Modelling the Detection Rate of Terrestrial Laser Scanning in Multi Scan Mode

T. Ritter[1], C. Gollob[1], A. Nothdurft[1]

[1]University of Natural Resources and Life Sciences, Vienna, (BOKU), Institute of Forest Growth, Peter-Jordan-Str- 82, Vienna 1190, AUSTRIA
Email: {tim.ritter ; christoph.gollob ; arne.nothdurft}@boku.ac.at

1. Introduction

Terrestrial laser scanning (TLS) has been successfully applied in the context of manifold forestry applications and enables a fast and automatic acquisition of the forest structure (Fardusi et al. 2017). A major challenge of TLS applications in forestry is occlusion (Abegg et al. 2017), because the laser is often obstructed by other trees or understory vegetation. In order to obtain a complete point cloud, the multi scan mode is preferably used in most studies (Ritter et al. 2020). However, systematic studies regarding efficiency of different scanner position layouts and size or shape of sample plots are still rare. Recently, Ritter et al. (2020) developed a methodology to model the detection probability of multi-scan TLS, by extending the traditional distance sampling framework (Buckland et al. 2001) to account for multiple scan positions. Data from single scans was sufficient to parameterize the underlying detection model, making the model easily adoptable to different forest types and sighting conditions. By comparing the model results to real world data of circular sample plots with different radii and scanner position layouts (Gollob et al. 2019), it was shown that beside a minor discretization bias associated with small sample sizes, the model was able to accurately predict the detection probability of TLS on these plots (Ritter et al. 2020).

In this research, the methodology proposed by Ritter et al. (2020) is used to model the detection probability of TLS for rectangular sample plots of different size and aspect ratio and for different scanner position layouts. In total, 54 Variants are compared regarding their detection rate and sampling effort.

2. Data and Methods

The distance sampling framework (Buckland et al. 2001) is based on the assumption that the detectability of objects typically decreases with increasing distance r between the observer (i.e. the laser scanner in our application) and the object of interest (i.e. a tree) and can be modelled by a distance-depending detection function $g(r)$. For single scan applications, the mean detection probability (detection rate) within a circular sample plot of area a and radius ω can be estimated by

$$\hat{P}_a = \frac{2}{\omega^2}\int_0^{\omega} r \times g(r)dr \tag{1}$$

(Astrup et al. 2014).

Ritter et al. (2020) extended the framework to multi scan applications with I scanner positions, assuming that the probability of detecting an arbitrary tree located at position j in a distance of r_{ij} from the scanner position i is independent from the probability to detect the same tree from any other scanner position $i' \neq i$ for $i', i \in \{1, \dots, I\}$. This probability can then be estimated by $g(r_{ij})$, so that the probability to detect a tree located at location j becomes

$$P_j = 1 - \prod_{i=1}^{I}\left(1 - g(r_{ij})\right) \tag{2}$$

An arbitrary sized and shaped sample plot can be described by a set of J raster cells. For every raster cell centroid, Eq. 2 can be applied to predict the probability to detect a tree located within the cell. Thus, the mean detection probability (detection rate) P_a per sample plot can be estimated as the arithmetic mean of all raster cell estimates P_j within the plot (Eq. 3)

Published in: Markus Hollaus, Norbert Pfeifer (Eds.): Proceedings of the SilviLaser Conference 2021, Vienna, Austria, 28–30 September 2021.
Technische Universität Wien, 2021. DOI: 10.34726/wim.1861
This paper was peer-reviewed. DOI of this paper: 10.34726/wim.1913

$$\widehat{P_a} = \frac{1}{J}\sum_{j=1}^{J}\left(1 - \prod_{i=1}^{I}\left(1 - g(r_{ij})\right)\right) \tag{3}$$

(r_{ij}) can be parameterized from single scan reference data (Ritter et al. 2020).

In the following, we use the extended hazard rate type detection function (Ritter et al. 2020) with parameter estimates obtained by fitting the function to freely available single scan data from Lower Austria (Gollob et al. 2020). The detection probability of trees having a diameter at breast height (dbh) of 20cm or more, was modeled for the algorithms of (Gollob et al. 2019) on rectangular sample plots with different size and aspect ratio (Table 1) and with different scanner position layouts (Figure 1).

3. Results and Discussion

The modelled detection probabilities P_j for the cells of a 0.1m × 0.1m raster obtained with the different multi scan layouts are depicted in Fig. 1. The detection rate $\widehat{P_a}$ for different rectangular sample plots, centered at the origin of the local coordinate system are presented in Table 1.

