

Entropy-based Pre-filtering of High-density Forest Point Clouds for Individual Tree Detection Algorithms

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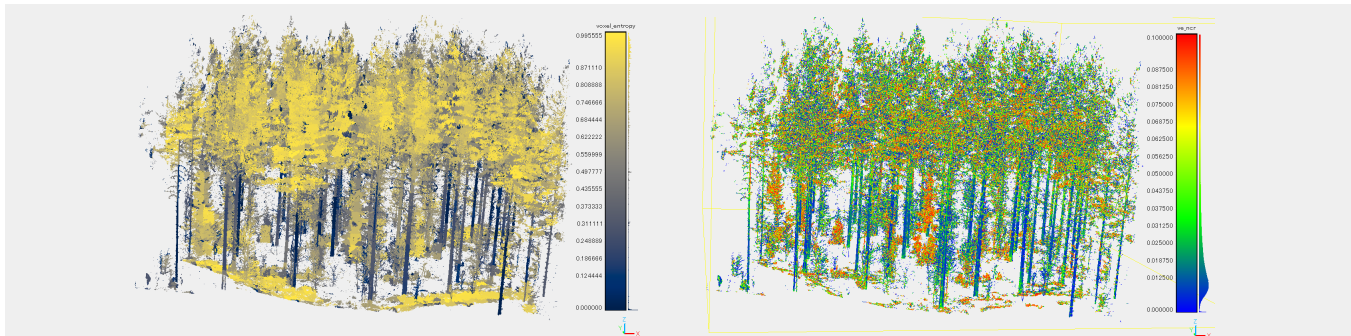


Figure 1: Voxel entropy (left) and entropy pre-filtered local curvature (right) features of a forest point cloud.

The novel and computationally inexpensive voxel entropy feature shows potential for wood-leaf discrimination in forest point clouds.

Abstract

Light Detection and Ranging have enabled the creation and analysis of highly detailed 3D point cloud representations of outdoor areas through Terrestrial Laser Scanning and Mobile Laser Scanning. In the field of forestry, one important spatial data processing task is detecting individual tree stems, which is often a prerequisite for individual tree location mapping, wood volume estimation, and other tree inventorization analysis. The high point densities achieved through Terrestrial Laser Scanning and Mobile Laser Scanning allow for high accuracy in delineating individual tree stems, but lead to a high computational cost due to the large point counts. This study proposes a computationally efficient approach for removing points unlikely to belong to tree stems, based on point distribution entropy within local regions. The approach is motivated by the observation that stems exhibit low entropy, whereas canopy regions tend to have higher entropy. The point filtering algorithm works in linear time and can lead to significant processing time gains while often maintaining accuracy for downstream digital forestry tasks.

CCS Concepts

• **Applied computing** → Physical sciences and engineering; **Agriculture**; • **Mathematics of computing** → *Cluster analysis*.



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Forestry, Tree Stem Segmentation, Individual Tree Detection, LiDAR, entropy

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1 Introduction

Terrestrial Laser Scanning (TLS) is a method of capturing detailed three-dimensional (3D) point cloud representations of indoors and outdoors areas, including forests. Unlike in two-dimensional (2D) imaging, rays of the laser scanner can penetrate dense vegetation and map out tree structure in high-definition, enabling advanced analysis of forest plots.

Arguably, one of the most important forest point cloud analysis tasks is Individual Tree Detection, also known as Individual Stem Detection in the domain of TLS due to the well defined stems, in contrast to the lower density and occlusion-prone Airborne Laser Scanning counterparts. Accurately detected individual tree stems may serve as seed points for Individual Tree Segmentation, the task of discriminating points corresponding to each individual tree in the scene, and lead to improvements in segmentation performance when compared to treetop detection-based approaches [3].

Although the high density of forest TLS point clouds enables advanced analysis, it also poses unique challenges related to the unwieldy file sizes of point clouds of large outdoors areas. In the context of Individual Stem Detection, researchers often opt to use

simplified versions of the point cloud such as 2D rasters [2], which discard a lot of important spatial information. Conversely, a popular method by [6] uses the entire point cloud as input. However, due to calculating computationally intensive geometric features for every point in the dense forest scene, despite its excellent results, the algorithm may be prohibitively slow. A balanced approach would begin with a computationally efficient filter to eliminate trivially non-stem points, followed by a refinement using point-wise geometric features.

