# A Novel Framework to Automatically Fuse Multiplatform LiDAR Data in Forest Environments Based on Tree Locations 

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#### Abstract

The emerging near-surface light detection and ranging (LiDAR) platforms [e.g., terrestrial, backpack, mobile, and unmanned aerial vehicle (UAV)] have shown great potential for forest inventory. However, different LiDAR platforms have limitations either in data coverage or in capturing undercanopy information. The fusion of multiplatform LiDAR data is a potential solution to this problem. Because of the complexity and irregularity of forests and the inaccurate positioning information under forest canopies, current multiplatform data fusion still involves substantial manual efforts. In this article, we proposed an automatic multiplatform LiDAR data registration framework based on the assumption that each forest has a unique tree distribution pattern. Five steps are included in the proposed framework, i.e., individual tree segmentation, triangulated irregular network (TIN) generation, TIN matching, coarse registration, and fine registration. TIN matching, as the essential step to find the corresponding tree pairs from multiplatform LiDAR data, uses a voting strategy based on the similarity of triangles composed of individual tree locations. The proposed framework was validated by fusing backpack and UAV LiDAR data and fusing multiscan terrestrial LiDAR data in coniferous forests. The results showed that both registration experiments could reach a satisfying data registration accuracy (horizontal root-meansquare error (RMSE) $<30 \mathrm{~cm}$ and vertical RMSE $<20 \mathrm{~cm}$ ).


[^0]
#### Abstract

Moreover, the proposed framework was insensitive to individual tree segmentation errors, when the individual tree segmentation accuracy was higher than $80 \%$. We believe that the proposed framework has the potential to increase the efficiency of accurately registering multiplatform LiDAR data in forest environments.


Index Terms-Forest, multiplatform light detection and ranging (LiDAR), registration, tree location.

## I. Introduction

LIGHT detection and ranging (LiDAR) can be used to accurately estimate forest structure attributes [e.g., tree height, diameter at breast height (DBH), canopy cover, leaf area index, and crown base height] from its rich 3-D information [1]. It has been proven to be a highly useful remote sensing technique in the practices of forest inventory [2]-[4] and forest management [5]-[7]. Currently, airborne, unmanned aerial vehicle (UAV)-borne, mobile, and terrestrial LiDAR systems are the most commonly used LiDAR platforms in forest-related applications [8]-[11]. However, each of these LiDAR platforms has its own limitations. The down-looking airborne and UAV-borne LiDAR systems can provide highly accurate tree canopy information but lack tree trunk information [12]; mobile LiDAR systems (e.g., backpack LiDAR) can provide detailed tree trunk information, but the limited vertical field of view and measurement range may result in the missing of upper canopy information [13]; single-location scans of terrestrial laser scanning (TLS) suffer from the occlusion effect of branches and leaves, and the registration of multiscan TLS data can be highly time-consuming [14], [15]. The fusion of multiplatform LiDAR data has the potential to provide an ultimate solution to address the limitations of each LiDAR platform.

Currently, there are three commonly used point cloud registration frameworks, including target-, feature-, and pointbased methods [16]-[18]. Target-based methods usually need the assistance of exterior information to register LiDAR point clouds, e.g., positioning information from a global positioning system (GPS) [19], registration targets that can be easily identified [20], [21], or color information provided by cameras [22], [23]. Feature-based methods work similar to targetbased methods, which use tie points/lines/polygons to register LiDAR point clouds, but these features are identified within


Fig. 1. Five-step process of the proposed multiplatform LiDAR registration framework. Red points represent the LiDAR data acquired from the side-view backpack LiDAR, and green points represent the vertical UAV LiDAR data.

LiDAR point clouds (e.g., buildings, roofs, roads, and traffic signs) [24]. Point-based methods directly match LiDAR point clouds based on the geometric information provided by LiDAR points, and the iterative closest point (ICP) algorithm is one of the most widely used methods under this category [25], [26]. However, point cloud registration frameworks are typically problematic in forested scenes. The exterior registration information required by the target-based methods is either unavailable, inaccurate, or hard to acquire in forests. For example, GPS positioning information might become unreliable under forest canopies because of multipath errors and the attenuation of GPS signals [27]. Furthermore, arranging ground targets or acquiring color imagery can be very time-consuming and expensive [28]. Feature-based methods are widely used in indoor and urban environments, where regular features (e.g., parallel and orthogonal line segments [29], [30] and conjugate least-squares surfaces [31], [32]) can be easily found. Forest environments have much higher complexity and irregularity than indoor and urban environments, and similar regular features as in indoor and urban environments can be hardly found or might be completely absent. Point-based methods, such as ICP, usually require the LiDAR point clouds to be coarsely registered before running the algorithm. However, such coarse registration in forest environments is usually achieved by manually selecting tie points, which is a labor-intensive and time-consuming process.

Recently, marker-free data fusion solutions have been proposed to overcome the issues of missing referencing features in forests. For example, Henning and Radtke [33] and Liu et al. [34] proposed to use geometric features within the LiDAR point clouds (e.g., stem centers and stem curves) to register multiscan TLS data; Kelbe et al. [35] proposed a
multiscan TLS data registration method through the use of populated triplet sets of DBHs , tree locations, and eigenvalues; Polewski et al. [36] used simulated annealing to find the optimal 3-D transformation between the respective coordinate systems of two tree location sets derived from backpack and UAV LiDAR data. These methods either rely on tree stem geometric information or look for a globally optimized registration solution using constraints of tree attributes, such as DBHs and tree locations. However, tree stem geometric information is unavailable in top-view LiDAR data (e.g., UAV LiDAR data), and globally optimized solutions might fail when the estimation accuracies of tree attributes are low. How to accurately and efficiently register multiplatform LiDAR point clouds in forested scenes is still a big challenge in LiDAR forest applications.

In this article, we propose a novel multiplatform LiDAR data registration framework for forest applications based on the unique spatial distribution of trees in a forest stand, with tree pairs identified from multiplatform LiDAR data as the only required features in the registration process. This article is organized as follows. Section II introduces the methodology of the proposed data registration framework, Section III describes the experimental design and results for evaluating the proposed framework, Section IV discusses the robustness and limitations of the proposed framework, and Section V gives the conclusion.

## II. Methodology

The proposed framework includes five steps, i.e., individual tree segmentation, triangulated irregular network (TIN) generation, TIN matching, coarse registration, and fine registration (see Fig. 1). The detailed information of each step is presented in Sections II-A-II-E.

## A. Individual Tree Segmentation

Extracting individual tree locations is the prerequisite of the proposed point cloud registration framework. Individual tree segmentation is a point cloud processing step that can automatically identify individual tree locations from LiDAR point clouds. There have been numerous individual tree segmentation algorithms proposed in the literature, which can be generally divided into two groups: canopy height model (CHM) segmentation [37]-[39] and point cloud segmentation (PCS) [40]-[42]. LiDAR data acquired from different platforms and forest conditions usually require different segmentation schemes to obtain optimized segmentation results. Jakubowski et al. [43] made a comprehensive comparison of the performance of CHM segmentation and PCS under different forest conditions. The individual tree segmentation method should be chosen based on the data acquisition platform and forest conditions. The output individual tree coordinates (i.e., $X, Y$, and $Z$ ) can be used as the input of the proposed framework. The $Z$-coordinate of each tree is represented by the elevation of the tree base. In this article, we used the mean elevation of all ground points within a $1-\mathrm{m}$ buffer to represent the $Z$-coordinate so that the influence of different tree position definitions from different platforms (e.g., treetop from UAV-borne LiDAR and tree base from terrestrial LiDAR) can be minimized.

