Quantifying TLS Data and Diameter Estimation Uncertainty

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1 Introduction

Uncertainties in vegetation volume and biomass account for a large part of the uncertainty of terrestrial carbon cycle models (Bloom et al., 2016). Biomass is frequently calculated with allometric equations using the tree diameter (Asner et al., 2013; Paul et al., 2013), meaning that errors in the tree diameter propagate into quantities used in environmental modelling. Terrestrial laser scanning (TLS) with geometrical tree reconstruction is a useful technology to measure vegetation volume and biomass, thus it is important to quantify the uncertainty of tree diameter estimation using TLS data.

Studies have shown that uncertainties in the laser scanning data and methodologies applied to it result in errors in the properties derived with it (Boehler et al., 2003; Lichti et al., 2005). Additionally, studies have been performed that assess the uncertainty of results obtained with TLS data of trees (Disney et al., 2018; Wang et al., 2019), however the consideration of uncertainty for the reconstruction of trees is rare. Furthermore, to the authors' best knowledge no study exists that quantifies this uncertainty and accounts for it prior to the determination of tree properties, i.e. during data processing and the reconstruction of tree geometry.

The uncertainty in the detected hit location comes primarily from the finite laser beam width which widens with range and beam divergence angle, as well as the incidence angle of the beam with the object (Hartzell et al., 2015). It is thus affected by the scanner's specifications, the object's surface and the locations of the scanner. This study views the point cloud not as discrete locations, but instead as a set of continuous probability distributions centred on their reported hit locations. In particular, this means that it is possible to rigorously account for points from separate scanning positions with significantly different uncertainties.

The uncertainty is propagated to the diameter estimate through Monte Carlo sampling, where with each iteration the point cloud is shifted randomly according to the computed probability distributions of each point. Moreover, a maximum likelihood based circle fitting method that uses the distribution information directly is presented.

2 Data & Methods

For this paper simulated laser scanning data are used, enabling a sensitivity analysis of the uncertainty and the algorithm's performance with changing scanning parameters. The simulated data are generated by creating a deterministic point cloud which assumes there is no uncertainty, after which they are randomly shifted in their respective radial and propagation (range) directions according to their respective probability distributions (Hartzell et al., 2015). The resulting stochastic point cloud is used for the remainder of the algorithm, and the true hit locations and geometry are assumed to be unknown.

The uncertainty of the tree stem - or branch - centre and diameter is determined through Monte Carlo sampling, akin to (Shapiro & Philpott, 2007). A schematic overview of the method is given in Figure 1. The sampling revolves around the same principle as the creation of the synthetic point cloud, however without prior knowledge of the geometry. The point cloud uncertainty estimated from the initial shape fit is used to shift the original point cloud randomly for each Monte Carlo iteration. The uncertainty of the shape parameters is computed by taking the α and $1-\alpha$ quantiles of the resulting series of geometrical parameters.

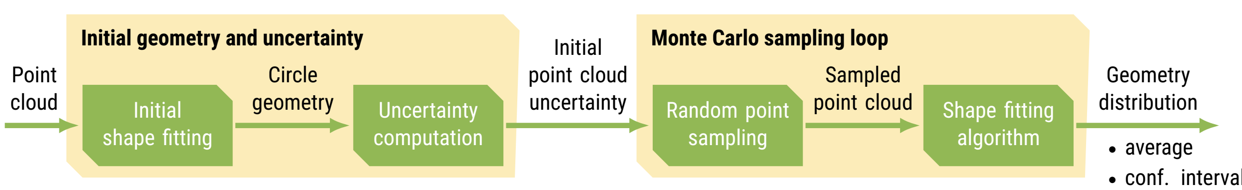

Figure 1: Overview of the method used to determine the tree stem shape parameters and their uncertainty.

