Accurate Calculation of Tree Stem Traits in Forests Using Localized Multi-View Registration

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ABSTRACT:

In recent years, there has been a high demand in forestry and forest research for the accurate measurement of tree traits from point clouds captured by terrestrial laser scanners. However, the reliability of the calculated values is not sufficient due to the difficulty of accurate registration of each tree over a large area of forest. To solve this problem, we introduce localized multi-view registration for correcting the registration matrix of each tree stem. In addition, we discuss methods for registering the whole point clouds of a forest by using the registration matrices locally calculated for tree stems. Especially, we discuss a method to align tree stem points that do not have sufficient overlapping points required in registration. The proposed method was applied to actual forest point clouds and diameter at breast height (DBH) was compared to the manually measured DBH. Experimental results showed that the proposed method was effective in reducing registration errors and in calculating tree stem traits with high accuracy.

1. INTRODUCTION

Accurate measurement of tree traits is important in forestry and forest research. Recently, terrestrial laser scanners (TLS) have made it possible to acquire point clouds of forests with high density and accuracy. Point clouds can be used to efficiently calculate tree traits in large-scale forests (Liang et al., 2016). In the measurement of large areas such as forests, it is necessary to acquire point clouds at many locations, and the coordinates of point clouds must be transformed into a unified coordinate system using a registration technique. However, it is difficult to accurately align all points in a large area even if registration is carefully performed to point clouds. Therefore, registration errors often result in inaccurate calculations of tree traits, especially when points on trees are only partially captured because they are occluded or far from the measurement position.

Many methods have been proposed for registration of point clouds (Dong et al., 2020), However, it is not easy to compute a rigid transformation for accurately aligning all trees in a large forest, because conventional registration methods tend to prioritize alignment accuracy in areas of high point density, and neglect trees with low point densities. In point clouds of a large forest, point density at each position varies greatly according to the distance from the laser scanner and the tree diameter. As a result, some trees may be significantly misaligned. Non-rigid registration methods have been proposed, but such methods are very time-consuming, and it is difficult to perform non-rigid registration to large-scale point clouds in a reasonable calculation time on common PCs.

In our experiments, conventional registration was applied to large-scale point clouds of a forest in Japan. While many trees were properly aligned, some trees were significantly misaligned, as shown in Figure 1. When diameter at breast height (DBH) was calculated from point clouds of trees, inaccurate DBH values were obtained from points of misaligned tree stems due to large registration errors.

To solve such a problem, calculating rigid registration locally for a partial point cloud is effective instead of calculating for the entire point cloud. (Kawasaki et al., 2022) proposed a method for locally correcting registration errors to improve the accuracy of tree stem traits. However, this method is only applicable to tree stems with sufficient overlapping points in multi-view registration. Therefore, alignment errors cannot be corrected for tree stems without overlapping points and points other than tree stems. As a result, in some trees, precise DBH could not be calculated.

In this paper, we extend our previous method by integrating locally calculated registration matrices, and calculate the registered coordinates for the entire point clouds. Although the proposed method is non-rigid registration, it can calculate the registered coordinates in reasonable computation time on a typical PC, even for very large point clouds.

We assume that point clouds of a forest are aligned by a conventional registration method such as iterative closest point (ICP). Our method corrects alignment errors in registration for each tree stem. In our method, we first extract all tree trunks from point clouds using the method proposed by (Masuda et al., 2021). Then, the registration matrix is locally computed for each tree using the points of neighbor tree stems. If overlapping points on a tree stem is too small, the registration matrix cannot be computed accurately. For such tree stems, the locally corrected coordinates are calculated using the registration matrices of neighbor tree stems. For points other than tree stems, the coordinates are corrected by interpolating the registration matrices of tree stems using the distance weights.



(a) Correctly aligned points

(b) Misaligned points

Figure 1. Registration of point clouds captured in a large area of forest

To evaluate the effectiveness of the proposed method, we computed the DBH values of trees from point clouds of a forest in Japan before and after registration correction and compared them with manually measured DBH values.

