A Combination Method based on CSF and Minimum Weighted Graph Cuts to Determine Location and Height of Individual Tree from Airborne LiDAR data

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ABSTRACT: Airborne Laser Scanning(ALS) is an emerging data acquisition technique in the territory of forestry for its increasing ability in offering reliable estimates on tree distribution. Accurate information for tree location from ALS data is the basics for forestry resources monitoring, management and analysis. Current strategies are mostly achieved by identifying treetops, which can be divided into raster-based and point-based methods. However, the two kinds of approach have perceived their problems including limitations on accuracy and robustness, sensitive to spatial resolution and applicability in different situation. To overcome the drawbacks, the present paper aims to propose an individual tree localization strategy by combining cloth simulation filtering and minimum weighted undirected graph. In the workflow, ALS point cloud data was initially filtered by CSF to select the potential local maxims(LMs). After that, Minimum Weighted Undirected Graph Cuts algorithm(MWUGC) was applied on the LMs to form tree top clusters, each of which contains a true treetop. To avoid multi-tops phenomenon in a single cluster, two spatial constraints were applied, which compared the distance in Z direction and the distance to centroid of the cluster. Finally, points with highest Z value and shortest distance to corresponding centroid were the true treetops. Furthermore, the present method was evaluated by comparing the results with artificial interpretation. Meanwhile comparison test was conducted to explore the differences between CHM-based watershed method and the present method. The results show that the present algorithm performs better than traditional method.

1. INTRODUCTION

Forest serves its functions in global atmospheric circulation, absorption for pollutions and mitigating heat islands' effects. Timely forestry documentation and accurate forest biological parameter inversion is of important for understanding forest growth, support preservation work and management decisions, as well as scientific research. Among these tasks, individual tree information in terms of location and height is the basics. Traditionally, individual tree information acquisition mainly relies on field surveys and manual measurement by using tape, GPS and total station(Xinlian L et al, 2018). But these methods could perceive their problems. They are labor-intensive and time-consuming, meanwhile, the results tend to be susceptible to terrain fluctuation, which can hardly meet the requirement for further analysis and monitoring mission. Remote sensing imagery has shown its potentials in the forestry field in terms of low-cost and capability on highly efficient data acquisition(Lina Tang et al, 2015). It thus has been widely applied into forestry monitoring(Jonathan P. Dash et al, 2019), forestry damage assessment(Zayd Mahmoud Hamdi et al, 2019)and ground biomass estimation(Henrik J. Persson, 2016). But remote sensing imagery cannot reflect the structural information under tree crown. What's more, image-based tree localization is mainly derived from canopy height model(CHM), and CHM is generated from digital surface model(DSM) and digital elevation model(DEM). The information accuracy on tree location and height tend to be variable according to the variations on spatial resolution of an image.

In recent years, airborne laser scanner(ALS) has become an emerging data acquisition technique in the territory of forestry for its ability in offering reliable estimates on tree distribution(Harri Kaartinen et al, 2012). Individual tree localization and height extraction from ALS data is a nodal problem in forest remote sensing and many different algorithms have been proposed to address it(Zhen, Z et al, 2016). These methods can be mainly divided into two categories: raster-based methods and point cloud based method. The basic concept of raster-based method is converting 3D point cloud to 2D images, and then a local maxima filter was used to search the treetop. Specifically, DSM and DEM firstly generated from point clouds through spatial interpolation, both of which were further used to generate CHM. Based on the CHM, clustering algorithms like meanshift(Xiao, W et al, 2019) as well as K-means(Morsdorf, F et al, 2003) and computer vision segmentation approaches including marker-controlled watershed(Tao S et al, 2014), region growing(Li, W et al, 2012), valley following(Leckie, D et al, 2003), template matching(Lee, H et al, 2010) or pouring algorithm(H. Weinacker et al, 2004)were applied to acquire the location of the treetops. However, these approaches are limited by image spatial resolution. Low spatial resolution would not precisely reflect detail features, while high resolution would lead to pattern noise. Both of these phenomena affect the final result. More recent research tend to adopt point cloud based method, which directly retrieve location and height information from point cloud. Voxelization would be firstly implemented to deal with large data size and high density of point cloud. The location and height information are obtained by clustering algorithm or local maxima searching method. Nina Amiri et al(Nina Amiri et al, 2018) presented a top-down individual tree detection method. It firstly extracts global Z maximum, and then spatial constraints were used to delineate the individual tree. All individual trees were extracted by repeatedly executing the first two steps. Wanqian Yan et al(Yan, W et al, 2018) proposed an automated hierarchical approach for single tree detection from ALS point clouds by voxel-based meanshift and improved 3D normalized Ncuts. Wenkai Li et al(Li, W et al, 2014) detected individual treetops by searching the global Z maximum and delineated individual tree by applying four types of spatial constraints.

