Automatic stem mapping using single-scan terrestrial laser scanning data and Mean Shift clustering

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Abstract. As an effective tool for evaluation of forest structure parameters, terrestrial laser scanning (TLS) can capture forest data efficiently and automatically. In this paper, a stem mapping method of TLS data is proposed, based on Mean Shift clustering. The ground points first are extracted by cloth simulation filter (CSF) and used to generate ground model. A subsequent classification based on Random Forest (RF) identifies candidate stem points using 21-dimensional geometric features. After obtaining the candidate stem points, we utilize Mean Shift clustering to extract individual stems, instead of the usual Euclidean clustering method, and adopt adaptive density filtering to remove non-stem cluster. Finally, RANSAC cylinder fitting is used from the sliced point cloud, the intersection of the cylinder axis and the ground is taken as the stem location. The results show that Mean Shift clustering is more effective than Euclidean clustering in stem detection. Additionally, the precision and recall of stem mapping based on the proposed method are 88.83% and 93.94% respectively.

1. Introduction
Terrestrial laser scanning (TLS) has the ability to detect stems of below the canopy. It can effectively penetrate the forest interior to obtain high-density and high-precision point cloud data in a fast, nondestructive and automatic way [1, 2], which makes it possible to automatically collect the reference data and quantitative forest inventories [3].

The stem location within forest sample plots can be used as a fundamental parameter for extraction of information regarding the vertical structure [4], registration [5], or calibration [6]. So far, three main method types of stem mapping have been proposed, which are two-dimensional-layer methods, image-based methods and the single-point methods. In the two-dimensional-layer methods, the point cloud is usually sliced horizontally into a series of sections at a certain height, or the 3D points are projected onto a plane for postprocessing. Tanaey et al. [7] used least-square shape-fitting and a circular Hough transform to measure the diameter at breast height (DBH) based on slicing the point cloud. The least square fitting is proved to be the most accurate method, with an RMSE of 0.019 m. Pueschel et al. [8] systematically evaluated the influence of scanning mode and three circle fitting algorithms on the extraction of stem diameter and volume, and proposed the method of extracting stem points based on the vertical slice of point cloud and circle fitting. Though image-based methods use mature image processing technology to stem detection, its applicability is limited. Aschooff et al. [9] used the method
of transforming multiple slices extracted from different heights in X/Y projection into regular raster image, mapped the stem contour into Hough-transformation circle rings, and extracted accurately based on the circle and ellipse fitting. In the single-point methods, the feature extraction and classification are usually used to detect the target of interest. Liang et al. [10] proposed a two-scale property to extract stem points, which used cylinder fitting to calculate the stem radius and direction. Due to the greater influence of point density, the overall detection accuracy was 73%. Wang et al. [11] separated stems between 2 m and 4 m above the ground by point projection density and Z-normal vector value, detected complete stems by DBSCAN clustering, and extracted stem parameters based on RANSAC cylinder fitting. Chen et al. [12] used local point features by establishing an adaptive KNN and classified the stem points by support vector machine (SVM) method based on Cuckoo search (CS). Then Euclidean clustering of points was carried out and the least square cylinder fitting was used to merge the stem cluster and build a stem model.

In the study of stem mapping based on TLS data, the variability of scan mode and the point density poses great challenges. It is necessary to further develop the technology of stem mapping with TLS. To avoid multi-scan point cloud matching, a stem mapping method in large areas is proposed to use single-scan TLS data in this paper. Compared with some previous studies, the proposed method need not merge stem points. Instead, Mean Shift clustering is used to separate stems from neighboring stems. Furthermore, the method contains adaptive density filtering algorithm to deal with non-stem cluster. There are four main steps: classification, clustering, filtering and cylinder fitting. The single components and the respective methods are explained in Section 2.

2. Material and methods

2.1. Study area and data
The test data was obtained by Riegl VZ-400 scanner with angular density of 0.04° and maximum scanning distance more than 100 m. The main tree species is arbor, a few shrubs in understorey and mainly grass vegetation on the ground. The number and relative position of the reference stems are obtained by interactive measurement on the screen of TLS intensity image.

2.2. Preprocessing of TLS data
TLS data are classified by cloth simulation filter (CSF) algorithm [13] to separate the ground points from non-ground points. Then a regular grid is created from ground points. The lowest point in each subgrid is selected to build a triangulation net as the ground model and the non-ground points are used as the input data for classification.