2. OVERVIEW OF REGISTRATOIN METHOD

In this research, point clouds of a cedar forest were measured using FARO Focus 3D with an angular resolution of 0.018 degrees. As shown in Figure 2, there are 641 trees with unique identification numbers in the 75m x 65m plot of the forest. Point clouds were captured at 37 locations indicated by the blue circles. The number of points is approximately 3.6 billion points. Targets were placed in the forest for registration. Faro Scene was used for initial registration.

Since our method locally corrects the alignment error of each tree, it is necessary extract points of each tree from point clouds. Many methods have been proposed to detect tree stems from point clouds (Masuda et al., 2021, Olofsson, et al., 2014; Raumonena, et al., 2015; Zhang, et al. 2019). In this research, we use the method proposed by (Masuda, et al., 2021). In this method, crosssectional points of all trees are calculated from large-scale point clouds in an out-of-core manner. The memory size for maintaining cross-sectional points is relatively small, and tree stems are detected only using the cross-sectional points. Therefore, a very large number of tree stems can be detected with a limited RAM. Figure 3(a) shows tree stems extracted from cross-sectional points.

The notations in this paper are defined as follows. Let $\mathbf{P}_1, \mathbf{P}_2, ..., \mathbf{P}_n$ be the point clouds measured at *n* locations; $t_1, t_2, ..., t_m$ be the *m* tree stems in the forest; $\mathbf{T}_{i,j}$ be points of tree stem t_j in \mathbf{P}_i . For obtaining $\mathbf{T}_{i,j}$, the axis-aligned bounding box (AABB) is generated from the cross-sectional points of tree stem t_j , as shown in Figure 3(b), and points inside the AABB are extracted

In the next step, the alignment error of each tree is corrected. In this paper, the tree to be corrected is called the *target tree*. As shown in Figure 4(a), point clouds of both the target and neighbor trees are used to compute the registration matrix for correcting alignment error of the target tree. Suppose Λ_j is the index set of point clouds containing tree stem t_j . To correct the alignment error of tree stem t_j , multi-view registration is applied to $\mathbf{T}_{i,j}$ ($i \in \Lambda_i$). Figure 4(b) shows the corrected points of the target tree.

Our method is only applicable to tree stems with sufficient overlap of points in multi-view registration. If the registration

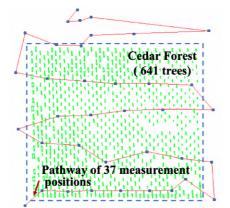
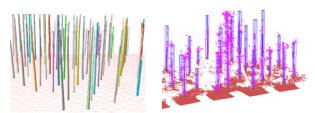
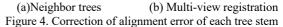


Figure 2. Laser scanning positions in a cedar forest



(a) Extraction of tree stems (b) Extraction of tree stem points Figure 3. Extraction of tree stem points from point clouds





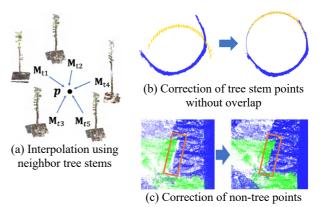


Figure 5. Correction of alignment errors using the localized registration matrices of neighbor tree stems

matrix $M_{i,j}$ cannot be calculated for each $\mathbf{T}_{i,j}$, the corrected points $\mathbf{T}'_{i,j}$ are calculated using the localized registration matrices of the neighbor tree stems. In addition, for points other than tree stems, the corrected coordinates are computed by interpolating the registration matrices of neighbor trees with Gaussian distance weights. Figure 5 shows an example of correcting alignment errors for non-overlapping tree stem points and non-tree points.