## B. TIN Generation

This article assumes that every forest stand should have a unique spatial distribution of trees and this spatial pattern should not change in a short time period within which multiple LiDAR data sets are acquired. In other words, the spatial relationship between each tree and its neighboring trees should be constant. To identify the spatial pattern of tree distributions, the plane coordinates (i.e., $X$ and $Y$ ) of each individual tree and its neighboring trees are transformed to a simple geometric feature by constructing a TIN using the Delaunay triangulation [44]. Based on the abovementioned assumptions, a particular tree identified from different LiDAR platforms should form a similar TIN with its defined neighbors. Therefore, we should be able to find the corresponding tree pairs by matching the TINs generated from different LiDAR platforms.

In the process of TIN generation, each tree location is considered as a search point and its neighboring tree locations can be found by the $k$-nearest neighbor search method. Moreover, in order to avoid ambiguous TINs, the search point does not participate in the TIN generation. For example, as shown in Fig. 2, the three search points have the same search neighbors. In the case of TIN generation including the search point itself, the generated TINs would be the same; if the search point is excluded, the generated TINs would be distinctive from each other. Two sets of TINs generated from segmented trees in multiplatform LiDAR data are represented as $\operatorname{TIN}^{1}=$ $\left\{\operatorname{TIN}_{1}^{1}, \operatorname{TIN}_{2}^{1}, \ldots, \operatorname{TIN}_{k}^{1}\right.$ and $\operatorname{TIN}^{2}=\left\{\operatorname{TIN}_{1}^{2}, \operatorname{TIN}_{2}^{2}, \ldots, \operatorname{TIN}_{l}^{2}\right.$, where $k$ and $l$ are the numbers of trees derived from two LiDAR data sets, respectively.

## C. TIN Matching

The plane coordinates (i.e., $X$ and $Y$ ) of the same trees obtained by the individual tree segmentation from different


Fig. 2. Illustration of the TIN generation and ambiguous TIN elimination for tree locations using a point cloud from one platform.

LiDAR data can be slightly different. For example, the individual tree locations obtained from UAV-borne LiDAR data are centers of tree crowns, whereas the individual tree locations obtained from mobile and terrestrial LiDAR data are the centers of tree bases. Meanwhile, the incomplete point cloud of trees and the dense tree distribution can bring many undetected and falsely detected trees in segmentation. These errors caused by individual tree segmentation from different LiDAR data may bring failures in the tree matching process if very strict rules were used. Therefore, a tolerant matching method should be used to match TINs. To avoid falsely matched TINs during the tolerant-matching process, the matched TINs are further filtered by using a random sample consensus (RANSAC)-based method.

During the tolerant-matching process, a voting strategy is used to count the number of similar triangles between two TINs and find the best matched TIN pairs iteratively. Each TIN in $\operatorname{TIN}^{1}$ is compared with all TINs in $\operatorname{TIN}^{2}$ to calculate the matching scores based on the similarities among the triangles within each TIN pair. The similarity of triangles is evaluated by two parameters, the area similarity $S$ and the angle similarity I. Assuming that $\operatorname{Tri}_{p}^{i, 1}$ is the $p$ th triangle in $\operatorname{TIN}_{i}^{1}$, and $\operatorname{Tri}_{q}^{j, 2}$ is the $q$ th triangle in $\operatorname{TIN}_{j}^{2}$, the area similarity $S$ can be calculated from the following equation:

$$
\begin{equation*}
S=1-\frac{\left|l_{a} l_{b} \sin C-l_{a}^{\prime} l_{b}^{\prime} \sin C^{\prime}\right|}{\frac{l_{a} l_{b} \sin C+l_{a}^{\prime} l_{b}^{\prime} \sin C^{\prime}}{2}} \tag{1}
\end{equation*}
$$

where $l_{a}$ and $l_{b}$ are two sides of $\operatorname{Tri}_{p}^{i, 1}, l_{a}^{\prime}$ and $l_{b}^{\prime}$ are two sides of $\operatorname{Tri}_{q}^{j, 2}$, and $C$ and $C^{\prime}$ are the angles between $l_{a}$ and $l_{b}$ and between $l_{a}^{\prime}$ and $l_{b}^{\prime}$, respectively. The triangle pair $\operatorname{Tri}_{p}^{i, 1}$ and $\operatorname{Tri}_{q}^{j, 2}$ has three angle similarity components, i.e., $I_{A}, I_{B}$, and $I_{C}$, where $A, B$, and $C$ are the three angles of $\operatorname{Tri}_{p}^{i, 1}$. Zhou et al. [45] proposed the criteria of calculating angle similarity based on the Gaussian distribution. Taking $I_{C}$ as an example, the angle similarity $I_{C}$ between $C$ and $C^{\prime}$ can be


Fig. 3. Illustration of the voting process for TIN matching. Elements in green represent marked elements and elements in red represent the largest element excluding marked elements.
calculated as

$$
\begin{align*}
I_{C} & =\cos ^{3}\left(\frac{\pi}{2}(1-u(C))\right)  \tag{2}\\
u(C) & =e^{-\frac{1}{2 \sigma^{2}}\left(C-C^{\prime}\right)^{2}} \tag{3}
\end{align*}
$$

where $\sigma=C / 6$. The final angle similarity $I$ is calculated as the average of the three angle similarity components

$$
\begin{equation*}
I=\left(I_{A}+I_{B}+I_{C}\right) / 3 \tag{4}
\end{equation*}
$$

The overall similarity OS between the triangle pair $\operatorname{Tri}_{p}^{i, 1}$ and $\operatorname{Tri}_{q}^{j, 2}$ is calculated as

$$
\begin{equation*}
\mathrm{OS}=(I+S) / 2 \tag{5}
\end{equation*}
$$

Note that if $I$ or $S$ was smaller than the user-defined thresholds $T_{I}$ or $T_{S}$, the OS value should be set to zero instead of being calculated from (5). By iterating the calculation between all triangle combinations, an OS matrix (OSM) can be built as

$$
\mathrm{OSM}=\left[\begin{array}{cccc}
\mathrm{OS}_{11} & \mathrm{OS}_{12} & \cdots & \mathrm{OS}_{1 n}  \tag{6}\\
\mathrm{OS}_{21} & \mathrm{OS}_{22} & \cdots & \mathrm{OS}_{2 n} \\
\vdots & \vdots & \vdots & \vdots \\
\mathrm{OS}_{m 1} & \mathrm{OS}_{m 2} & \cdots & \mathrm{OS}_{m n}
\end{array}\right]
$$

where $m$ and $n$ are the number of triangles in $\operatorname{TIN}_{i}^{1}$ and $\operatorname{TIN}_{j}^{2}$, respectively.

The voting process for the TIN pair of $\operatorname{TIN}_{i}^{1}$ and $\operatorname{TIN}_{j}^{2}$ is shown in Fig. 3. Within OSM, the largest OS is first identified and marked, and all the elements on the corresponding row and column of the matrix are set to zero. Then, the new largest OS, excluding the previous largest OS, is identified and marked, and all the elements on the corresponding row and column of the matrix are set to zero. This process is repeated until all unmarked elements become zero. Each of the remaining marked elements is treated as an equal-weighted vote with a value of one, and the final vote score (VS) between $\operatorname{TIN}_{i}^{1}$ and $\mathrm{TIN}_{j}^{2}$ is calculated as the sum of all votes.

