# ACCURATE CALCULATION OF TREE STEM TRAITS IN FORESTS BY LOCAL CORRECTION OF POINT CLOUD REGISTRATION

Haruna Kawasaki\*1, Hiroshi Masuda\*2

\*¹The University of Electro-Communications, Japan – haruna.kawasaki@uec.ac.jp
\*2The University of Electro-Communications, Japan – h.masuda@uec.ac.jp

## Commission II, WG II/3

KEY WORDS: Forest, Traits, Point-Cloud, Registration, Terrestrial Laser Scanner

#### ABSTRACT:

In recent years, it has become important in forestry and forest research to accurately calculate tree stem traits from point clouds captured using the terrestrial laser scanner. However, it is difficult to accurately align a large number of trees in a forest over a large area. Therefore, the reliability of traits calculated from point clouds has been problematic. In this paper, we propose a method to automatically correct misaligned point-clouds and calculate accurate tree stem traits. In our method, a different registration matrix is calculated for each tree to correct the misalignment. When the target tree is specified, point-clouds measured in the vicinity of the target tree and points of the neighbor trees are selected for multi-view registration, and a registration matrix suitable for the target tree is calculated. The experimental results show that the proposed method is effective in correcting misalignment and precisely calculating tree stem traits.

#### 1. INTRODUCTION

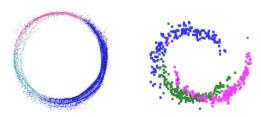
Accurate measurement of tree stem traits is important in forestry and forest research. In recent years, terrestrial laser scanners (TLS) have made it possible to acquire point clouds of forests with high density and accuracy, and tree stem traits are often extracted from point clouds (Liang, X., et al., 2016).

In a wide-area environment such as a forest, point clouds need to be acquired from multiple locations, and the coordinates of multiple point clouds need to be transformed to a unified coordinate system using point-cloud registration. However, it is often difficult to align all the points in a wide-area environment. As a result, inaccurate tree stem traits may be measured due to misalignment in registration.

So far, many methods have been proposed for registration of point clouds (Dong, Z., et al. 2020). However, it is not easy to align point clouds, in which each of a large number of trees in a wide-area forest is precisely aligned. In our experiments, we applied several registration methods to point clouds of forests. While many stems could be adequately aligned as shown in Figure 1(a), some stems were significantly misaligned as shown in Figure 1(b), and therefore incorrect diameters were calculated. One cause of such misalignment is that the density of point clouds varies considerably in a wide-area forest with the distances from the laser scanner and with the diameters of tree stems. This problem makes it difficult to reliably and precisely calculate traits of a large number of tree stems from point clouds. In such cases, it is desirable to correct multi-view registration and recalculate stem traits.

In this paper, we propose a method for correcting misaligned point clouds and calculating accurate tree stem traits. Given a set of initially registered point clouds, our method extracts tree stems from these point clouds and calculates a correction matrix for each tree stem using point clouds of neighbor tree stems. Each tree stem is re-aligned using the corrected registration matrix. In our evaluation, the diameters at breast height (DBH) were

calculated before and after registration correction and compared with manually measured BDH values.



(a) Correctly aligned stem (b) Misaligned stem Figure 1. Registration of point clouds of a forest

# 2. OVERVIEW

In this study, point clouds were measured in a cedar forest located at the Forestry and Forest Products Research Institute in Tsukuba City, Ibaraki Prefecture. Point clouds were captured using a FARO Focus 3D with an angular resolution of 0.018 degrees. The cedar forest was measured from 37 locations as shown in Figure 2. In this district, there were 729 trees with unique identification numbers. In the measurement, targets were placed in the forest for registration, and the point clouds were initially registered using Faro Scene. The point clouds are shown in Figure 3. The number of points was approximately 3.6 billion.

Figure 4 shows the procedure of this method. In our method, we first detect tree stems from point clouds. Many methods have been proposed for detecting tree stems from point clouds (Olofsson, et al., 2014; Raumonena, et al., 2015; Zhang, et al. 2019). In this study, we used the method proposed by (Masuda, et al., 2021). This method enables us to detect a large number of tree stems from large-scale point clouds in an out-of-core manner. Figure 4(a) shows the detected 729 tree stems.

To maintain points of each tree stem separately, a bounding box is created for points of each tree stem, as shown in Figure 4(b). Then, the bounding box is used to select points inside the box and

points on the ground from each point cloud, as shown in Figure 4(c). The selected points are stored in a file.