3. EXTRACTION OF TREE STEM POINTS FROM POINT CLOUDS OF FOREST

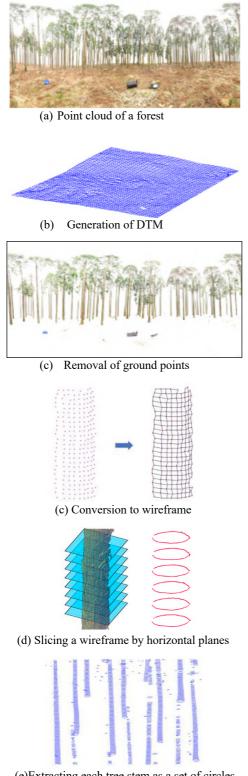
3.1 Extraction of Tree Stems

In this research, points of each tree stem are extracted from point clouds. Figure 6 shows the process of tree stem extraction.

First, ground points are eliminated from point clouds. The ground points can be detected by creating the digital terrain model (DTM). The point cloud is divided into a grid on the horizontal plane, the ground height is estimated by obtaining the minimum height at each section. In this research, points within 30cm from the ground were removed to eliminate weed points.

By removing the ground points from the point clouds, points of tree stems are separated, as shown in Figure 6(b). Tree stems are

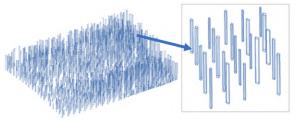
extracted from the remaining points using the method proposed by (Masuda, et al., 2021). In this method, each tree stem is detected using section circles calculated from point clouds. Section circles can be calculated at arbitrary intervals by converting a point cloud into a continuous wireframe model, as shown in Figure 6(c). It is easy to convert a point cloud to a wireframe model. Each point cloud acquired by a TLS can be mapped onto a two-dimensional grid using the azimuth and



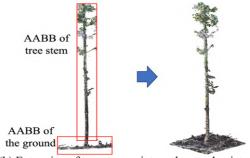
(e)Extracting each tree stem as a set of circles Figure 6. Extraction of tree stems from point clouds elevation angles of the laser beam, as shown in Figure 6(a). A wireframe model can be generated by adding edges between adjacent points on the two-dimensional grid.

Then, the wireframe model is sliced with horizontal planes placed at small intervals to compute the cross-sectional points of tree stems, as shown in Figure 6(d). Since point clouds are converted into wireframe models in this method, cross-sectional points can be calculated at small intervals even from a sparse point cloud.

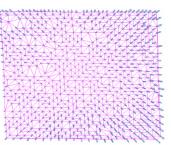
The cross-sectional shapes of each tree stem can be approximated as circles or ellipses. Circles or ellipses can be robustly detected from section points by using the RANSAC method. As shown in Figure 6(e), each tree stem can be robustly detected as a sequence of vertically aligned circles or ellipses, even if the tree stem is partially occluded by leaves and branches and some circles or ellipses are missing.



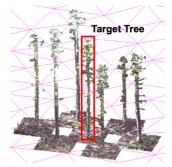
(a) Axis-aligned bounding boxes of tree stems



(b) Extraction of tree stem points and ground points Figure 7. Extraction of tree stem points



(a) Adjacency graph for tree stems



(b)Neighbor trees used for registration of the target tree Figure 8. Extraction of points used for registration

3.2 Extraction of Tree Stem Points

In order to extract points of each tree, the AABB of each tree stem is created, as shown in Figure 7(a). Initially, the AABB is generated to enclose the set of circles detected in Figure 6(d). Then, the AABB is enlarged by setting an offset value for robust selection of tree points, as shown in Figure 7(b). In this research, the offset value was set to 25 cm. In addition, ground points are added to the tree stem points because ICP-based registration using only tree stem points without ground points cannot achieve highly accurate alignments in the height direction. To obtain the ground points, another AABB is created at ground level below the tree stem. In this research, the size of the AABB is set to 200 cm wide and 30 cm high to enclose the ground points. Figure 7(b) shows the extracted tree points.