After calculating the VS between $\operatorname{TIN}_{i}^{1}$ and all TINs in $\mathrm{TIN}^{2}$, the $\mathrm{TIN}(\mathrm{s})$ with the largest VS is/are picked out. If the largest VS value is smaller than the user-defined voting score threshold $T_{\mathrm{VS}}$, the search point in data set 1 is treated as no matched tree location point can be found in data set 2 . If the largest VS value is larger than user-defined threshold $T_{\mathrm{VS}}$ and
there is only one matched point in data set 2 , the search point in data set 1 and the matched tree location point in data set 2 are treated as a pair of trees. If the largest VS value is larger than user-defined threshold $T_{\mathrm{VS}}$ and there are more than one matched points in data set 2 , the thresholds $T_{I}$ and $T_{S}$ are iteratively increased to eliminate the one-to-many phenomenon using the following equations:

$$
\begin{align*}
T_{I}^{\prime} & =(1-f) T_{I} \times 1.1^{N}  \tag{7}\\
T_{s}^{\prime} & =(1-f) T_{s} \times 1.1^{N}  \tag{8}\\
f & =\frac{p_{l_{\max }-50}}{50} \times 10 \% \tag{9}
\end{align*}
$$

where $N$ is the number of iterations that should be smaller than the user-defined maximum number of iterations $T_{N}$, and $p l_{\max }$ is the percentile of the maximum side in a triangle among all sides of triangles of the whole study area. Since $p_{l_{\text {max }}}$ is between 0 and 100, the scale factor $f$ should be in the range of $[-0.1,0.1]$. The scale factor $f$ here is used to give looser thresholds in areas with sparse trees and give stricter thresholds in areas with dense trees because the individual tree segmentation error is higher in areas with dense trees.

The whole TIN matching process can be described as the following pseudo codes.
For $i=1$ to $k$
Generate $T I N_{i}^{1}$ from the neighbors of the search tree point $i$
For $j=1$ to $l$
Generate $T I N_{j}^{2}$ from the neighbors of the search tree point $j$
For $p=1$ to $m$
For $q=1$ to $n$
Calculate $S$ and $I$ between $\operatorname{Tr} i_{p}^{i, 1}$ and $\operatorname{Tr} i_{q}^{j, 2}$
If $S \geq T_{S}$ and $I \geq T_{I}$
$\operatorname{OSM}(p, q)=(S+I) / 2$
Else

$$
\operatorname{OSM}(p, q)=0
$$

End for
End for
Do when all unmarked elements in $O S M$ are not 0 Find and mark the largest unmarked $O S M$ (row, col)
Set unmarked $\operatorname{OSM}($ row,:) and $\operatorname{OSM}(:$, col $)$ as 0 End do
$V S(i, j)=$ the number of marked elements in $O S M$ End for
If $\max (V S(\mathrm{i},:))<T_{V S}$
There is no matched tree location point for $i$
Else if $\max (V S(i,:)) \geq T_{V S}$ and count( $\left.\max (V S(i,:))\right)$ ==1

The matched tree point in $T I N^{2}$ for tree location point $i$ is found
Else if $\max (V S(i,:)) \geq T_{V S}$ and count(max $\left.(V S(i,:))\right)$ > 1

Updating the thresholds $T_{I}$ and $T_{S}$ and iterate the
TIN matching process until count $(\max (V S(i,:)))$
$==1$ or the number of iterations $>T_{N}$
End For

From the abovementioned process, a set of tree location pairs can be collected from two LiDAR data sets from different platforms. The number of matched tree pairs is usually much higher than the required number of tree pairs for performing coarse registration. To ensure the coarse registration quality, the matched tree pairs are filtered and optimized by the RANSAC algorithm [46], [47] using the OpenCV implementations with default parameters.

## D. Coarse Registration

The matched tree pairs are acquired through the TIN matching of plane coordinates (i.e., $X$ and $Y$ ), while the 3-D coordinates (i.e., $X, Y$, and $Z$ ) of matched tree pairs from multiplatform LiDAR data are used to calculate the rotation matrix and translation vector to transform the target point cloud to the source point cloud. Considering the fact that the distance measurements from different LiDAR platforms are all highly accurate [48], it is reasonable to set the scale factor of the rotation matrix as 1 . Therefore, the coarse registration process can be expressed as

$$
\left[\begin{array}{l}
X  \tag{10}\\
Y \\
Z
\end{array}\right]=R\left[\begin{array}{l}
X^{\prime} \\
Y^{\prime} \\
Z^{\prime}
\end{array}\right]+T
$$

where $X, Y$, and $Z$ are the coordinates of the source point cloud, $X^{\prime}, Y^{\prime}$, and $Z^{\prime}$ are the coordinates of the target point cloud, and $R$ and $T$ are the rotation matrix and translation vector, respectively.

## E. Fine Registration

In the fine registration step, the ICP algorithm, a pointbased matching method based on minimizing the cumulative distance between two point clouds [49], is used to further improve the multiplatform LiDAR data registration accuracy. To reduce the chance of mismatching errors in ICP results, the ICP algorithm should be performed on the overlapped areas of different LiDAR data sets with distinct characteristics. For example, if two multiplatform LiDAR data sets share a large portion of ground points and the ground is a rugged terrain, their ground points can be selected to run the ICP algorithm; if two multiplatform LiDAR data sets share a large portion of tree trunks, their point clouds within the height range of tree trunks can be selected to run the ICP algorithm.

## III. Experimental Analysis

## A. Study Area and Data Collection

The study area is located in the Mulan Paddock, Hebei, China ( $42.12^{\circ} \mathrm{N}, 117.35^{\circ} \mathrm{E}$ ). It is a planted forest and the dominant tree species are Pinus sylvestris var. mongolica Litv. and Pinus tabuliformis Carrière. Three study sites were selected within the study area. Site 1 has an area of $7890 \mathrm{~m}^{2}$ with an $8-\mathrm{m}$ elevation variation, site 2 has an area of $5814 \mathrm{~m}^{2}$ with a $46-\mathrm{m}$ elevation variation, and site 3 has an area of $1885 \mathrm{~m}^{2}$ with a $3-\mathrm{m}$ elevation variation. The average canopy cover is $71 \%, 46 \%$, and $65 \%$ in sites 1,2 , and 3 , the average tree height is 18,17 , and 20 m , and the average tree density is 283,275 , and 1056 trees/ha. Three widely

TABLE I
Specifications of the Three LiDAR Platforms Used in This Article

|  | UAV | Backpack | Terrestrial |
| :---: | :---: | :---: | :---: |
| Sensor | HESAI | Velodyne Puck | VZ-400i |
|  | Pandar40 | VLP-16 | (Riegl) |
|  | (GreenValley | (GreenValley |  |
|  | LiAir 200) | LiBackpack 50) |  |
| Scan range | 0.3-200 m | 100 m | 400 m |
| Relative accuracy | $\pm 5 \mathrm{~cm}$ | $\pm 5 \mathrm{~cm}$ | $\pm 0.5 \mathrm{~cm}$ |
| Pulse repetition rate | 720 KHz | 300 KHz | 122 KHz |
| Angular | $0.33^{\circ}$ | $2^{\circ}$ | better |
| resolution <br> (Vertical) |  |  | $0.005^{\circ}$ |
| Angular resolution (Horizontal) | $0.2^{\circ}$ | $0.1^{\circ}-0.4^{\circ}$ | better $0.005^{\circ}$ |