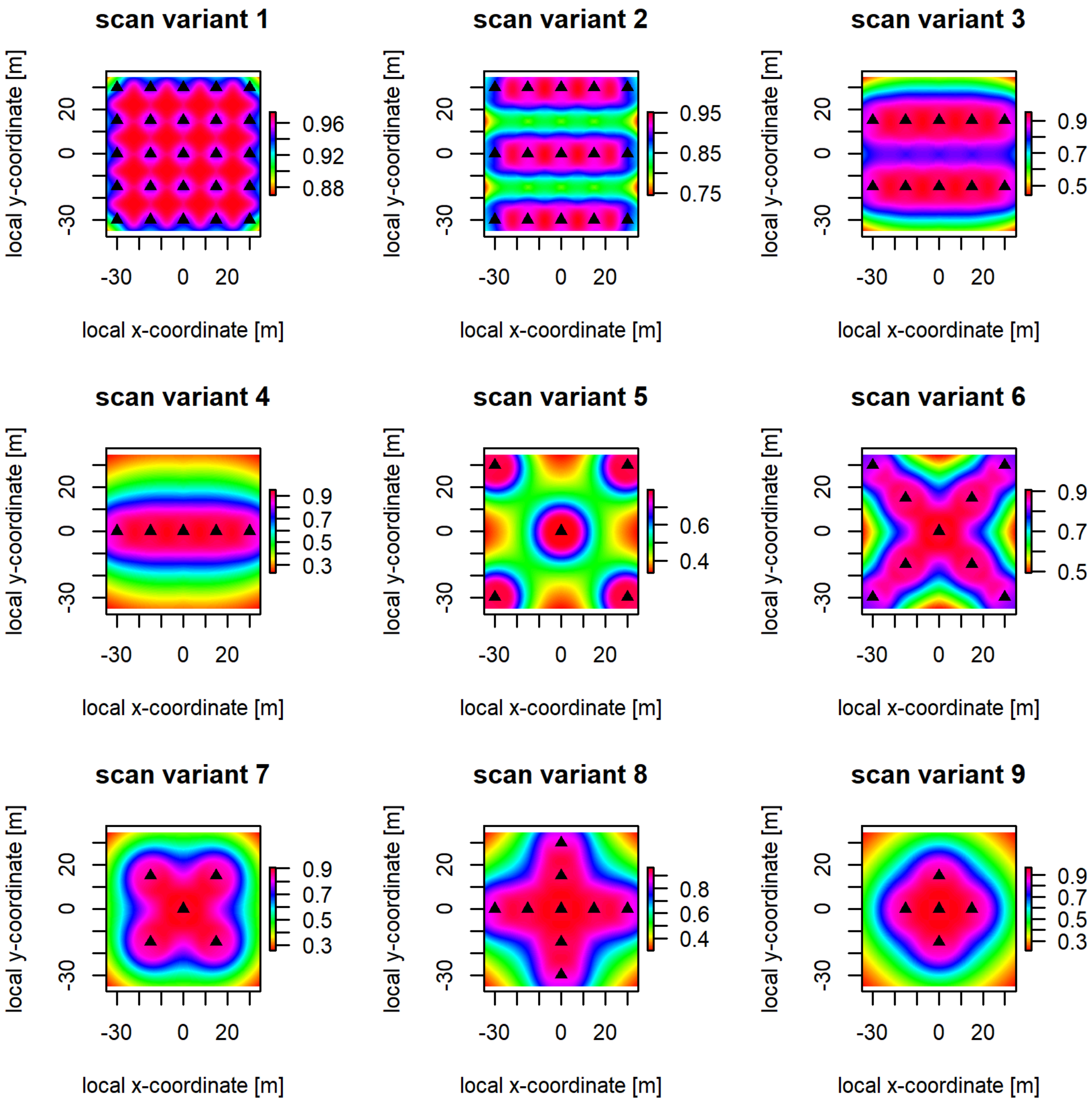

Figure 1. Modelled detection probability P_j for different scan variants. The black triangles symbolize scanner positions.

