a non-stochastic method in which LiDAR pulses are simulated thanks to a fixed number of rays. The DART model is able to produce high-quality simulations in regards to the spectral attributes of the point clouds. On the other hand, HELIOS++ chooses to trade off realism for computational efficiency.

The quality of a LiDAR simulation not only depends on the simulation method, it also depends on the quality of the reconstructed scene. Terrestrial LiDAR Scanning (TLS) is a common remote sensing method for tree reconstruction [9, 10]. [9] proposed an algorithm to reconstruct trees from TLS and extended their work to create a complete tree model library from a few reconstructed trees [11].

The impact of point cloud densities has been studied on forest biomes for ground extraction [12], tree attributes [13], and various structural indices like Canopy Closure or Leaf Area Index (LAI) [14]. However, computer vision studies have only focused on single tree segmentation using unsupervised machine learning K-means algorithm [15]. Due to the lack of labeled datasets, semantic segmentation tasks with DL algorithms, have not received much consideration.

Simulated datasets for DL training have been frequently used, as they provide an affordable alternative to real datasets while maintaining a high level of informativity. Although most of the open-access datasets are focused on anthropological scenes, like urban areas for autonomous driving [16], some works focus on forests, such as [17], which have used RGB images. However, to the best of our knowledge, none of these studies have aimed to simulate point clouds with the intent of training DL algorithms.

3. METHODOLOGY

Our methodology is composed of three phases, (1) forest plot modeling, (2) LiDAR simulations, and (3) DL training and testing.

3.1. Forest Plot Modeling

The objective of this first phase is to produce a series of models representing plots of boreal forests. The boreal forest in Quebec is typically composed of two species: *Picea mariana* (black spruce) and *Abies balsamea* (balsam fir), with stands density ranging between 1000 and 3000 stem/ha [18].

Modeling a plot is performed by placing existing models of tree on a 25x25 m^2 Digital Elevation Model (DEM). The plot models need to represent the diversity in size and structure that can be observed in reality. However, reproducing real-life examples is not necessarily the optimal choice to efficiently train a DL network because they can be repetitive and lack of challenging structures [19]. In fact, training is usually more efficient if all possible situations are equally represented in our samples. Therefore, parameters describing the trees and forest structures are not chosen to build realistic plots but rather plots where all cases are uniformly distributed.

We used TLS-reconstructed tree models from the library of [11] (Figure 1). Because a complete tree model can exceed 56 GB, we simplified each trunk model by edge collapse, removing every branch less than 5 cm in diameter. Furthermore, we simplified sprouts to simple 3D boxes, while keeping the same surface in each direction, in order to preserve light transmittance and LAI characteristics. In total, 328 tree models were used, 227 for *Abies balsamea*, and 101 for *Picea mariana*.

For ground modeling, we extracted ground points from a 1 km² ALS acquisition of Quebec forest where topography shows a great diversity of slope. Ground points were then

Fig. 1. Examples of *Abies balsamea* (left) and *Picea mariana* (right) models from [11]. Colors for visualization only.

converted to a raster DEM from which we randomly select a 25x25 m² subsample per plot.

In order to populate plots with the desired number of trees, we generated heights, diameters at breast height, and LAIs from random uniform distributions. We then selected the tree model from the library that best fit with these characteristics. We chose to assign each tree a random position on the terrain without consideration of factors such as light competition or slope. Finally, a random rotation along the vertical axis was applied to each tree.

3.2. LiDAR Simulation

In the second phase, we carried out LiDAR simulations with HELIOS++ [8] on each plot. For each plot, the simulated flight path was divided into 10 legs, 5 traveling from south to north, and 5 west to east. Legs 1,5,6 and 10 were at swath limits, legs 3 and 8 were at nadir, and legs 2,4,7,9 were in between. The 10250 simulations were computed on high-performance computing servers with nodes of 128 GB of RAM and 32 cores. The output of the simulation was a set of 10 point clouds per plot, one per leg.

3.3. Deep Learning

With the intent of emulating different levels of point density, we created 10 sets from a combination of previously simulated legs. We replicate similar overlapping conditions as regular airborne acquisitions. Table 1 present the resulting average point density for each of the sets.