used LiDAR platforms, including a backpack LiDAR platform, a UAV-borne LiDAR platform, and a TLS platform, were used to collect multiplatform LiDAR data within the three study sites in August 2018. Their hardware models and specifications are listed in Table I. The UAV LiDAR system (Green Valley International LiAir 200) integrates a HESAI Pandar40 laser scanner and a high-precision inertial navigation system, whose relative positioning accuracy is specified as $\pm 5 \mathrm{~cm}$. The backpack LiDAR system (Green Valley International LiBackpack 50) is equipped with a Velodyne Puck VLP-16 laser scanner, and its relative positioning accuracy is specified as $\pm 5 \mathrm{~cm}$. The Riegl VZ-400i is a high-precision TLS scanner, and its measurement accuracy is $\pm 0.5 \mathrm{~cm}$. Sites 1 and 2 were covered by both UAV and backpack LiDAR data. The UAV LiDAR data in sites 1 and 2 were collected from a single flight line and two flight lines, respectively. The flight altitude was about 150 m above ground at both study sites, and the overlap ratio between the flight lines in site 2 was about $50 \%$. The point density of the collected UAV LiDAR data is about $158 \mathrm{pts} / \mathrm{m}^{2}$ in site 1 and $238 \mathrm{pts} / \mathrm{m}^{2}$ in site 2 [see Fig. 4(b) and (c)]. The backpack LiDAR data at study sites 1 and 2 were all collected following a " S "-shape trajectory with a $\sim 10-\mathrm{m}$ horizontal spacing. The collected backpack LiDAR data had an average point density of $2,042 \mathrm{pts} / \mathrm{m}^{2}$ in site 1 and $2092 \mathrm{pts} / \mathrm{m}^{2}$ in site 2 [see Fig. 4(b) and (c)]. It should be noted that the extent of UAV LiDAR data was slightly larger than that of backpack LiDAR data to ensure that they fully covered the backpack data. Site 3 was only covered by the TLS data. The Riegl VZ-400i scanner was used to cover the study area using four separate scans. The distance between scan position 1 and scan positions $2-4$ was about 13,15 , and 20 m , while the overlap ratio was about $51 \%$, $40 \%$, and $33 \%$, respectively. Six high-reflectance targets were installed in site 3, and they were used to manually register the TLS scans using the Riegl RiSCAN Pro software. In order to reduce the errors of individual tree segmentation caused by incomplete scan of trees, we used a rectangle with a size of $25 \mathrm{~m} \times 25 \mathrm{~m}$ to clip the original TLS data of each scan. The average point density of each TLS scan was about 22 $167 \mathrm{pts} / \mathrm{m}^{2}$ [see Fig. 4(b) and (c)].


Fig. 4. (a) Location of the study area. (b) Collected UAV (Left) and backpack (Right) LiDAR data in study site 1, and their corresponding individual tree segmentation results (black dots). (c) Collected UAV (Left) and backpack (Right) LiDAR data in study site 2, and their corresponding individual tree segmentation results (black dots). (d) Collected four TLS scans in study site 3, and their corresponding individual tree segmentation results (black dots).

In study sites 1 and 2, we put a $60 \mathrm{~cm} \times 90 \mathrm{~cm}$ referencing standard white board in an open area so that it could be seen by both the backpack LiDAR and UAV LiDAR [see Fig. 5(a)]. The referencing white board was used to evaluate the relative positioning accuracy of the collected backpack and UAV LiDAR data [see Fig. 5(b) and (c)]. By fitting a plane from the points falling on the referencing white board, the distance between each point and the fit plane was calculated. The relative positioning accuracy was calculated as the root-mean-square error (RMSE) of these points to the fit plane. As can be seen in Fig. 6, the backpack and UAV LiDAR


Fig. 5. Example of (a) setup of the referencing standard white board, and its corresponding point clouds obtained from (b) backpack LiDAR and (c) UAV LiDAR systems.


Fig. 6. Relative positioning accuracy of the collected backpack LiDAR data and UAV LiDAR data at the two study sites.
data at both sites had a relative positioning error lower than 10 cm , which agreed with the nominal specifications from the manufacturer. The referencing white board was also used to evaluate the multiplatform LiDAR data registration accuracy in the following experiment.

## B. Experiment Design

1) Data Processing: It is inevitable to have noise in the collected LiDAR data due to factors such as tree movement with winds and flying birds. In this article, we used the outlier removal tool integrated in the GreenValley International LiDAR360 software (https://greenvalleyintl.com/software) to remove noise points in all collected LiDAR data. All LiDAR data were filtered to classify ground points using the improved progressive TIN densification filtering algorithm proposed by Zhao et al. [50], which has shown to be robust under different forest and terrain conditions. Finally, the obtained ground points were used to normalize the original LiDAR point clouds to produce the input data for individual tree segmentation by using the LiDAR360 software.
2) Individual Tree Segmentation: Different segmentation strategies were used to segment the UAV LiDAR data and the backpack and terrestrial LiDAR data. For the UAV LiDAR data, the top-down PCS algorithm proposed by Li et al. [40] was used to identify individual tree locations; for the backpack and terrestrial LiDAR data, the bottom-up PCS algorithm proposed by Tao et al. [42] was used. These algorithms use a similar principle in the segmentation process, which first identifies seed points of individual trees and then labels other points by finding the shortest path to seed points using the comparative shortest path algorithm. The difference is that the top-down PCS algorithm finds seed points by recognizing

TABLE II
List of Parameters in the Proposed Multiplatform LidAR Data Registration Framework and Their Corresponding Values Used in This Article

| Parameter | Description | Value |
| :--- | :--- | :--- |
| $N N$ | The number of neighboring tree points used to | 9 |
|  | build TIN |  |
| $T_{S}$ | The initial threshold for area similarity | 0.8 |
| $T_{I}$ | The initial threshold for angle similarity | 0.7 |
| $T_{V S}$ | The threshold for voting score | 5 |
| $T_{N}$ | The max number of iterations | 3 |

treetops, but the bottom-up PCS algorithm finds seed points by recognizing tree bases. The PCS methods were selected in this article because studies have shown that they outperformed CHM methods in coniferous forests and were less influenced by undercanopy low-vegetation points [43].

To evaluate the individual tree segmentation results, we visually counted the number of trees and marked their corresponding locations from the backpack or terrestrial LiDAR data. Three accuracy statistics, i.e., recall $(r)$, precision $(p)$, and F -score $(F)$, were calculated by comparing with individual tree locations derived visually

$$
\begin{align*}
r & =\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}  \tag{11}\\
p & =\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}  \tag{12}\\
F & =2 \times \frac{r \times p}{r+p} \tag{13}
\end{align*}
$$

where true positive (TP) denotes the number of trees correctly detected, false negative (FN) denotes the number of trees that were not detected, and false positive (FP) denotes the number of trees falsely detected. $r$ indicates the tree segmentation completeness, $p$ indicates the correctness of the detected trees, and $F$ is the overall accuracy taking both commission and omission errors into consideration. Note that the individual tree segmentation accuracies of the UAV and TLS LiDAR data were calculated from the corresponding postregistered data sets so that they could be compared with individual tree locations derived visually.
3) Multiplatform LiDAR Data Registration: Two experiments were conducted to evaluate the performance of the proposed multiplatform LiDAR data registration framework, i.e., the registration between backpack LiDAR data and UAV LiDAR data and the registration among multiscan TLS data. Overall, there are five parameters in the proposed registration framework (see Table II). Among these parameters, $T_{I}$ and $T s$ are two iteratively increasing thresholds, which can be set to relatively small values as initial values, and $T_{N}$ can be set to a relatively large value based on experience. The remaining two parameters number of neighbors (NN) and $T_{\mathrm{VS}}$ can be estimated using a trial and error method. A detailed discussion of the parameter setting will be described in Section IV. The two experiments used the same set of parameter values without any changes. The only difference in the registration procedures of the two experiments was that the registration of backpack and UAV LiDAR data used ground points to perform the fine