2.3. Candidate stem points recognition
In the process of terrestrial laser scanning (TLS), the complexity of forest scenes caused by different point densities, scanning area and the occlusion effect [8, 14-16], which brings many challenges to forest inventory. Based on 3D scene analysis, taking advantage of the geometric features of stem points, the candidate stem points are classified from non-ground points [12, 13]. In this section, we refer to 21-dimensional geometric features proposed by Weinmann et al. [17], and Random Forest (RF) method [18] to classify the non-ground points into stem and crown classes. Then the points labelled as stem are used as candidate stem points for further processing.

2.4. Mean Shift clustering
After classification, candidate stem points are obtained, and most of the non-stem points such as foliage, branch and grass are excluded. Due to the adaptability of feature vectors and the uncertainty of noise, there are still a few non-stem points preserved in the candidate stem points. But those points are much sparser than the stem points.

Based on this characteristic, we utilize the Mean Shift clustering [19] to further refine candidate stem points obtained from the classification. As a density-based spatial clustering algorithm, Mean Shift...
cleverly uses the density of the points to generate a reasonable number of clusters. The result is controlled by one parameter—bandwidth value. The bandwidth value can generally be chosen according to the knowledge of some specific fields. The clustering process is shown in Figure 1.

![Flowchart of Mean Shift clustering algorithm.](image)

In this section, the candidate stem points within the height of 4 m are projected on the horizontal plane for the Mean Shift clustering.

For a stem point set $X = \{x_i \in \mathbb{R}^2, i = 1, 2, \ldots, n\}$ in the horizontal plane, the mean shift vector of any point $x_i$ in the point set is

$$M_h(x) = \frac{1}{t} \sum_{x_i \in S_h} (x_i - x)$$

(1)

Where $S_h$ is a high-dimensional sphere with bandwidth $h$ centered on $x$, which represent the effective region, including $t$ sample points.

The mean shift vector always move toward an area of densest point cloud, the main process is obtained by iteration

- Calculate the mean shift vector $M_h(x)$
- Translate the window $x^{j+1} = x^j + M_h(x^j)$

If the distance between the clustering center at the end of iteration and the previously obtained clustering center is less than $h$, they will be merged. Otherwise, the result will be treated as a new stem cluster until all the points are classified.

### 2.5. Density adaptive filtering

After Mean Shift clustering, there are still a few non-stem clusters. These small cluster points are relatively sparse and interfere with the stem detection, so it is necessary to set a threshold of point number to eliminate them. Since the point density decreases with an increase of the distance from the scanner and the number of cluster points is significantly different, which could result in poor filtering performance if a fixed threshold is set conventionally. This paper adopts a density-based adaptive method to filter small clusters [12].

### 2.6. RANSAC cylinder fitting

Random Sampling Consensus (RANSAC) [20] is an iterative method that can estimate the parameters of a mathematical model from an observational dataset containing outliers. Additionally, considering that the surface of the stem is approximately a cylinder [21, 22], for each point cluster, slices are generated on different height and used for RANSAC cylinder fitting [23]. Only the cylinders meeting below conditions are preserved:

- Radius is within $[R_{min}, R_{max}]$
- The axis of the cylinder is approximately parallel to the $Z$ axis

For each stem cluster, the intersection point of the cylinder axis that meet the conditions and the ground model is calculated as the stem position.
3. Results and analysis

Seven parameters are defined in the proposed method. In Mean Shift clustering, the bandwidth $h$ is set to 1.2m. Three parameters need to be set in adaptive density filtering. First, $\gamma = 0.35$ is the preset occlusion scalar, which indicates the degree of invisibility of stems in the plot. Another two are the minimum stem height $h_{\text{min}}$ and stem radius $r_{\text{min}}$, which are preset as 6 m and 0.01m respectively. For the last three parameters, $R_{\text{min}}$ and $R_{\text{max}}$ depend on the radius of the stem in the scan area which are set to 0.01m and 0.5m respectively, the maximum allowed absolute angular distance in degrees between the direction of fitted cylinder and the $Z$ axis is set to 5.

3.1. Classification results

In the course of the experiment, the number of points is reduced after ground filtering and classification. Table 1 lists the number in two steps. The number of stem points after stem classification for less than 15% of the non-ground points, as shown in Table 1.

| Original | Ground points | Non-ground points |
|----------|---------------|-------------------|
| 24128206 | 8270240       | 13885716          |
|          |               | 1972250           |

3.2. Clustering and filtering results

We compare the Mean Shift clustering with the commonly used Euclidean clustering [12, 14], as shown in Figures 2 and 3.