In the laser scanning medium, tree leaves produce more reflections compared to stems and branches [5], resulting in higher point density and more homogeneous distribution of points in the canopy layer. This observation aligns with a general, albeit imprecise, intuition about entropy: orderly structures exhibit low entropy, while more disordered or uniform structures exhibit higher entropy. A concrete definition of entropy within a point cloud could therefore be useful for filtering out canopy points.

The contributions of this study are: (1) Voxel entropy – a novel point cloud feature that describes the homogeneity of point distribution in discrete 3D volumes, which can be computed in linear time and is well suited for large and dense point clouds; (2) A demonstration of the novel voxel entropy feature as a pre-processing step in existing Individual Tree Detection workflows, showing its applicability in digital forestry.

This paper is part of the Theses and Dissertations track – Kasparas Karlauskas is the PhD student, Povilas Treigys is the supervisor.

2 Materials and Methods

2.1 High-density forest LiDAR data

This study makes use of two TLS forest point cloud datasets: wood-leaf segmentation dataset by [4] and individual tree detection dataset by [1].

2.1.1 Wood-leaf segmentation dataset. Point-labelled data for wood-leaf segmentation by [4] was used to evaluate the discriminative power of the novel voxel entropy when pre-filtering forest plot point clouds. The dataset contains three TLS point clouds of three single-species forest plots. A summary of the data characteristics in table 1 reveals that leaf points make up the majority of forest point clouds even in the TLS domain.

Table 1: Characteristics of the wood-leaf segmentation dataset

Plot	Area m ²	n_{points} $1 \cdot 10^6$	Wood %	Leaf %
Chinese_scholar_tree	1368	25.3	16	84
Dahurian_Larch	760	65.2	20	80
White_Birch	1200	44.2	13	87

2.1.2 Individual tree detection dataset. Individual tree detection algorithms were evaluated using TLS scans of forest plots from [1]. The data used consists of field measurements, digital terrain models, and multi-scan TLS point clouds of six diverse forest plots. The plots are split into difficulty categories *easy*, *medium* and *difficult*

based on intuitive sense of difficulty due to occlusions, variety in stem radii, etc. A summary of the study plots is provided in table 2. The forest plots were height-normalized using the included digital terrain models, then all points with $z > 0.3 \text{ m}$ were removed along with the ground and low vegetation.

Table 2: Characteristics of the Individual Tree Detection dataset

Plot	Difficulty	n_{trees}	Area m ²	n_{points} $1 \cdot 10^6$
1	Easy	51	1168	111
2	Easy	84	1188	114
3	Medium	148	1148	120
4	Medium	78	1140	129
5	Difficult	131	1080	125
6	Difficult	236	1064	111

Data characteristics table based on [6].

2.2 Individual Stem Detection

In this section a baseline Individual Tree Detection algorithm from [6] is briefly summarized, followed by the voxel entropy-based pre-processing method proposed in this study. First, some terminology and notation used in this study is outlined.

A **point cloud** $P := \{p_m\}_{m=1}^n$ is a set of points in three-dimensional Euclidean space, where $p_m := (x_m, y_m, z_m)$ is the m -th point and n is the number of points. **Voxels** are axis-aligned cuboid volumes of dimensions $v_x \times v_y \times v_z$, where v_x, v_y and v_z are the cuboid's extent in the x -, y - and z -axes, respectively. **Voxelizing** a point cloud means partitioning the space occupied by P into a regular grid of voxels and aggregating points within the same voxel. Each voxel is indexed by a triplet $(i, j, k) \in \mathbb{Z}^3$ such that the voxel's corner with the minimum coordinates is at (iv_x, jv_y, kv_z) . The set of points within the voxel indexed by (i, j, k) is denoted by V_{ijk} and is a subset of P .

2.2.1 Normal Change Rate for Individual Stem Detection. The general outline of the Individual Stem Detection algorithm in [6] is as follows: (1) Calculate Normal Change Rate for every point, filter out points with value less than the threshold (0.1 in the study); (2) Identify candidate tree stem clusters by connected component segmentation of the voxelized remaining points (voxel size 0.01 m in the study); (3) Filter out non-stem clusters based on the ratio of height and width standard deviations (maximum ratio 1.5 in the study); (4) Remove branch points based on point column density in a 2D raster (pixel size 0.03 m in the study); (5) Repeat connected component segmentation with larger voxel dimensions (voxel size 0.1 m in the study); (6) Determine diameter at breast height (DBH) by circle fitting and reject clusters with DBH under threshold (DBH threshold 0.05 m in the study).