Our method corrects misaligned point clouds for each tree stem. To stably calculate rotations and translations for registration, neighboring trees of the target tree are selected and their point clouds are merged, as shown in Figure 4(d). Multiview registration is calculated using these merged points.

Point clouds for the target tree are aligned by applying a registration algorithm. To achieve robust alignment, we used

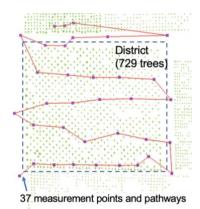


Figure 2. Measurement in a cedar forest



Figure 3. Point clouds of cedar forest

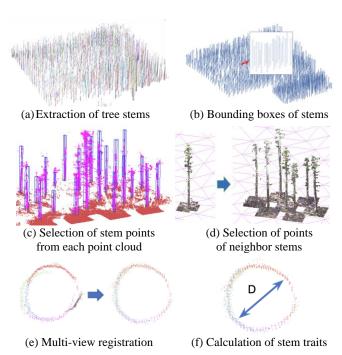


Figure 4. Procedure of local registration correction

sparse ICP (Bouaziz, et al., 2013), which minimizes the 0.4 power sum of the distances between corresponding points. In this calculation, the points of the target tree are given a large weight so that the target tree is aligned better. Finally, the tree stem traits of the target tree are calculated from corrected points, as shown in Figure 4(e) and (f).

#### 3. METHOD

## 3.1 Extraction of tree stems from point clouds

Tree stems are extracted from point clouds using the method proposed by (Masuda, et al., 2021). Figure 5 shows a process of stem extraction. A point cloud captured by the TLS can be mapped onto the 2D plane based on the scanned order in azimuth and elevation directions, as shown in Figure 5(a). Therefore, each point cloud can be converted into a wireframe model by connecting neighbor points on the 2D plane, as shown in Figure 5(b). The wireframe model is sliced by horizontal planes placed at small intervals, and cross-sectional points are calculated, as shown in Figure 5(c). Cross-sectional points are calculated from each point cloud and merged at various heights, as shown in Figure 5(d). Then, circles are fitted to the merged points. Finally, tree stems are extracted as vertically aligned circles, as shown in Figure 5(e). Since cross-sectional points are calculated for each point cloud, this process can be performed in an out-of-core manner even if the data size of point clouds exceeds the limit of RAM.

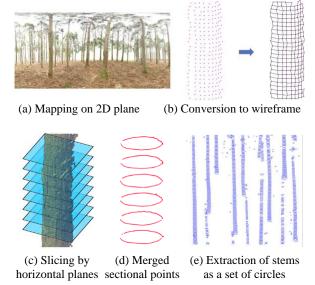
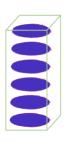


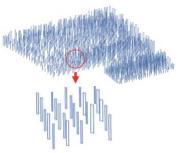
Figure 5. Extraction of tree stems from point clouds.

## 3.2 Extraction of each stem from each point cloud

In our method, points of each stem are extracted from each point cloud, and the extracted points are stored in a single file. Registration correction is calculated for each stem by selecting a subset of the point cloud files.

First, the range of each stem is calculated of a bounding box. Since each stem is extracted as a circles as shown in Figure 5(e), the bounding box is calculated so that circles are enclosed as shown in Figure 6(a). The bonding boxes are calculated for all stems, as shown in Figure 6(b). In this example, 729 bounding boxes are obtained.

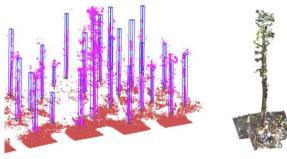




(a) Bounding box

(b) Bounding boxes of all tree stems

Figure 6. Extraction of regions of tree stems



(a) Selected points from a single point cloud(b) A single treeFigure 7. Extraction of each stem from each point cloud

The bounding box of each stem is used to divide each of the point clouds measured at various scanner locations. Since the bounding box may not include misaligned points, it is enlarged for robustly selecting stem points. In this study, we specified an offset of 25 cm for each bounding box. In addition, ground points are needed to precisely align the Z-coordinates in calculating a registration matrix. Therefore, a new bounding box is created at the bottom of the bounding box of the stem to select points on the ground. For the ground points, we created a bounding box with a width 200 cm larger than the bounding box of each stem and a height of 30 cm. Figure 7(a) shows stem points including points on the ground, which were selected from a single point cloud.