TABLE III
Accuracy Assessment for the Individual Tree Segmentation Results From the Backpack and UAV LiDAR Data at the Two Study Sites

|  | Site 1 |  | Site 2 |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Backpack | UAV | Backpack | UAV |
| $T P$ | 213 | 289 | 156 | 187 |
| $F N$ | 10 | 49 | 4 | 9 |
| $F P$ | 11 | 22 | 2 | 22 |
| $r$ | 0.955 | 0.855 | 0.975 | 0.954 |
| $p$ | 0.951 | 0.873 | 0.987 | 0.895 |
| $F$ | 0.953 | 0.864 | 0.981 | 0.924 |

registration, whereas the registration of multiscan terrestrial LiDAR data used all points. Moreover, for the registration of TLS data, we used the data from scan position 1 as the target data and the TLS data from scan positions $2-4$ as the source data to be aligned with the reference coordinate system.
4) Accuracy Assessment: The registration accuracy of backpack and UAV LiDAR data was evaluated using the referencing white board. The backpack LiDAR points falling on the referencing white board were first used to fit a plane $\mathrm{Z}=f(X, Y)$. Then, the horizontal and vertical distances of each transformed UAV LiDAR point falling on the referencing white board to the fit plane were calculated, and the horizontal error $E_{H}$ and vertical error $E_{V}$ were calculated as

$$
\begin{align*}
& E_{H}=\sqrt{\frac{\sum_{i=1}^{n}\left(X_{i}^{\prime} Y_{i}^{\prime} \rightarrow Z=f(X, Y)\right)^{2}}{n}}  \tag{14}\\
& E_{V}=\sqrt{\frac{\sum_{i=1}^{n}\left(Z_{i}^{\prime} \rightarrow Z=f(X, Y)\right)^{2}}{n}} \tag{15}
\end{align*}
$$

where $n$ is the number of UAV points falling on the referencing white board, and $X_{i}^{\prime} Y_{i}^{\prime} \rightarrow Z=f(X, Y)$ and $Z_{i}^{\prime} \rightarrow Z=$ $f(X, Y)$ represent the horizontal and vertical distances from a point to the fit plane.

Since the installed referencing white board was not within the scanning area of TLS scans, the abovementioned accuracy assessment methods could not be used for the evaluation of multiscan TLS data registration. Considering the high positioning accuracy of TLS data and the high overlap rate between TLS scans, the registration accuracy of multiscan TLS data was represented by the residual after running ICP. The obtained ICP residual value was compared with the manual registration residual obtained using the Riegl RiSCAN Pro software.

## C. Backpack LiDAR and UAV LiDAR Registration Results

The individual tree segmentation results from the backpack and UAV LiDAR data in the two study sites were shown in Fig. 4(b)-(e). Overall, the backpack LiDAR data allowed a very high individual tree segmentation accuracy. The $F$-values of the two study sites were all higher than 0.95 (see Table III). The individual tree segmentation accuracy from UAV LiDAR data was relatively lower compared to that from backpack LiDAR data (see Table III). The individual tree segmentation accuracy in site 2 was slightly higher than that of site 1 , which


Fig. 7. (a) Schematic of tree location displacement obtained from backpack and UAV LiDAR data sets. (b) Average tree location displacements in sites 1 and 2. Red dots in (a) represent tree locations derived from backpack LiDAR data, and green dots represent tree locations derived from UAV LiDAR data. $d$ and $d^{\prime}$ ' represent the distance between two neighboring trees. The displacement in (b) was calculated as the horizontal distance difference of a pair of trees before the registration.


Fig. 8. Profiles of the registered backpack LiDAR data (red dots) and UAV LiDAR data (green points) in (a) site 1 and (b) site 2.
might be caused by the fact that the canopy coverage in site 2 was much lower than that in site 1 . Here, the displacement of tree locations was quantified by the difference in the distances between a pair of neighboring trees from different LiDAR data sets (see Fig. 7). On average, there was an around $30-$ and $40-\mathrm{cm}$ displacement in sites 1 and 2, respectively [see Fig. 7(b)].

The TIN matching process identified seven pairs of trees from site 1 and 11 pairs of trees from site 2 , which were used to perform the coarse registration. The standard deviations of residuals between tree locations after coarse registration were 0.84 and 0.93 m for sites 1 and 2, respectively. The two LiDAR data sets were closely aligned with each other following fine registration that the fused backpack UAV LiDAR point clouds in tandem provided more complete forest structural information than either platform alone (see Fig. 8), and the horizontal error and vertical error after the fine registration step were 0.300 and 0.146 m , respectively, for site 1 , and were 0.211 and 0.187 m , respectively, for site 2 .

## D. Multiscan TLS Data Registration Results

The individual tree segmentation accuracy of the nonregistered TLS data was more than $95 \%$ for all four scans (see Table IV). After TIN matching, there were 11, 10, and 8 trees reserved to calculate the rotation matrix and translation vector for the coarse registration between the TLS data from scan position 1 and those from scan positions 2-4, respectively. The standard deviation of residuals between tree locations

TABLE IV
Accuracy Assessment for the Individual Tree Segmentation Results From the Multiscan TlS Data

|  | Scan 1 | Scan 2 | Scan 3 | Scan 4 |
| :--- | :--- | :--- | :--- | :--- |
| $T P$ | 73 | 66 | 74 | 63 |
| $F N$ | 1 | 2 | 3 | 1 |
| $F P$ | 1 | 0 | 1 | 2 |
| $r$ | 0.986 | 0.971 | 0.961 | 0.984 |
| $p$ | 0.986 | 1.000 | 0.987 | 0.969 |
| $F$ | 0.986 | 0.985 | 0.974 | 0.977 |



Fig. 9. (a) Final registration results of the four TLS scans on site 3 using the proposed framework. (b) Profile example of the registered TLS point cloud and enlarged examples of two tree segments in the profile. The black rectangle in (a) represents the extent of the profile and the " + " marks represent the scanning positions.
after coarse registration between the TLS data from scan position 1 and those from scan positions $2-4$ was 0.161 , 0.154 , and 0.157 m . The four TLS scans matched with each other very well after the fine registration (see Fig. 9), and the standard deviation of residuals was $0.038,0.050$, and 0.053 m , compared with a value of $0.013,0.009$, and 0.011 m obtained by manual registration using Riegl RiSCAN Pro software.

## IV. Discussion

Multiplatform LiDAR data registration is increasingly in demand in LiDAR forest applications. Through the fusion of multiplatform LiDAR data, it can overcome the limitations of single-platform/single-scan LiDAR data and allow for the more complete derivation of forest structure parameters [51]. However, due to the complexity and irregularity of forests and the often absent or inaccurate GPS positioning information, traditional point cloud registration methods can hardly be used in forest environments [52]. Recently, there have been successful attempts to develop marker-free registration methods to increase the efficiency of multiplatform LiDAR data registration. Generally, these methods can be divided into two categories, i.e., looking for geometric features for registration inside the multiplatform LiDAR data (e.g., stem centers and stem curves) and looking for a globally optimized transformation solution based on LiDAR-derived tree attributes (e.g., tree height and DBH) [33]-[36]. The methods using geometric features inside the point clouds have a similar idea as the proposed framework, which is using the unique tree
characteristics as the referencing features [33], [34]. However, compared with the proposed framework, these methods have disadvantages of less adaptability to different platforms. Currently, methods based on tree stem geometric features cannot be used in registrations involving top-view LiDAR data (e.g., UAV LiDAR data), because top-view LiDAR data cannot capture complete tree stem information. As to the methods using globally optimized transformation solution, they might not be achievable when the required tree attributes were inaccurate or missing. For example, the method proposed by Kelbe et al. [35] required accurate tree stem maps and DBH estimations, which can be hard to obtain from UAV LiDAR data [53], and the method proposed by Polewski et al. [36] required a precondition that the $Z$-axis of multiplatform LiDAR data should be well aligned or could be aligned by tree stem orientations, which can be hard to satisfy in complex forest environments due to the inaccurate GPS information under the forest canopy and the lack of trunk information in down-looking LiDAR platforms. The proposed registration framework only required tree locations to fuse multiplatform LiDAR data and does not require any exterior information to assist the registration process, which can largely improve the multiplatform LiDAR data registration applicability.