The tree stem points extracted from each point cloud are stored in a separate file with a tree index and a point-cloud index. For point clouds used in this research, there are 641 trees measured at 37 points. Therefore, the maximum number of files is $37 \times 641 = 23,717$. In practice, however, tree points located far from the laser scanner are very sparse and should be ignored for calculating tree traits. Therefore, files are generated only when the distance from the laser scanner is smaller than d_s and the number of points of the tree stem is greater than n_s . In this research, we used $d_s = 20m$, and $n_s = 256$. As a result, the number of files generated was reduced to 6,366.

4. LOCALIZED MULTI-VIEW REGISTRATION FOR ALIGNING EACH TREE STEM

4.1 Selection of Tree Points for Localized Multi-View Registration

For accurate registration, the points of the target tree and the points of the neighbor trees are used. The neighbor trees are detected using the adjacency graph for tree stems. As shown in Figure 8(a), the center points of the AABBs of tree stems are projected onto the horizontal plane and the Delaunay triangulation is performed to the projected points. The result of the triangulation is used as the adjacency graph of tree stems. We define the neighbor trees as those connected to the target tree by edges in the graph. Figure 8(b) shows the points of the target tree and the neighbor trees.

4.2 Process of Localized Multi-View Registration

The tree points extracted from each point cloud are aligned using multi-view registration. Let Λ_T be the index set of the target tree and the neighbor trees, and $\mathbf{T}_{i,j}$ be points of tree t_j in point cloud \mathbf{P}_i . The tree points used for registration is $\mathbf{Q}_i = {\mathbf{T}_{i,j}}$ $(j \in \Lambda_T)$. Let Λ_j is the index set of point clouds containing tree stem t_j . Let Λ_p be the index set of point clouds to be registered. Point clouds to be registered are ${\mathbf{Q}_i}$ $(i \in \Lambda_p)$.

Multiview registration for tree stem t_j is applied to $\{\mathbf{Q}_i\}$ ($i \in \Lambda_i$). This calculation is performed in the following procedure.

(1) The set of unprocessed point clouds is denoted as *Unregistered* and the set of registered points is denoted as *Registered*. Initially, *Unregistered* = $\{\mathbf{Q}_i\} (i \in \Lambda_j)$ and *Registered* = $\{\}$.

(2) Among the point clouds in *Unregistered*, the point cloud with the largest number of points of the target tree stem is selected and added to *Registered*. This point cloud is regarded as the fixed point-cloud for multi-view registration

(3) For multi-view registration, a point cloud that has a large overlap with the registered points is selected. Let $v_{i,j}$ be the irradiation direction from the scanner position of point cloud \mathbf{P}_i to the center of tree stem t_j , as shown in Figure 9. Let θ be the angle between the two irradiation directions, as shown in Figure 10. Point clouds with small θ have a large number of overlapping points. Suppose that $\mathbf{T}_{k,j}$ is the candidate point cloud whose θ is smallest to one of the point clouds in *Registered*. If the smallest angle is larger than the threshold θ_{max} , the multi-view registration process is terminated. In this research, we used $\theta_{max} = 130$ deg.

(4) For each point in $\mathbf{T}_{k,j}$, the neighbor points are searched from all points in *Registered* using nearest neighbor search. If the number of neighbor points is smaller than the threshold n_{min} , the candidate $\mathbf{T}_{k,j}$ is discarded and the next candidate point cloud is selected. In this research, we used $n_{min} = 1024$.

(5) The registration matrix is computed to align $\mathbf{T}_{k,j}$ to the already registered points. If the ICP calculation is converged, the transformed points of $\mathbf{T}_{k,j}$ is added to *Registered*.

(6) Steps (3)-(5) are repeated as long as there are point clouds that can be registered.

ICP or its derivatives can be used for multi-view registration. In our implementation, we used Sparse ICP (Bouaziz et al., 2013), which is robust to mismatched point pairs in the ICP calculation. This method uses FLANN (Muja & Lowe, 2014) for nearest neighbor search. In our implementation, the points of the target tree are given larger weights in the ICP calculation. In this paper, the weight of the target tree was set 3 times larger than the weights of other trees.