Figure 7(b) shows points of a tree stem extracted from a single point cloud. The points of each stem is stored in a file with a name that includes the measurement number and the tree number. We denote each point-set as  $T_j^i$ , in which i ( $1 \le i \le n$ ) is the measurement number and j is the tree number. In our example, the numbers of measurement locations were sequentially defined from 1 to 37, and the tree numbers were uniquely determined in this plot by the Forestry and Forest Products Research Institute.

When the number of measurement locations is large, the number of files becomes very large. Therefore, files are created only when the distance from the scanner position is within a threshold  $d_s$  and the number of points in the bounding box is greater than the threshold  $n_b$ . In this study, we specified  $d_s$  as 20m and  $n_b$  as 128. By specifying these thresholds,  $37 \times 729 = 26,973$  files for 729 trees could be reduced to 6,366 files.

## 3.3 Selection of stem points for correcting registration

For correcting registration of each stem, a subset of stem files are selected. When the target tree stem is specified, points of neighbor trees are used for registration. To efficiently select neighbor trees, an adjacency graph is created for trees in the forest by projecting the center position of each stem onto a

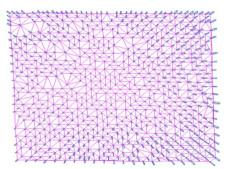
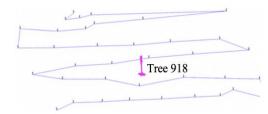
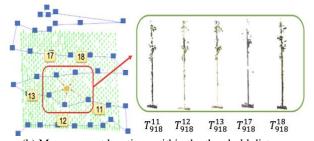


Figure 8. Adjacency graph of trees



(a) Measurement locations and the target tree



(b) Measurement locations within the threshold distance Figure 9. Selection of point clouds for the target tree

horizontal plane and triangulating the projected positions using the Delaunay triangulation, as shown in Figure 8. The tree numbers are maintained at the nodes of the adjacency graph.

Suppose that the target tree number is t, and the point sets  $\{T_j^i\}$  ( $i \in I_t, j \in J_t$ ) are used for correcting registration of the target tree. The point clouds measured at locations  $I_t$  are selected whose measurement positions are less than a threshold distance from the target tree. In this study, the threshold distance was set to 20m. For tree numbers  $J_t$ , one or two rings of trees in the adjacency graph are selected. In this study, one-ring trees, which are directly connected to the target tree in the adjacency graph, are selected as neighbor trees. Then, points in  $\{T_i^i\}$  ( $j \in J_t$ ) are merged as  $P_t^i$ , and the multi-view registration is applied to  $\{P_t^i\}$  ( $i \in I_t$ ).

As an example, we describe the case of tree number 918 in Figure 9(a). First, point clouds measured near the target tree are selected, as shown in Figure 9(b). In this case, measurement locations { 11, 12, 13, 17, 18 } are selected, because the distances from the target tree are less than 20 m. Therefore, point clouds to be registered are {  $T_{918}^{11}$ ,  $T_{918}^{12}$ ,  $T_{918}^{13}$ ,  $T_{918}^{118}$  }.

However, points of the target tree are not sufficient to stable calculate the degree of rotation around the Z-axis. Therefore, points of neighbor trees are added to point clouds for registration. For this target tree, six trees are connected in the adjacency graph, as shown in Figure 10. By merging the points of neighbor trees,

point-clouds  $\{P_{918}^{11}, P_{918}^{12}, P_{918}^{13}, P_{918}^{17}, P_{918}^{18}\}$  are obtained. These point clouds are used for correcting registration of the target tree.

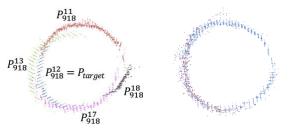
Figure 10. Neighbor trees in the adjacency graph

## 3.4 Multi-view registration

Suppose that point clouds to be registered are  $\{P_t^i\}$  ( $i \in I_t$ ), and point clouds of the target tree are  $\{T_t^i\}$  ( $i \in I_t$ ), where t is the number of the target tree. In our method, multi-view registration is calculated as follows.

- (1) If  $T_t^m$   $(m \in I_t)$  has the largest number of points,  $P_t^m$  is defined as  $P_{target}$ , and  $\Lambda$  is defined as  $\{m\}$ .
- (2)  $T_t^n$   $(n \in I_t, n \notin \Lambda)$  is defined as  $P_{source}$  if it has the largest number of neighbor points in  $P_{target}$ .
- (3) The  $P_{target}$  and  $P_{source}$  are registered and the transformation matrix is calculated.
- (4) The points in  $P_{source}$  are transformed and the coordinates are added to  $P_{target}$ . The index n is added to  $\Lambda$ .
- (5) Repeat the above steps (2)-(4) until the calculation converges.