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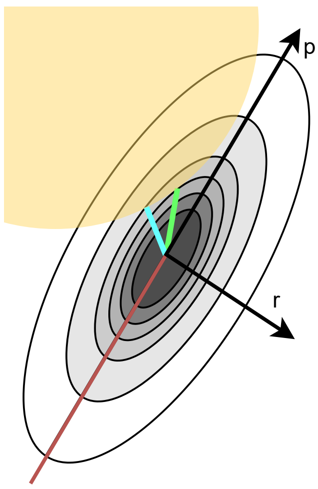
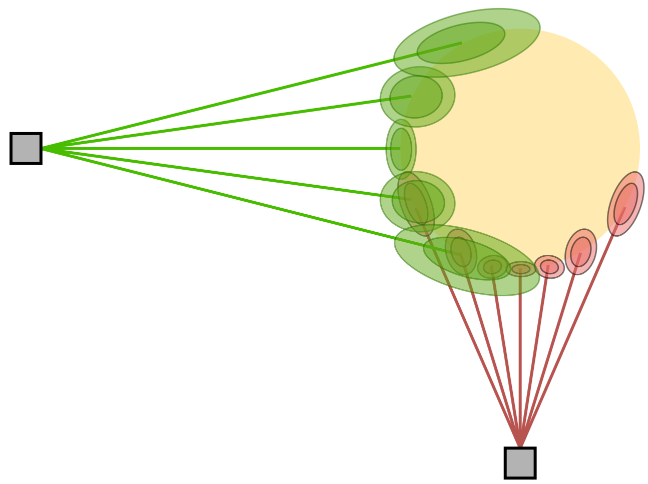
The sampled point cloud is used as the basis for shape fitting, however to compute the probability distribution around each point the geometry of the object has to be assumed. To reduce the effect of errors in the initial geometry estimate, initial shape fitting is performed for each Monte Carlo iteration as well. Next, the optimal shape parameters are determined by maximising the likelihood of the circle, given the point cloud's probability distributions computed according to the initial shape fit. An example of this is shown in Figure 2a. This enables the shape fitting algorithm to more effectively use points originating from different scanners or striking the object with a higher incidence angle, as it considers the differences in their uncertainty. A schematic example of this is given in Figure 2b. It should be noted that these probability distributions are not changed by the optimiser's estimates, to prevent the optimiser from changing the geometry to alter the uncertainty rather than to more accurately resemble the underlying shape.



(a) The blue and green lines are the closest and highest likelihood intersections with the yellow circle estimate respectively.



(b) The green and red points have different uncertainty magnitudes and directions.

Figure 2: Schematic overview of the probability distribution of a single point (a) and the point clouds from two scanners (b).

If the initial geometry estimate is poor, points that are further away have a negligible and near-constant likelihood, and are thus ignored by the optimiser. As such, the second objective of the shape fitting algorithm is to minimise the expected squared distance of the points to the circle, given their respective probability distributions. This second objective is intentionally affected by points that are distant to the estimated geometry, which necessitates outlier filtering before shape fitting.

3 Results & Discussion

The method proposed above has been tested on a scanning setup akin to Figure 2b, where the left and bottom scanners are at 100 and 50 metres distance from a 0.1 metre diameter tree stem. The specifications of the Faro Focus (FARO, 2020) were used, with both the normal (0.30 mrad) and double (0.60 mrad) the beam divergence δ, to show the effect of greater uncertainty. The results of 100 Monte Carlo iterations are shown in Table 1 for linear least squares (LS), linear least squares weighted by the inverse distance between scanner and tree stem (WLS), and the maximum likelihood method (ML).

The estimate from the maximum likelihood method is closest to the true solution, with least squares having the greatest error. The performance difference between maximum likelihood and (weighted) linear least squares increases with uncertainty. The ML method is thus able to estimate geometry with lower quality data, however the performance benefit is small if the data quality is high. ML further has the thinnest confidence intervals, aside from the radius estimate with greater uncertainty where WLS outperforms it.

Table 1: The results for two beam divergence angles δ and three shape fitting methods. The errors of the estimated radius and centroid location, as well as the width of the 95% confidence interval (CI), are relative to the true radius.

δ [mrad]	Method	Radius		Centroid	
		Error [%]	CI width [%]	Error [%]	CI width [%]
0.30	LS	11.2	27.5	7.9	46.0
	WLS	9.1	23.0	6.3	37.2
	ML	4.2	22.0	2.5	28.3
0.60	LS	27.3	80.2	18.5	159.0
	WLS	23.1	58.4	16.3	117.3
	ML	7.6	69.6	2.7	88.0

4 Conclusion

Key tree parameters can be computed using geometrical tree models reconstructed from TLS data. The data and geometry derived from TLS data can contain significant uncertainty however, which this paper quantifies for diameter estimation and utilises to reconstruct the diameter more accurately.

The input data uncertainty is quantified through analytical computations of the laser beam properties, after which the circle is fitted to maximise the likelihood taking the probability distribution of each point into account. This enables the shape fitting method to distinguish between points that come from different scanners and have different directions and magnitudes of uncertainty.

A comparison was performed between the maximum likelihood method and (distance weighted) linear least squares for two scenarios of different uncertainty. The maximum likelihood had the lowest errors in radius (4.2 and 7.6%) and location of the centroid (2.5 and 2.7%), with the performance difference to the least squares approaches increasing with higher uncertainty.

Further research is planned to extend the presented methodology to the 3rd dimension by fitting cylinders to 3-dimensional point clouds. Additionally, the robustness of the method to surface roughness and non-circular cross-sections will be analysed.

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