Overall, the proposed framework worked well in both experiments in this article. The fusion of backpack and UAV LiDAR data sets achieved vertical accuracy better than 20 cm and horizontal accuracy better than 30 cm on sites 1 and 2 . Considering the positioning uncertainty within the backpack and UAV LiDAR data and the error propagation effect during the registration, the registration results should satisfy many forest-related applications. The horizontal displacement after registration for site 1 was much larger than that for site 2 (see Fig. 8). The possible reason might be that the terrain in site 1 was much flatter than site 2 . Since the differences in $Z$-values in flat terrain were not obvious, the process of the ICP algorithm might lack features in the Z-direction. In this case, the ICP algorithm may converge to a local optimum [54], [55], which therefore leads to larger horizontal errors. The accuracy of the registration of multiscan TLS data was much higher than that for the registration of backpack and UAV LiDAR data. This indicates that the performance of the proposed framework might be improved by increasing the precision of LiDAR data. Although the registration accuracy of multiscan TLS data registration is still lower than that of using a manual registration method based on referencing targets, it can be used as a preliminary step before performing manual registration to increase the efficiency. Future studies can consider using the referencing targets as exterior information to further improve the registration accuracy.

Individual tree segmentation is the prerequisite for the proposed registration framework, and the accuracy of individual tree segmentation might have a considerable influence on the registration accuracy. In this article, the side-view backpack LiDAR data can obtain rich tree trunk information, and the corresponding individual tree segmentation accuracy is much higher than UAV LiDAR data (see Table III). Therefore, this article matched UAV LiDAR data to backpack LiDAR data to reduce the influence of incorrectly segmented trees. To further

| 75 | 13 | 11 | 9 | 0 | 0 | 0 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 80 | 18 | 13 | 11 | 7 | 0 | 0 |
| 85 | 25 | 20 | 17 | 9 | 5 | 1 |
| 90 | 37 | 22 | 20 | 7 | 7 | 3 |
| 95 | 41 | 26 | 21 | 14 | 10 | 10 |
| 100 | 63 | 35 | 25 | 11 | 7 | 6 |
| $r$ | $p$ | 100 | 95 | 90 | 85 | 80 |

Fig. 10. Influence of individual tree segmentation accuracy on the TIN matching results. $r$ and $p$ represent the recall and precision, respectively, and each element in the matrix represents the number of matched tree pairs. Elements colored in red indicate that there are enough matched tree pairs for registration, and elements colored in green indicate that the number of matched tree pairs is insufficient for registration.
evaluate the influence of individual tree segmentation accuracy on the registration accuracy, we simulated a scenario where the individual tree segmentation accuracy was $100 \%$ and randomly removed/added errors from/to the UAV LiDAR segmentation results in site 1 to manipulate the values of $r$ and $p$ from UAV individual tree segmentation results, which were changed from $100 \%$ to $75 \%$ with a step of $5 \%$. As can be seen in Fig. 10, with the decrease of $r$ and $p$, the number of matched tree pairs also decreased. However, when $r$ and $p$ were both higher than $80 \%$, there were enough matched tree pairs to perform the following coarse and fine registration steps. Currently, most individual tree segmentation practices from LiDAR can reach an overall accuracy higher than $85 \%$ [56], [57]. Therefore, we believe that the proposed framework can be used to register multiplatform LiDAR data effectively in most forest environments.

There are five user-defined parameters in the algorithm, as listed in Table II. $T_{S}$ and $T_{I}$ are two iteratively updated parameters, which can be assigned with relatively small values (around 0.75 ) to ensure that the TIN matching process can find enough tree pairs. $T_{\mathrm{VS}}$ is a VS threshold, which can be determined by a simple trial-and-error process. The number of matched tree pairs should be monitored in the trial-and-error process. The larger the $T_{\mathrm{VS}}$, the fewer the number of matched tree pairs. Since solving the rotation matrix and translation vector only requires three paired targets [58], [59], the registration process can be conducted once the trial-and-error process finds three matched tree pairs. However, the robustness of the transformation solution can be improved by introducing more referencing targets [58]-[60]. Therefore, we encourage users to continue the trial-and-error process with as many matched tree pairs (greater than eight pairs) as possible. $T_{N}$ determines the number of iterations, which can be set to a relatively large number to eliminate the "one-to-many" phenomenon in the TIN matching process. In summary, the abovementioned four parameters can either be determined by a simple trial-and-error process or do not have a significant influence on the registration framework. The only parameter that cannot be easily obtained and might have a significant influence on the registration accuracy is NN. To assess the sensitivity


Fig. 11. Influence of the NN on the TIN matching results on site 1 .
of the proposed framework to NN , we iteratively increased NN and ran the registration processes for site 1 repeatedly. To eliminate the influence of individual tree segmentation error on the results, the registration processes were running under a simulated scenario where the individual tree segmentation accuracy was $100 \%$. All other parameters were set the same as in Table II. Since $T_{\mathrm{VS}}$ was set to five and at least seven points were needed to build a TIN with five triangles, the number of matched tree pairs would be zero if $\mathrm{NN} \leq 7$. Therefore, NN was increased from 8 to 15 with a step size of one in this analysis. As can be seen in Fig. 11, with the increase of NN, the number of matched tree pairs first increased and then decreased, and the largest value appeared when NN was 11. The difference in the number of matched tree pairs was less than 10 when NN was set between 10 and 12 . Considering the redundant information provided by a large number of matched tree pairs for registration, it should be a safe choice to set NN as around twice the value of $T_{\mathrm{VS}}$.

Although the proposed framework shows great potential in solving the bottleneck of multiplatform LiDAR data registration in forest environments, it still has limitations that need to be addressed in future studies. First, the proposed framework might not work well in regularly planted forests, because the regular arrangement of stems will likely result in very similar TINs built from different tree locations. Using exterior information to assist the proposed framework (such as referencing targets) might be a solution to this issue. Moreover, this article only tested the proposed framework in very limited forest environments. Further studies are still needed to investigate how the framework performs in other more complex forest environments, such as deciduous forests. In dense deciduous forests, the tightly interlocked canopies might cause low accuracy of individual tree segmentation from UAV LiDAR data. Using areas around forest gaps with sparse tree distribution instead of the whole study area might be beneficial to increase the registration accuracy.