The procedure described in [6] does not account for the cases where points belonging to the same tree's stem end up in several vertically aligned clusters. In this study, an additional post-processing operation is performed: starting with the longest stem segment, every other surrounding segment around a 0.5 m radius projected

on the xy -plane is removed. Moreover, the absolute dimensions of segments are not taken into account either, meaning that any cluster with a height and width standard deviation ratio over the threshold is allowed. In this study, segments shorter than 1.0 m are rejected.

The largest computational cost is incurred in step (1) due to processing each point and its local neighbourhood individually, as opposed to the 3D voxel and 2D raster representations of the filtered point cloud used in subsequent steps. Normal Change Rate (NCR) is a measure of surface curvature in the point's local neighbourhood and is calculated by:

$$\text{NCR}_m := \frac{\lambda_{m,0}}{\lambda_{m,0} + \lambda_{m,1} + \lambda_{m,2}} \quad (1)$$

where $\lambda_{m,0} \leq \lambda_{m,1} \leq \lambda_{m,2}$ are the eigenvalues of the covariance matrix of the (x, y, z) coordinates in the m -th point's local neighbourhood, i.e. a set of points within distance r_{NCR} away from p_m . NCR has a range of values from 0 when all points in the local neighbourhood lie on the same plane, and $\frac{1}{3}$ when points are distributed isotropically inside the r_{NCR} radius sphere. In the context of Individual Stem Detection, r_{NCR} needs to be small enough so that the stem's surface appears roughly planar, i.e. $r_{\text{NCR}} \ll r_{\text{stem}}$ and is set to 5 cm in [6]. The time complexity of NCR evaluation is $O(n \log n)$ due to repeated kd-tree searches.

2.2.2 Voxel Entropy-based pre-processing. In information theory, Shannon entropy is defined as:

$$H(X) := - \sum_{x \in X} p(x) \log p(x) \quad (2)$$

where $x \in X$ is a random variable from a distribution X and $p(x)$ is the probability of sampling x from X .

To calculate entropy inside a voxel, the information about the layout of inlier points needs to be expressed as a probability distribution. By voxelizing the inside of each voxel, i.e. creating subvoxels of dimensions $\frac{v_x}{s_x}, \frac{v_y}{s_y}$ and $\frac{v_z}{s_z}$ where s_x, s_y and s_z are integer numbers of splits along the x -, y - and z -axes, respectively, the probability density associated with each subvoxel is defined to be:

$$p(S_{i'j'k'}^{ijk}) := \frac{|S_{i'j'k'}^{ijk}|}{|V_{ijk}|} \quad (3)$$

where $S_{i'j'k'}^{ijk}$ is the set of points inside the subvoxel of V_{ijk} with the local subvoxel indices $i'j'k'$, $|A|$ is the number of elements in a set. This is the probability that a random in-voxel point sampled from V_{ijk} will be inside the subvoxel $S_{i'j'k'}^{ijk}$. Plugging eq. (3) into eq. (2) yields the expression for voxel entropy:

$$H(V_{ijk}) = - \sum_{i'} \sum_{j'} \sum_{k'} \frac{|S_{i'j'k'}^{ijk}|}{|V_{ijk}|} \log \frac{|S_{i'j'k'}^{ijk}|}{|V_{ijk}|} \quad (4)$$

which can be computed in a single pass over the entire point cloud, i.e. in linear time, by accumulating point counts associated with each voxel and subvoxel index. For more intuitive thresholds, this feature can be normalized to have a maximum value of 1.0. The maximum voxel entropy for a specific subvoxel splitting scheme can be achieved in the case where all subvoxels contain an equal

amount of points, which simplifies to $H_{\text{max}} = \log(s_x s_y s_z)$. The expression for normalized voxel entropy is:

$$H_{\text{norm}}(V_{ijk}) = - \frac{1}{\log(s_x s_y s_z)} \sum_{i'} \sum_{j'} \sum_{k'} \frac{|S_{i'j'k'}^{ijk}|}{|V_{ijk}|} \log \frac{|S_{i'j'k'}^{ijk}|}{|V_{ijk}|} \quad (5)$$

In the rest of this study, voxel entropy refers to normalized voxel entropy.

2.2.3 Individual tree detection accuracy metrics. Tree coordinates are computed as the mean x and y of post-processed cluster inlier points. Each ground truth tree is matched to the nearest unmatched prediction within a 0.3, m radius. Matched pairs form the true positives (TP), while unmatched predictions and ground truth locations form false positives (FP) and false negatives (FN), respectively. Precision, recall, and F1 score are then computed as:

$$\text{prec} = \frac{|\text{TP}|}{|\text{TP}| + |\text{FP}|}, \quad \text{rec} = \frac{|\text{TP}|}{|\text{TP}| + |\text{FN}|}, \quad \text{F1} = \frac{2 \cdot \text{prec} \cdot \text{rec}}{\text{prec} + \text{rec}} \quad (6)$$

3 Results

3.1 Voxel Entropy of stem and canopy points

To examine whether the intuition that wood and stem points can be distinguished by the entropy of their containing voxels holds, voxel entropy is computed on the wood-leaf segmentation dataset by [4], using various voxel sizes and subvoxel counts.