We randomly split the 10250 plots into training, validation, and test groups containing 70%, 10% and 20% of the plots, respectively. This split was kept the same for all sets. The class labels were derived from HELIOS++ hit object output. Since no correct radiometric characteristics of foliage and wood material were provided for the simulation step, intensity values were not reliable and were not used as input.

Set	1	2	3	4	5	6	7	8	9	10
Average point density (points/m^2)	23	45	67	89	112	135	158	179	202	225
All plots IoU										
Abies balsamea	90.5	91.3	91.7	92.5	92.6	92.7	93.1	93.8	94.5	94.6
Picea mariana	81.9	83.3	85.8	86.5	86.2	86.9	86.8	88.5	90.1	90.3
mIoU	86.2	87.3	88.8	89.5	89.4	89.8	89.9	91.2	92.3	92.5
High Tree Density plots IoU										
Abies balsamea	87.0	87.4	88.5	88.7	88.6	89.6	89.7	90.4	91.6	91.4
Picea mariana	78.2	78.6	82.5	81.4	80.7	83.0	82.6	83.9	86.4	86.1
mIoU	82.6	83.0	85.5	85.1	84.7	86.3	86.1	87.1	89.0	88.8

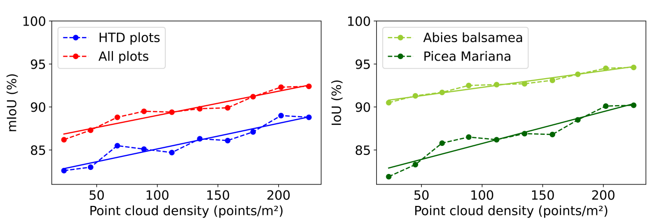
Table 1. Average point density per set, and semantic segmentation scores (IoU and mIoU) of models trained on respective set, averaged for all plots and for plots with the highest tree density.

Therefore, only x, y, and z coordinates are considered as input features.

As our focus was on geometric features, we selected KPConv network [20] for the point clouds semantic segmentation. We trained one network for each density set, resulting in 10 models. Every model went through the same training procedure : 140 epochs, each of 300 steps.

4. RESULTS AND ANALYSIS

We calculated IoU scores on the test split for each of the 10 KPConv models and presented them in Table 1. It also provides IoU score for plots with high tree density (3100 stem/ha). A 3D viewer of models and semantic segmentation results is available at polarsensing.net/igarss2023. Ground



(a) (b)

Fig. 2. (a) Linear regression of mIoU on tree classes for high tree density plots (blue) and all plots (red), (b) Linear regression of IoU for *Abies balsamea* (green) and *Picea mariana* (black green) for all plots.

IoU scores were exceptionally high across all point density experiments (99% IoU). We explain this score by the fact that low and medium vegetation were not integrated in our models. Due to this high score, we computed a mIoU without the ground class to better underline the performance of the semantic segmentation of the tree classes.

Figure 2(a) shows the strong linear correlation between point cloud density and the mIoU score for all plots and High Tree Density (HTD) plots (i.e., r^2 of 0.93 and 0.9 for, respectively). Regardless of the tree density, this regression demonstrates an average of 0.3 point of percentage improvement for tree classes per 10 points/m^2 density increment (All: 0.3, HTD: 0.28). *Picea mariana* class benefits more from point cloud densification, with a 0.37 point mIoU per 10 points/m^2 (r^2=0.91), in contrast to *Abies balsamea* with a 0.19 point mIoU per 10 points/m^2 (r^2=0.97). This phenomenon can be linked to the average LAI of both species, as fewer leaves means fewer LiDAR returns. In fact, we can see from the model library that *Picea mariana* trees have a lower LAI than *Abies balsamea* trees (69.1 and 147.8, respectively) if filtered by a diameter at breast height superior to 0.2 m.

5. CONCLUSION

In this paper we proposed a full Virtual LiDAR Scan (VLS) workflow to investigate the effects of point cloud density on the semantic segmentation segmentation of tree species in boreal forest. We show that increasing the point cloud density improves the IoU score of tree species at an average of 0.3 point per 10 points/m^2.

Our next steps will first focus on improving the modeling of forest plots by (1) complexifying the forest vertical structure with the addition of low and medium vegetation, and (2) extending the model library to newer tree species. Then, we will concentrate on giving more insight about the use of VLS for other computer vision tasks like individual tree segmentation and panoptic segmentation.

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