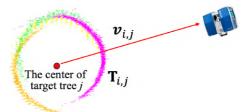


Figure 9. Irradiation direction of point cloud

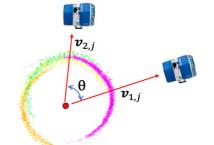


Figure 10. Tree stem with large overlap ($\theta < \theta_{max}$)

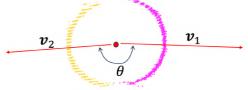


Figure 11. Tree stem with small overlap ($\theta > \theta_{max}$)

If there is no overlapping points for any combination of $\mathbf{T}_{i,j}$ in $\mathbf{Q}_i = \{\mathbf{T}_{i,j}\}$, multi-view registration cannot be applied. For example, in Figure 11, the angle between the irradiation directions of the two point-clouds is larger than θ_{max} and there are few overlapping points. In our experiments, approximately 10% of all tree stems could not be aligned due to insufficient overlap of the point clouds. The method for aligning such tree stems is discussed in a later section.

4.3 Accuracy Evaluation of Localized Multi-View Registration

The proposed method was applied to the 37 point clouds of the forest plot with 641 trees. First, the point clouds were registered using conventional ICP. Next, the localized multi-view registration was applied to correct the registration for each tree stem.

In our experiments, the alignment errors were corrected and the accuracy of DBH was improved for 577 of the 641 tree stems. 64 tree stems could not be corrected mainly due to insufficient point cloud overlap. Figure 12 shows examples of corrected tree stem points.

DBH was calculated before and after correcting alignment errors and compared with manual measured DBH values. In this study, DBH was calculated at 1.3m from the ground by fitting a circle to the cross-sectional points shown in Figure 6(d).

Figure 13 shows the relationship between the calculated and manually measured DBH for 577 tree stems before and after the correction. Table 1 shows the RMSE values and the number of tree stems with a difference of more than 2cm in DBH. For many tree stems, the calculated DBH values were close to the manually measured values after correction. These results show that the proposed method could significantly improve the registration accuracy and the reliability of calculation of tree traits.

We examined six cases in Table 1 that differed by more than 2cm from the manual measurements even after the registration correction. The reason for the large differences was due to distorted tree stem shapes or protruding barks, as shown in Figure 14. These cases were not registration problems, but problems with DBH calculations.

5. INTEGRATION OF LOCALIZED REGISTRATION

5.1 Coordinate Transformation of Unregistered Points

In Figure 15, registered tree points are shown in blue and unregistered points are shown in green. In local multi-view registration, since only tree stems with sufficient overlapping points are corrected, there are many points that are not transformed. In this section, we describe a method to align these unregistered points.

5.2 Transformation of Non-Tree Points

As shown in Figure 16, there may be a discontinuity at the boundary between the registered tree points and the unregistered non-tree points. Such discontinuities deteriorate the display quality of forest point clouds.

To transform a non-tree point p in P_i , the locally computed registration matrices of neighbor tree stems are interpolated with the distance weights from p, as shown in Figure 17. The transformed point p' can be calculated by the following equation.

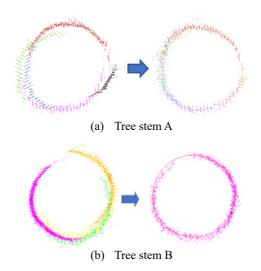


Figure 12. Corrected alignment of tree stem points

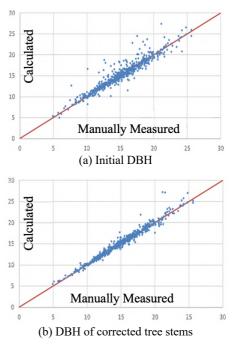


Figure 13. Comparison of DBH of tree stems

 Table 1. RMSE of DBH and the number of trees

 with large error of more than 2cm

	Initial DBH	Corrected DBH
RMSE	12.0 mm	6.8mm
Error > 2cm	37 tree stems	6 tree stems

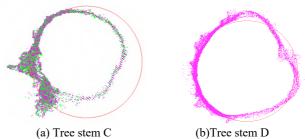


Figure 14. Examples of distorted tree stem shapes that cannot be approximated by circles