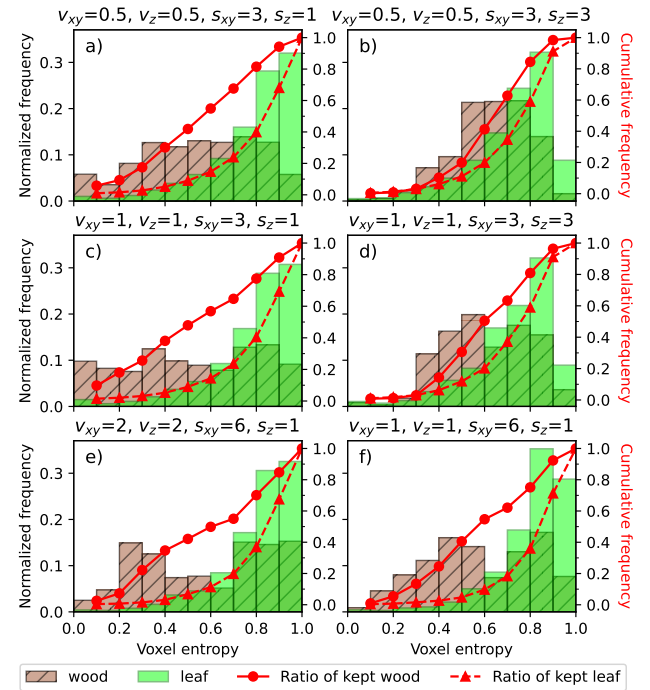


Figure 2: Voxel entropy values of wood and leaf points computed with parameters listed in subfigure captions.

A common feature of all subfigures in fig. 2 is that the frequency of leaf points has a sharp decrease at voxel entropy threshold 0.8.

Comparisons fig. 2.a–b and fig. 2.c–d show that a better separation between wood and leaf point voxel entropy values is achieved when projecting all points to the xy -plane by using the vertical subvoxel count $s_z = 1$. Comparison fig. 2.c–e shows that when keeping the subvoxel dimensions the same, a voxel size of 2 m leads to a decrease in remaining wood points after filtering – voxels that are too wide may include excessive surrounding vegetation. Finally, the comparison fig. 2.c–f shows that when the number of horizontal plane subvoxels is increased from 3×3 to 6×6 , a slight decrease in points retained at 0.8 voxel entropy threshold. The parameters used for computing voxel entropy are set to $v_x = v_y = v_z = 1$ m, $s_x = s_y = 3$, $s_z = 1$ for the rest of this study.

3.2 Individual Stem Detection on entropy pre-filtered point clouds

Individual tree detection accuracy metrics and point feature calculation run time in minutes are provided in table 3. Performance between NCR-only and Voxel Entropy pre-filtered individual tree detection is comparable across all study plots, with a tendency for the NCR-only approach to have a higher recall due to more of the original points being present. In terms of computation time, significant speed gains from 30 % to 60 % are achieved when employing Voxel Entropy pre-filtering.

Table 3: Individual tree detection accuracy metrics for the study plots

Plot #	Feature ^a	time ^b	TP	FP	FN	prec	rec	F1
1	NCR	84	46	6	5	0.88	0.90	0.89
	VE + NCR	1 + 63	44	9	7	0.83	0.86	0.85
2	NCR	57	67	26	17	0.72	0.80	0.76
	VE + NCR	1 + 40	67	23	17	0.74	0.80	0.77
3	NCR	180	87	10	61	0.90	0.59	0.71
	VE + NCR	2 + 108	87	9	61	0.91	0.59	0.71
4	NCR	187	46	17	32	0.73	0.59	0.65
	VE + NCR	2 + 128	43	9	35	0.83	0.55	0.66
5	NCR	231	64	40	67	0.62	0.49	0.54
	VE + NCR	3 + 133	59	30	72	0.66	0.45	0.54
6	NCR	169	78	8	158	0.91	0.33	0.48
	VE + NCR	2 + 124	65	7	171	0.90	0.28	0.42

a Features used for point filtering before the clustering step: NCR = Normal Change Rate, VE = Voxel Entropy.

b Time taken to compute individual point features in minutes. If several features are computed, the times are given in a sum in their respective order in the Feature column. Plaintext times are for multiprocessing using 16 Intel® Xeon® Gold 6252 Processor CPU cores, while *italicized* times are computed using a single CPU core.