In this calculation, large weights are given to points of the target tree. In this study, the weight for the target tree was set three times larger. In our implementation, we used FLANN (Muja & Lowe,



(a) Initial point clouds

(b) Corrected point clouds

Figure 11. Correction of registration for tree No. 918

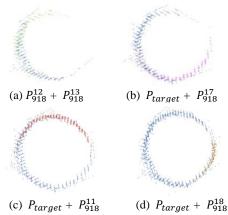


Figure 12. Process of multi-view registration

2014) for neighbor search, and sparse ICP (Bouaziz, et al. 2013) for the point-to-plane registration.

Figure 11 shows the result of the multi-view registration of tree number 918 in Figure 9. Before the correction, the point clouds were obviously misaligned, but our method was able to correct them to reasonable positions.

Figure 12 illustrates the process by which point clouds were sequentially aligned. First,  $P_{918}^{12}$  was selected as  $P_{target}$ , and the neighbor point clouds were aligned sequentially as shown in Figure 12(a)-(d). In this process, the aligned point cloud was added to  $P_{target}$  for the next registration.

#### 3.5 Calculation of DBH

After correction of registration for each tree stem, tree traits are calculated. In this study, DBH was calculated using points corrected for each stem. For this calculation, a horizontal plane is place at 1.3m from the ground, and cross-section points are calculated as in Figure 5. Then, a circle is fitted to the cross section points, as shown in Figure 11, and the DBH is calculated. In our current implementation, circles are fitted to cross-section points, but we note that more flexible approximation such as B-spline curves can be used for representing contour shapes (Eto, 2020).

By correcting misalignment, DBH values are expected to be smaller than the ones calculated from the initial point clouds. Table 1 shows the DBHs of tree number 918 calculated using point clouds in Figure 11(a) and (b). The results show that the DBH becomes smaller after correction. Compared to the manual measurement, the error was reduced from 4.4 mm to 2.5 mm after correction.

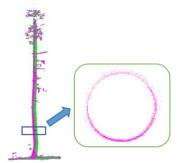


Figure 13. Calculation of DBH

Table 1. Calculated value of DBH for tree No.918

There I, chiedlated value of BBIT for thee I toly to						
	Initial point clouds	Corrected point clouds				
DBH	14.2 cm	13.3 cm				
Error	4.4 mm	2.5 mm				

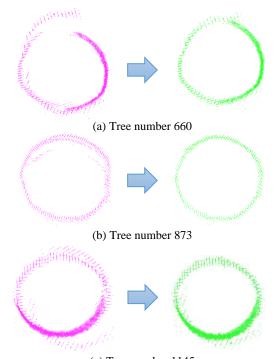
# 4. EXPERIMENTS

We evaluated the proposed method for correcting misalignment using point clouds of the forest shown in Figure 3. First, we randomly selected tree stems and visually investigated the cross-sectional shapes of point clouds before and after the correction. We also selected tree stems for calculating DBH values and comparing with manual measurement. Finally, we evaluated computation time. In the calculation of point-to-plane registration, it is common to reduce the number of points in the source point cloud. In this evaluation, we examined computation

time and DBH accuracy while varying the ratio of point cloud reduction.

## 4.1 Visual evaluation of misalignment of point clouds

In Figure 11, the cross-section of tree number 918 was shown. We also evaluated the randomly selected tree numbers 660, 873, and 1145 in the same plot. Figure 14 shows the cross-sectional shapes of the initial point-clouds and the corrected point-clouds. In these examples, some point clouds were misaligned. By applying our method, the misaligned point clouds could be significantly improved in these cases.



(c) Tree number 1145

Figure 14. Visual evaluation of cross-sections of stems (Left: the initial point clouds; Right: corrected point clouds)

## 4.2 Accuracy of DBH Calculation

We selected 10 trees in the plot and calculated their DBH before and after correction. Table 2 shows the results. After correction, DBH decreased by more than 5 mm in 6 of the 10 trees. We also compared the calculated DBH with the manually measured DBH,

Table 2. Calculation of DBH

Tree number	Initial point clouds (cm)	Corrected point clouds (cm)	Difference (cm)	
660	11.0	10.9	-0.1	
662	15.2	14.6	-0.6	
718	11.9	11.8	-0.1	
799	15.6	15.0	-0.6	
804	10.7	11.2	0.5	
873	16.8	15.9	-0.9	
905	19.2	17.7	-1.5	
917	15.8	16.5	0.7	
918	14.2	13.3	-0.9	
1309	11.3	10.8	-0.5	
Mean Error	0.85	0.23		

and calculated the mean error. The mean error was 8.5 mm for the initial point cloud, but after correction it decreased to 2.3 mm. The proposed method could reduce the mean error by 73%.