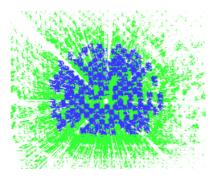
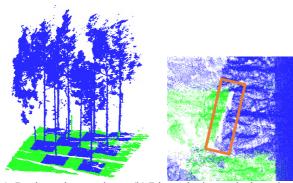


Figure 15. Registered tree stem points in forest point clouds



(a) Registered tree points (b) Discontinuity on the boundary
 Figure 16. Discontinuity of transformed points

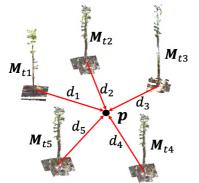


Figure 17. Registration correction of non-tree points using locally registered tree stem points.

$$\boldsymbol{p}' = \frac{1}{\sum_{j \in \Lambda_T} w_j} \sum_{j \in \Lambda_T} w_j M_{i,j} \boldsymbol{p}$$

$$w_j = \exp(-d_j^2/h^2),$$
(1)

where d_j is the distance of tree stem t_j from point \boldsymbol{p} ; Λ_T is the index set of all tree stems for which the registration matrix can be locally calculated; h is a parameter that depends on the tree spacing. In this paper, we used h = 15. In our experiments, the transformed point \boldsymbol{p}' was not sensitive to the parameter h.

All unregistered points other than trees are transformed using Equation (1). Figure 18 shows an example. In Figure 18(a), since the ground points under the tree stem have been locally aligned, there are small gaps and steps at the boundary between the locally aligned points and the unregistered points. To eliminate such discontinuities, the unregistered points are transformed by blending registration matrices of neighbor tree stems using

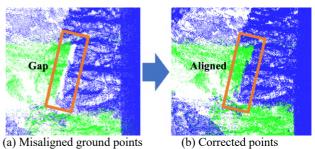


Figure 18. Correction of misaligned non-tree points by interpolating the matrices of neighbor tree stems

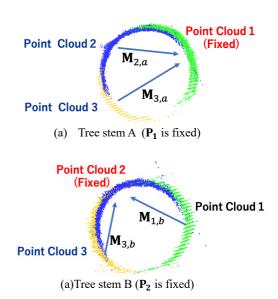


Figure 19. Calculations with different coordinate systems

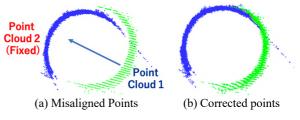
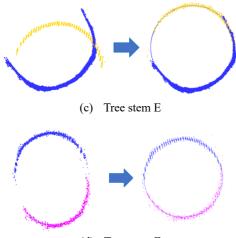


Figure 20. Tree stem C with few overlapping points

Table 2. Exchange of the fixed point cloud

	Initial Matrix	Transformed
Point Cloud 1	I (fixed)	$M_{2,a}^{-1}$
Point Cloud 2	М _{2,а}	<i>I</i> (fixed)
Point Cloud 3	М _{з,а}	$M_{2,a}^{-1}M_{3,a}$

Equation (1). As shown in Figure 18(b), the discontinuous regions can be smoothly connected and the visual quality of point clouds can be improved. This process can be performed in practical time, even when a wide range of matrices are used for calculation. In our experiment, the computation time for transforming 170 million non-tree points was 3 minutes and 20 seconds, even when the matrices of all tree stems were used for transforming each point. We evaluated calculation time using a PC with a 3.70 GHz Intel Core i9 CPU and 64GB RAM.



(d) Tree stem F

Figure 21. Corrected alignment of tree stem points with few overlapping points

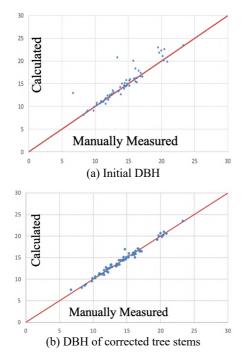


Figure 22. DBH Comparison of 64 trees without overlap

Table 3. DBH of 64 trees without overlap

	Initial DBH	Corrected DBH
RMSE	16.0 mm	6.8 mm
Error>2cm	8 tree stems	1 tree stem

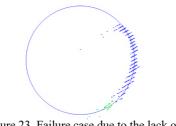


Figure 23. Failure case due to the lack of many tree stem points.