## V. Conclusion

This article proposes an automatic point cloud registration framework for multiplatform LiDAR data fusion in forest environments. Based on the assumption that each forest stand has a unique spatial distribution of trees, the proposed framework identifies tree pairs from multiplatform LiDAR data by a TIN matching strategy. The identified tree pairs are then used to coarsely match the target point cloud to the source point cloud,
and the final registration result could be obtained by running an ICP-based fine registration process. The proposed framework was tested to register backpack LiDAR data and UAV LiDAR data and register multiscan TLS data. Overall, the proposed framework achieved satisfying accuracies in both experiments. The vertical error of the registration between the backpack and UAV LiDAR data was less than 20 cm for both study sites, and the horizontal error was less than 30 cm . The registration error was much lower for the fusion of multiscan TLS data. The average registration error was about 4.7 cm . Individual tree segmentation errors can reduce the number of matched tree points. However, as long as the number of matched tree points was enough for solving the rotation matrix and translation vector, the increase of tree segmentation errors $(<20 \%)$ did not have a significant influence on the registration accuracy. Moreover, the proposed framework was not overly sensitive to the settings of user-defined parameters. All parameters can be easily calculated or obtained by a simple trial-and-error process.

## References

[1] H. Latifi, F. E. Fassnacht, J. Müller, A. Tharani, S. Dech, and M. Heurich, "Forest inventories by LiDAR data: A comparison of single tree segmentation and metric-based methods for inventories of a heterogeneous temperate forest," Int. J. Appl. Earth Observ. Geoinf., vol. 42, pp. 162-174, Oct. 2015.
[2] M. Bouvier, S. Durrieu, R. A. Fournier, and J.-P. Renaud, "Generalizing predictive models of forest inventory attributes using an area-based approach with airborne LiDAR data," Remote Sens. Environ., vol. 156, pp. 322-334, Jan. 2015.
[3] S. Saarela et al., "Model-assisted estimation of growing stock volume using different combinations of LiDAR and Landsat data as auxiliary information," Remote Sens. Environ., vol. 158, pp. 431-440, Mar. 2015.
[4] A. E. L. Stovall, A. G. Vorster, R. S. Anderson, P. H. Evangelista, and H. H. Shugart, "Non-destructive aboveground biomass estimation of coniferous trees using terrestrial LiDAR," Remote Sens. Environ., vol. 200, pp. 31-42, Oct. 2017.
[5] F. Morsdorf, E. Meier, B. Kötz, K. I. Itten, M. Dobbertin, and B. Allgöwer, "LIDAR-based geometric reconstruction of boreal type forest stands at single tree level for forest and wildland fire management," Remote Sens. Environ., vol. 92, no. 3, pp. 353-362, 2004.
[6] M. A. Wulder, C. W. Bater, N. C. Coops, T. Hilker, and J. C. White, "The role of LiDAR in sustainable forest management," Forestry Chronicle, vol. 84, no. 6, pp. 807-826, 2008.
[7] Q. Ma, T. Hu, Y. Su, Q. Guo, J. J. Battles, and M. Kelly, "Individual tree level forest fire assessment using bi-temporal LiDAR data," in Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS), Jul. 2018, pp. 4308-4311.
[8] X. Liang, J. Hyyppä, A. Kukko, H. Kaartinen, A. Jaakkola, and X. Yu, "The use of a mobile laser scanning system for mapping large forest plots," IEEE Geosci. Remote Sens. Lett., vol. 11, no. 9, pp. 1504-1508, Sep. 2014.
[9] X. Liang et al., "Terrestrial laser scanning in forest inventories," ISPRS J. Photogramm. Remote Sens., vol. 115, pp. 63-77, May 2016.
[10] L. Wallace, A. Lucieer, Z. Malenovský, D. Turner, and P. Vopěnka, "Assessment of forest structure using two UAV techniques: A comparison of airborne laser scanning and structure from motion (SFM) point clouds," Forests, vol. 7, no. 3, p. 62, 2016.
[11] Y. Su, H. Guan, T. Hu, and Q. Guo, "The integration of uavand backpack LiDAR systems for forest inventory," in Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS), Jul. 2018, pp. 8757-8760.
[12] C. Paris, D. Valduga, and L. Bruzzone, "A hierarchical approach to three-dimensional segmentation of LiDAR data at single-tree level in a multilayered forest," IEEE Trans. Geosci. Remote Sens., vol. 54, no. 7, pp. 4190-4203, Jul. 2016.
[13] T. Hilker et al., "Comparison of terrestrial and airborne LiDAR in describing stand structure of a thinned lodgepole pine forest," J. Forestry, vol. 110, no. 2, pp. 97-104, 2012.
[14] P. W. Theiler, J. D. Wegner, and K. Schindler, "Globally consistent registration of terrestrial laser scans via graph optimization," ISPRS J. Photogramm. Remote Sens., vol. 109, pp. 126-138, Nov. 2015.
[15] L. Yan, J. Tan, H. Liu, H. Xie, and C. Chen, "Automatic registration of TLS-TLS and TLS-MLS point clouds using a genetic algorithm," Sensors, vol. 17, no. 9, p. 1979, 2017.
[16] L. Cheng et al., "Registration of laser scanning point clouds: A review," Sensors, vol. 18, no. 5, p. 1641, 2018.
[17] Z. Dong, B. Yang, F. Liang, R. Huang, and S. Scherer, "Hierarchical registration of unordered TLS point clouds based on binary shape context descriptor," ISPRS J. Photogramm. Remote Sens., vol. 144, pp. 61-79, Oct. 2018.
[18] B. Morago, G. Bui, T. Le, N. H. Maerz, and Y. Duan, "Photograph LiDAR registration methodology for rock discontinuity measurement," IEEE Geosci. Remote Sens. Lett., vol. 15, no. 6, pp. 947-951, Jun. 2018.
[19] I. Klein and S. Filin, "LiDAR and INS fusion in periods of GPS outages for mobile laser scanning mapping systems," Int. Arch. Photogramm. Remote Sens. Inf. Sci., vol. 38, no. 5, p. W12, 2011.
[20] L. Zhu and R. Shi, "Research on target accuracy for ground-based LiDAR," Proc. SPIE, vol. 7323, May 2009, Art. no. 73230K.
[21] H. Cho, S. Hong, S. Kim, H. Park, I. Park, and H.-G. Sohn, "Application of a terrestrial LiDAR system for elevation mapping in Terra Nova Bay, Antarctica," Sensors, vol. 15, no. 9, pp. 23514-23535, 2015.
[22] A. Wendt, "A concept for feature based data registration by simultaneous consideration of laser scanner data and photogrammetric images," ISPRS J. Photogram. Remote Sens., vol. 62, no. 2, pp. 122-134, 2007.
[23] B. O. Abayowa, A. Yilmaz, and R. C. Hardie, "Automatic registration of optical aerial imagery to a LiDAR point cloud for generation of city models," ISPRS J. Photogramm. Remote Sens., vol. 106, pp. 68-81, Aug. 2015.
[24] L. Cheng et al., "A symmetry-based method for LiDAR point registration," IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 11, no. 1, pp. 285-299, Jan. 2018.
[25] S. Rusinkiewicz and M. Levoy, "Efficient variants of the ICP algorithm," in Proc. 3DIM, May/Jun. 2001, pp. 145-152.