![Figure 2](image.png)

Figure 2. Comparison of two clustering methods (a) candidate stem points (13 stems); (b) Euclidean clustering (875 clusters); (c) Mean Shift clustering (13 clusters).
**Figure 3.** Comparison of two clustering methods after filtering. (a) Filter results based on Euclidean clustering (11 clusters); (b) Filter results based on Mean Shift clustering (13 clusters).

From the perspective of cluster number, before filtering, candidate stem points formed 875 clusters by Euclidean clustering, while only 13 clusters are generated after Mean Shift clustering, which accurately correspond to the 13 stems in candidate stem points. As shown in the red box in Figure 2 (a), there is an obvious error that four adjacent stems are merged into one cluster in the Euclidean clustering result, but these four stems are accurately divided into four clusters in the Mean Shift clustering (As shown in Figure 2 (b)). After filtering, the cluster number based on Euclidean clustering is reduced to 11 clusters. It means that the adaptive density filtering can reduce a large number of non-stem clusters, but this kind of situation that still exists, as shown in Figure 3 (a). In contrast, Mean Shift clustering method has better clustering effect.

### 3.3. Stem detection results

The results of stem mapping by our method and the Euclidean clustering based method are shown in Figure 4. To assess the accuracy, precision and recall can be formulated, as follows:

\[
Precision = \frac{T}{T + C} \quad (2)
\]

\[
Recall = \frac{T}{T + O} \quad (3)
\]

True stem \((T)\) indicates the number of correctly detected stems. Commission error \((C)\), or Type I error, means the number of falsely recognized stems. Omission error \((O)\), or Type II error, which is actually a stem but not recognized. Figure 4 shows the accuracy evaluation of stem mapping.

**Figure 4.** Stem mapping. (a) Euclidean clustering based method; (b) The proposed method (Mean Shift clustering based method)
Table 2. Results and assessments of stem mapping.

| Method                        | Reference stems | Detected stems | Type I error | Type II error | True stems | Precision | Recall |
|-------------------------------|-----------------|----------------|--------------|---------------|------------|-----------|--------|
| Euclidean clustering based method | 330             | 382            | 94           | 42            | 288        | 75.39%    | 87.27% |
| The proposed method           |                 | 349            | 39           | 20            | 310        | 88.83%    | 93.94% |

Table 2 shows that 288 of 330 reference stems are correctly detected by the Euclidean clustering based method, which is less than the proposed method. Both clustering methods have some error detections. Type I error is mainly caused by the non-stem points formed after classification, but there are also errors caused by the lack of the process of merging stem points, which mainly exists in the Euclidean clustering based method. There are two main reasons for Type II error. First, most of the unrecognized stems are far away from the scan center, especially in Figure 4 (b), and the points on the surface of these stems are usually sparse or separated into several small pieces, which is caused by density change and occlusion effect. Therefore, those points are wrongly identified as a non-stem clusters and deleted at the classification or filtering phases. Second, because of the neighboring stems that are very close to each other or connection of non-stem points, the points from different stems are clustered together. This kind of situation is more significant in the Euclidean clustering based method. Type I error and Type II error of the Euclidean clustering based method more than twice as much as the proposed method as shown in Table 2. The results and assessments show that the proposed method is better than the Euclidean clustering based method.

4. Conclusions
This paper presented an automatic method for stem mapping from the single-scan point cloud. We focus on detection of single stem, which used Mean Shift clustering to extract single stem from the classified candidate stem points. The proposed method is tested in a large plot area in which the distances of stems vary from 1m to 5m. Among 330 reference stems, 310 stems are detected correctly and the precision and recall are 88.83% and 93.94% respectively. The test results indicate that the proposed method has better performance of stem detection and higher accuracy of stem mapping, compared with the Euclidean clustering based method. For future work, we plan to further 1) find suitable feature combinations by feature selection methods to improve the accuracy and efficiency. 2) explore the evolving Mean Shift with adaptive bandwidth to enhance the quality of the density estimate.

Acknowledgments
This work is supported in part by National Natural Science Foundation of China under grant no. 41801394, in part by Chongqing Natural Science Foundation under grant no. cstc2019jcyj-msxmX0370, in part by the Science and Technology Research Program of Chongqing Municipal Education Commission under grant no. KJQN201900729 and in part by Innovative Research Program for Graduates of Chongqing Jiaotong University under grant no. CYS21339.

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