The scanner position layout strongly influences the detection rate. As an example, scan variant 5 on a 30m×30m sample plot yields a detection rate of 65.22% with a total of 5 scans, while scan variant 9 yields a detection rate of 93.06% with the same sampling effort (Table 1). The aspect ratio of the sample plot is another crucial factor, having two 900m² sample plots, one being 60m×15m, the other one being 30m×30m, detection rates obtained by the same scan variant differ remarkably, e.g., 86.85% vs. 93.06% for scan variant 9.

Table 1. Detection rate estimates for different scanner position layouts and sample plot sizes

Scan variant	Sample plot size					
	60m×60m (=3600m²)	60m×30m (=1800m²)	60m×15m (=900m²)	30m×30m (=900m²)	30m×15m (=450m²)	15m×15m (=225m²)
1 (25 scan positions)	96.49%	96.50%	96.50%	96.51%	96.51%	96.51%
2 (15 scan positions)	88.56%	88.56%	92.25%	88.82%	92.65%	92.65%
3 (10 scan positions)	87.08%	88.56%	84.86%	88.82%	84.99%	94.99%
4 (5 scan positions)	67.51%	85.54%	91.75%	86.55%	92.48%	92.48%
5 (5 scan positions)	54.81%	55.17%	57.37%	65.22%	71.17%	78.27%
6 (9 scan positions)	81.88%	82.76%	81.02%	88.26%	88.63%	90.12%
7 (5 scan positions)	75.19%	80.83%	79.73%	88.16%	88.62%	90.12%
8 (9 scan positions)	81.90%	90.27%	93.64%	93.78%	95.28%	96.04%
9 (5 scan positions)	72.02%	83.28%	86.85%	93.06%	94.96%	96.04%

The modelled detection rates for the scanner position layouts and sample plot shapes presented in this research were not compared to real world data. However, the methodology used for modelling was already intensively tested with several other sample plot shapes and scanner position layouts and proved to yield accurate results (Ritter et al. 2020). Thus, we are confident that the provided estimates are reliable.

The detection function was fitted to single scan reference data from lower Austria, making the results valid only for stands with comparable structure and sighting conditions. However, fitting the detection function to different reference data is straightforward and associated with a comparatively low effort (Ritter et al. 2020).

4. Conclusion

The methodology by Ritter et al. (2020) allows a model-based comparison of the detection rates with different scanning position layouts, sample plot-sizes and -shapes. The benefits from a well-planned multi-scan layout justify the necessary extra effort, especially in larger sampling campaigns

References

Abegg, M., Kükenbrink, D., Zell, J., Schaepman, M., Morsdorf, F., Abegg, M., Kükenbrink, D., Zell, J., Schaepman, M.E., and Morsdorf, F. 2017. Terrestrial Laser Scanning for Forest Inventories—Tree Diameter Distribution and Scanner Location Impact on Occlusion. Forests **8**(6): 184. doi:10.3390/f8060184.

Astrup, R., Ducey, M.J., Granhus, A., Ritter, T., and von Lüpke, N. 2014. Approaches for estimating stand-level volume using terrestrial laser scanning in a single-scan mode. Can. J. For. Res. **44**(6): 666–676. doi:10.1139/cjfr-2013-0535.

Buckland, S.T., Anderson, D.R., Burnham, K.P., Laake, J.L., Borchers, D.L., and Thomas, L. 2001. Introduction to distance sampling: Estimating abundance of biological populations. Oxford Univ. Press.

Fardusi, M.J., Fardusi, M.J., Chianucci, F., and Barbati, A. 2017. Concept to Practice of Geospatial-Information Tools to Assist Forest Management and Planning under Precision Forestry Framework: a review. Ann. Silvic. Res. **41**(1): 3–14. doi:10.12899/asr-1354.

Gollob, C., Ritter, T., and Nothdurft, A. 2020. Comparison of 3D point clouds obtained by terrestrial laser scanning and personal laser scanning on forest inventory sample plots. Data **5**(4): 1–13. doi:10.3390/data5040103.

Gollob, C., Ritter, T., Wassermann, C., and Nothdurft, A. 2019. Influence of Scanner Position and Plot Size on the Accuracy of Tree Detection and Diameter Estimation Using Terrestrial Laser Scanning on Forest Inventory Plots. Remote Sens. **11**(13): 1602. doi:10.3390/RS11131602.

Ritter, T., Gollob, C., and Nothdurft, A. 2020. Towards an optimization of sample plot size and scanner position layout for terrestrial laser scanning in multi-scan mode. Forests **11**(10): 1–23. doi:10.3390/f11101099.