4 Discussion and future work

The maximum processing time gains from using Voxel Entropy as a pre-filtering feature in algorithms of time complexity $O(n \log n)$ are linearly dependent on the decrease in point count. Nevertheless, the novel Voxel Entropy feature has properties that make it promising as a stand-alone feature in individual tree stem detection algorithms, which will be examined more extensively in subsequent work. Other

than the superior linear time complexity, Voxel Entropy is weakly dependent on point density as long as the structure of tree stems is still defined, unlike the previously discussed NCR, which is sensitive to the number of points in a small local neighbourhood. However, Voxel Entropy pre-filtering makes the clustering algorithms more prone to over-segmenting individual tree stems, especially in the presence of understory vegetation. Applications of Voxel Entropy require a more robust cluster post-processing procedure.

5 Conclusions

In this study, a novel point cloud feature Voxel Entropy was proposed. In a preliminary experiment, the feature's utility was demonstrated by showing significant separation between wood and leaf regions – filtering away points with Voxel Entropy < 0.8 removes up to half of leaf points while over 80 % of wood points remain. Furthermore, processing time gains in the range of 30 % ~ 60 % are achieved in individual tree detection using an algorithm based on local curvature features, while maintaining similar accuracy. The results hint at the potential for Voxel Entropy to serve as a standalone feature in Individual Stem Detection.

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References

- [1] Xinlian Liang, Juha Hyypä, Harri Kaartinen, Matti Lehtomäki, Jiri Pyörälä, Norbert Pfeifer, Markus Holopainen, Gábor Brolly, Pirotti Francesco, Jan Hackenberg, Huabing Huang, Hyun-Woo Jo, Masato Katoh, Luxia Liu, Martin Mokroš, Jules Morel, Kenneth Olofsson, Jose Poveda-Lopez, Jan Trochta, Di Wang, Jinhu Wang, Zhouxi Xi, Bisheng Yang, Guang Zheng, Ville Kankare, Ville Luoma, Xiaowei Yu, Liang Chen, Mikko Vastaranta, Ninni Saarinen, and Yunsheng Wang. 2018. International benchmarking of terrestrial laser scanning approaches for forest inventories. *ISPRS Journal of Photogrammetry and Remote Sensing* 144 (Oct. 2018), 137–179. doi:10.1016/j.isprsjprs.2018.06.021
- [2] Rubén Manso and Carlos Cabo. 2025. An algorithm for robust tree detection in ground-based point clouds based on classical mechanics. *Computers and Electronics in Agriculture* 229 (Feb. 2025), 109750. doi:10.1016/j.compag.2024.109750
- [3] Iurii Shendryk, Mark Broich, Mirela G. Tulbure, and Sergey V. Alexandrov. 2016. Bottom-up delineation of individual trees from full-waveform airborne laser scans in a structurally complex eucalypt forest. *Remote Sensing of Environment* 173 (Feb. 2016), 69–83. doi:10.1016/j.rse.2015.11.008
- [4] Peng Wan, Jie Shao, Shuangna Jin, Tiejun Wang, Shengmei Yang, Guangjian Yan, and Wuming Zhang. 2021. A novel and efficient method for wood–leaf separation from terrestrial laser scanning point clouds at the forest plot level. *Methods in Ecology and Evolution* 12, 12 (Dec. 2021), 2473–2486. doi:10.1111/2041-210x.13715 Publisher: Wiley.
- [5] Cailian Zhang, Chengwen Song, Aleksandra Zaforemska, Jiaxing Zhang, Rachel Gaulton, Wenxia Dai, and Wen Xiao. 2024. Individual tree segmentation from UAS Lidar data based on hierarchical filtering and clustering. *International Journal of Digital Earth* 17, 1 (Dec. 2024), 2356124. doi:10.1080/17538947.2024.2356124
- [6] Wuming Zhang, Peng Wan, Tiejun Wang, Shangshu Cai, Yiming Chen, Xiuliang Jin, and Guangjian Yan. 2019. A Novel Approach for the Detection of Standing Tree Stems from Plot-Level Terrestrial Laser Scanning Data. *Remote Sensing* 11, 2 (Jan. 2019), 211. doi:10.3390/rs11020211