## 4.3 Calculation time

Our method uses sparse ICP for point-to-surface registration. Sparse ICP is a robust method because it minimizes the sum of the 0.4 power of the distances of the corresponding points. However, this method is time consuming because it requires nonlinear optimization.

Since the computation time for registration is highly dependent on the number of points in the source point cloud, this problem can be alleviated by reducing the number of points. In our evaluation, we confirmed that misaligned point clouds could be adequately corrected even when the number of points was greatly reduced.

We discuss the computation time and DBH accuracy when calculating multi-view registration with a reduced number of points in the source point clouds. For tree number 917 in Figure 11, a multi-view registration was computed with a reduced number of points at several reduction rates.

We evaluated computation time and DBH accuracy at five reduction rates: 0%, 20%, 40%, 60%, and 90%. Table 3 shows the results. As expected, the larger the reduction rate, the shorter the computation time, but the lower the DBH accuracy. However, the results show that when the number of points was reduced, the computation time was greatly reduced, but the decrease in accuracy was relatively small and misalignment could be corrected.

Table 3. Timing and accuracy after point-cloud reduction

	Initial	Correction after point-cloud reduction				
Reduction	-	0%	20%	40%	60%	90%
Time [s]	-	110	78	56	34	7
DBH [cm]	14.2	13.3	13.4	13.4	13.5	13.8
Error [cm]	+1.4	+0.5	+0.6	+0.6	+0.7	+0.8

## 5. CONCLUSION

In this paper, we proposed a method for correcting misaligned point-clouds by locally re-calculating registration matrices for each tree stem. In our method, tree stems are extracted from point clouds, and each stem in each point cloud is separately managed. For aligning points of the target tree, point clouds measured near the target tree and points of neighbor trees are selected for multiview registration. In our evaluation, our method could adequately correct misaligned point clouds.

In this study, the number of evaluated trees was limited. In future work, we would like to quantitatively evaluate our method on a large number of trees in wide-area forests. We would also like to examine whether our method is effective in improving the accuracy of various tree stem traits. In addition, since our method takes time to process a large number of trees, we would like to investigate methods for further improving performance without the loss of accuracy.

## **ACKNOWLEGEMENTS**

The point clouds in this paper were provided by researchers at the Forestry and Forest Products Research Institute. We would like to thank for their helpful support.

## REFERENCES

Liang, X., et al. (2016). Terrestrial laser scanning in forest inventories. ISPRS Journal of Photogrammetry and Remote Sensing, 115, 63-77.

Dong, Z., et al. (2020). Registration of large-scale terrestrial laser scanner point clouds: A review and benchmark. ISPRS Journal of Photogrammetry and Remote Sensing, 163, 327-342.

Olofsson, K., Holmgren, J., & Olsson, H. Tree stem and height measurements using terrestrial laser scanning and the RANSAC algorithm. Remote Sens. 2014, 6, 4323–4344.

Raumonena, P., Casellab, E., Caldersc, K., Murphyd, S., Akerbloma, M. A. & Kaasalainena, M. (2015). Massive-scale tree modelling from TLS data, ISRPS Annals of Photogramm. Remote Sens. Spatial Inf. Sci., Volume II-3/W4, 189-196.

Zhang, W., Wan, P., Wang, T., Cai, S., Chen, Y., Jin, X., & Yan, G. (2019). A novel approach for the detection of standing tree stems from plot-level terrestrial laser scanning data. Remote Sensing, 11(2), 211.

Masuda, H., Hiraoka, Y., Saito, K., Eto, S., Matsushita, M., Takahashi, M. (2021). Efficient calculation method for tree stem traits from large-scale point clouds of forest stands, Remote Sensing, 13(13), 2476, 2021.

Bouaziz, S., Tagliasacchi, A., & Pauly, M. (2013). Sparse iterative closest point. Computer Graphics Forum, 32(5), 113-123.

Muja, M., & Lowe, D. G. (2014). Scalable nearest neighbor algorithms for high dimensional data. IEEE transactions on pattern analysis and machine intelligence, 36(11), 2227-2240.

Eto, S., Masuda, H., Hiraoka, Y., Matsushita, M., & Takahashi, M. (2020). Precise calculation of cross sections and volume for tree stem using point clouds, Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLIII-B2-2020, 205-2010.