[26] A. Gressin, C. Mallet, J. Demantké, and N. David, "Towards 3D LiDAR point cloud registration improvement using optimal neighborhood knowledge," J. Photogram. Remote Sens., vol. 79, pp. 240-251, May 2013.
[27] A. R. G. Large, G. L. Heritage, and M. E. Charlton, "Laser scanning: The future," in Laser Scanning for the Environmental Sciences. Hoboken, NJ, USA: Wiley, 2009.
[28] K. E. Anderson et al., "Estimating vegetation biomass and cover across large plots in shrub and grass dominated drylands using terrestrial LiDAR and machine learning," Ecol. Indicators, vol. 84, pp. 793-802, Jan. 2018.
[29] C. Brenner, C. Dold, and N. Ripperda, "Coarse orientation of terrestrial laser scans in urban environments," ISPRS J. Photogramm. Remote Sens., vol. 63, no. 1, pp. 4-18, 2008.
[30] J.-J. Jaw and T.-Y. Chuang, "Registration of ground-based LiDAR point clouds by means of 3D line features," J. Chin. Inst. Eng., vol. 31, no. 6, pp. 1031-1045, 2008.
[31] A. Gruen and D. Akca, "Least squares 3D surface and curve matching," ISPRS J. Photogramm. Remote Sens., vol. 59, no. 3, pp. 151-174, 2005.
[32] X. Ge and T. Wunderlich, "Surface-based matching of 3D point clouds with variable coordinates in source and target system," ISPRS J. Photogramm. Remote Sens., vol. 111, pp. 1-12, Jan. 2016.
[33] J. G. Henning and P. J. Radtke, "Multiview range-image registration for forested scenes using explicitly-matched tie points estimated from natural surfaces," ISPRS J. Photogramm. Remote Sens., vol. 63, no. 1, pp. 68-83, Jan. 2008.
[34] J. Liu et al., "Automated matching of multiple terrestrial laser scans for stem mapping without the use of artificial references," Int. J. Appl. Earth Observ. Geoinf., vol. 56, pp. 13-23, Apr. 2017.
[35] D. Kelbe, J. van Aardt, P. Romanczyk, M. van Leeuwen, and K. Cawse-Nicholson, "Marker-free registration of forest terrestrial laser scanner data pairs with embedded confidence metrics," IEEE Trans. Geosci. Remote Sens., vol. 54, no. 7, pp. 4314-4330, Jul. 2016.
[36] P. Polewski, W. Yao, L. Cao, and S. Gao, "Marker-free coregistration of UAV and backpack LiDAR point clouds in forested areas," ISPRS J. Photogramm. Remote Sens., vol. 147, pp. 307-318, Jan. 2019.
[37] J. Mustonen, P. Packalén, and A. Kangas, "Automatic segmentation of forest stands using a canopy height model and aerial photography," Scand. J. Forest Res., vol. 23, no. 6, pp. 534-545, 2008.
[38] L. Jing, B. Hu, J. Li, and T. Noland, "Automated delineation of individual tree crowns from LiDAR data by multi-scale analysis and segmentation," Photogramm. Eng. Remote Sens., vol. 78, no. 12, pp. 1275-1284, 2012.
[39] A. Khosravipour, A. K. Skidmore, M. Isenburg, T. Wang, and Y. A. Hussin, "Generating pit-free canopy height models from airborne lidar," Photogramm. Eng. Remote Sens., vol. 80, no. 9, pp. 863-872, Sep. 2014.
[40] W. Li, Q. Guo, M. K. Jakubowski, and M. Kelly, "A new method for segmenting individual trees from the lidar point cloud," Photogramm. Eng. Remote Sens., vol. 78, no. 1, pp. 75-84, 2012.
[41] X. Lu, Q. Guo, W. Li, and J. Flanagan, "A bottom-up approach to segment individual deciduous trees using leaf-off lidar point cloud data," ISPRS J. Photogramm. Remote Sens., vol. 94, pp. 1-12, Aug. 2014.
[42] S. Tao et al., "Segmenting tree crowns from terrestrial and mobile LiDAR data by exploring ecological theories," ISPRS J. Photogramm. Remote Sens., vol. 110, pp. 66-76, Dec. 2015.
[43] M. K. Jakubowski, W. Li, Q. Guo, and M. Kelly, "Delineating individual trees from LiDAR data: A comparison of vector- and raster-based segmentation approaches," Remote Sens., vol. 5, no. 9, pp. 4163-4186, 2013.
[44] V. J. D. Tsai, "Delaunay triangulations in TIN creation: An overview and a linear-time algorithm," Int. J. Geograph. Inf. Sci., vol. 7, no. 6, pp. 501-524, 1993.
[45] D. Zhou, G. Li, and Y.-H. Liu, "Effective corner matching based on Delaunay triangulation," in Proc. IEEE Int. Conf. Robot. Autom. (ICRA), vol. 3, Apr./May 2004, pp. 2730-2733.
[46] O. Chum, J. Matas, and J. Kittler, "Locally optimized RANSAC," in Proc. Joint Pattern Recognit. Symp., in Lecture Notes in Computer Science, vol. 2781, 2003, pp. 236-243.
[47] T. Fei, X.-H. Liang, Z.-Y. He, and G.-L. Hua, "A registration method based on nature feature with KLT tracking algorithm for wearable computers," in Proc. Int. Conf. Cyberworlds, Sep. 2008, pp. 416-421.
[48] N. Li, P. Cheng, M. A. Sutton, and S. R. Mcneill, "Three-dimensional point cloud registration by matching surface features with relaxation labeling method," Exp. Mech., vol. 45, no. 1, pp. 71-82, 2005.
[49] G. C. Sharp, S. W. Lee, and D. K. Wehe, "ICP registration using invariant features," IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 1, pp. 90-102, Jan. 2002.
[50] X. Zhao, Q. Guo, Y. Su, and B. Xue, "Improved progressive TIN densification filtering algorithm for airborne LiDAR data in forested areas," ISPRS J. Photogramm. Remote Sens., vol. 117, pp. 79-91, Jul. 2016.
[51] M. Hämmerle et al., "Simulating various terrestrial and UAV LiDAR scanning configurations for understory forest structure modelling," ISPRS Ann. Photogram., Remote Sens. Spatial Inf. Sci., vol. 4, pp. 59-65, Sep. 2017.
[52] W. Zhang, Y. Chen, H. Wang, M. Chen, X. Wang, and G. Yan, "Efficient registration of terrestrial LiDAR scans using a coarse-to-fine strategy for forestry applications," Agricult. Meteorol., vol. 225, pp. 8-23, Sep. 2016.
[53] R. A. Chisholm, J. Cui, S. K. Y. Lum, and B. M. Chen, "UAV LiDAR for below-canopy forest surveys," J. Unmanned Veh. Syst., vol. 1, no. 1, pp. 61-68, 2013.
[54] Y.-J. Lee and J.-B. Song, "Three-dimensional iterative closest pointbased outdoor SLAM using terrain classification," Intell. Service Robot., vol. 4, no. 2, pp. 147-158, 2011.
[55] Y.-J. Lee, Y.-H. Ji, J.-B. Song, and S.-H. Joo, "Performance improvement of ICP-based outdoor SLAM using terrain classification," in Proc. Int. Conf. Adv. Mechatronics, Toward Evol. Fusion IT Mechatronics (ICAM), 2010, pp. 243-246.
[56] G. Prieditis, I. Smits, S. Dagis, and D. Dubrovskis, "Individual tree identification using combined LiDAR data and optical imagery," in Proc. Int. Sci. Conf. Res. Rural Develop., Jelgava, Latvia, May 2012, pp. 16-18.
[57] E. Ayrey et al., "Layer stacking: A novel algorithm for individual forest tree segmentation from LiDAR point clouds," Can. J. Remote Sens., vol. 43, no. 1, pp. 16-27, 2017.
[58] L. Quan, "Self-calibration of an affine camera from multiple views," Int. J. Comput. Vis., vol. 19, no. 1, pp. 93-105, 1996.
[59] C.-P. Lu, G. D. Hager, and E. Mjolsness, "Fast and globally convergent pose estimation from video images," IEEE Trans. Pattern Anal. Mach. Intell., vol. 22, no. 6, pp. 610-622, Jun. 2000.
[60] R. I. Hartley, "In defence of the 8-point algorithm," in Proc. IEEE Int. Conf. Comput. Vis., Jun. 1995, pp. 1064-1070.


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