5.3 Registration of Tree Stems without Overlapping Points

For tree stems without sufficient overlapping points, alignment errors are corrected using the registration matrices of neighbor tree stems.

In localized registration, the point cloud containing the largest number of tree stem points is fixed. Therefore, the matrices for neighbor tree stems may be computed by fixing different point clouds, as shown in Figure 19. In this example, the registration matrices for tree stem A and B are calculated by fixing point clouds I and 2, respectively.

In order to interpolate the registration matrices, the fixed point cloud for each registration must be the same. Suppose the registration matrix of unregistered tree stem *C* is computed by fixing point cloud 2, as shown in Figure 20(a). To make the fixed point clouds identical in tree stem *A* and *B*, the registration matrix of tree stem *A* is transformed to the matrix when point cloud 2 is fixed, as shown in Table 2. This transformation multiplies the inverse matrix $M_{2,a}^{-1}$ of point cloud 2 to the registration matrices of all other point clouds. The transformed matrices are then used for transforming points of the unregistered tree stem. In Figure 20(b), the points of tree stem *C* can be aligned by applying Equation (1) using the transformed matrices.

5.4 Accuracy Evaluation for Trees without Overlapping Points

The method was applied 64 tree stems that could not calculate registration matrices due to few overlapping points required for registration. In most of these 64 trees, alignment errors could be corrected, as shown in Figure 21.

Figure 22 shows the relationship between the calculated and manually measured DBH before and after the correction. The results show that our method can calculate tree stem traits close to manually measured values even for tree stems with few overlapping points.

Table 3 shows the RMSE values and the number of tree stems with a difference of more than 2cm in DBH. Compared to Table 1, the DBH values of unregistered tree stems were inaccurate before correction. The proposed method could significantly improve the registration accuracy and the reliability of tree trait calculations even for tree stems with few overlapping points.

The only tree with an error of more than 2 cm after correction was examined. The reason was that the points on the tree stem was largely missing due to occlusion, as shown in Figure 23.

6. CONCLUSION

This paper proposed a method for correcting misaligned point clouds using localized multi-view registration. In our method, the registration matrix is calculated for each tree stem. We also proposed a method for transforming unregistered points by integrating the registration matrices for tree stems.

Our method was evaluated using point clouds of a forest in Japan. The experimental results showed that tree stem traits could be precisely calculated by using our method. In registering the entire point clouds, non-tree points were smoothly transformed without discontinuous gaps by integrating the registration matrices computed for neighbor tree stems. Tree stems with few overlapping points could also be corrected for alignment errors by integrating the registration matrices of neighbor tree stems after transforming them into a unified coordinate system. In future work, we would like to investigate a method to calculate the optimal laser scanning positions to obtain point clouds with sufficient overlap of points on each tree stem. In our evaluation, 10% of tree stems did not have sufficient overlapping points required for registration. This problem could be solved if appropriate measurement positions could be computed. In addition, we would like to evaluate our method using point clouds of a variety of forests. In this paper, we evaluated our method using point clouds of a test forest on flat ground. We believe that the proposed method can be applied to point clouds of mountain forests as long as the DTM can be calculated.

REFERENCES

Kawasaki, H., Masuda, H, 2022: Accurate calculation of tree stem traits in forests by local correction of point, Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLIII-B2-2022, 209-214, 2022/06/6-11

Chan, K.L., Qin K., 2017: Biomass burning related pollution and their contributions to the local air quality in Hong Kong. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, XLII-2/W7, 29-36. doi.org/10.5194/isprs-archives-XLII-2-W7-29-2017.

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.

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.

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