In this paper, we presents an alternative for treetops extraction by combining cloth simulation filtering (CSF) and minimum weighted undirected graph. The presented strategy starts with performing CSF on the original ALS data to filter out the potential point clouds. Then, Undirected weighted graph was established on the filtered output. Each point, at this stage, was viewed as a node, and edges were further set up by calculating weight of each edge, which utilizes Euclidean distance among nodes to quantitatively describe the spatial relationship among nodes. Based the established graph, connectivity analysis was implemented to obtain potential treetop clusters. Furthermore, height value comparison and centroid distance analysis was implemented within each cluster. This was to extract LMs by selecting points with maximums of Z value. The LMs represents treetop candidates. After that, Euclidean distances from the candidate points to the centroid of the clusters were calculated, and the point with the minimum distance was finally selected as the treetop and tree height value was therefore determined. To validate our algorithm, result evaluation and algorithm performance contrast experiment were conducted. Three different sampled plots were used for evaluation, and the number of extracted tree and average differences in XOY plane were used as the indexes to quantify the assessment, which show the high consistency with artificial interpretation in different forests conditions. In the comparison test, two subplots were used. The outputs display the performance of the present algorithm is much better than traditional one. This study demonstrates a novel method for treetop extraction and tree localization based on the ALS data, which shows its promising potential for the further use in individual tree delineation and parameters inversion.

2. METHOD

2.1 Overall Strategy

In the study, the strategy contains four parts(see figure 1). The ALS data was used as the input data, and tree location was determined based on treetop detection by using artificial interpretation, watershed algorithm and our approach. In the ground filtering part, CSF was firstly used to discriminate the ground and non-ground point cloud from the input data. The outputs from the first part were then used as the input for CHM-based approach and the present method. In the CHM-based method procedure, DEM and DEM were respectively generated from ground and non-ground point clouds through Inverse distance weighting. Based on CHM, watershed clustering and visual interpretation were applied to generate the reference result and comparison test result. On the other side, DEM and non-ground point cloud were combined to generate the tree point cloud with normalized terrain. Through point cloud inversion, CSF filtering, Graph cuts processing, treetops were finally extracted. The accuracy of the result was evaluated with reference results.

Specifically, the code framework comprises three modules: Lidar data I/O module, CSF module and treetops detection module. The I/O module was used to read and write the Lidar data. the input is Lidar point cloud with las. Format, while the output is X,Y,Z coordinates with list format. Second module aims to execute ground filtering and potential treetop cluster filtering. Data format in the module is list. Treetops detection module contains tree sections: graph creation, connectivity analysis and spatial discrimination conditions. Graph creation constructs the weighted undirected graph from point clouds(coordinates value in list format), and the output from this section was store in dictionary structure. Connectivity analysis explores whether a group of points belong to the same subgraph, and stores the subgraph as a unit in set data format. The last section is to filter out the true treetop by spatial constraint, and the output the X,Y,Z coordinates value of list format.

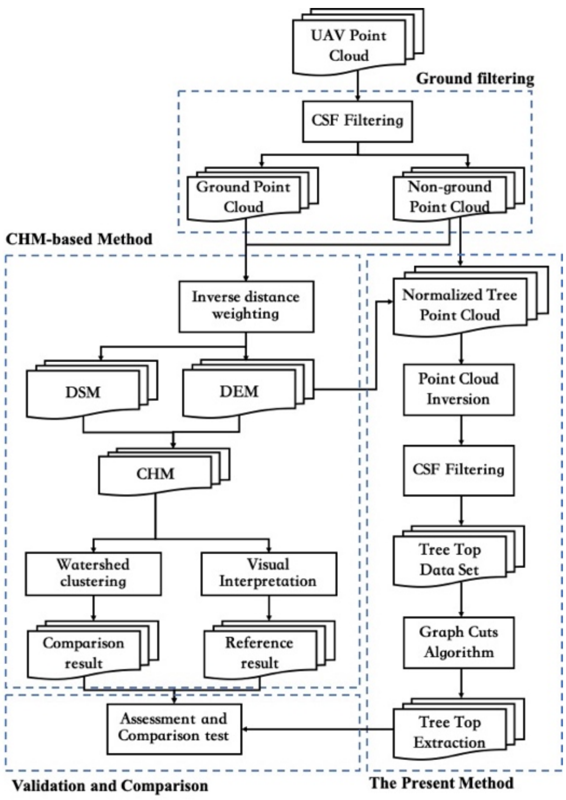


Figure 1 The overall technical routine

2.2 Cloth Simulation Filtering

Cloth Simulation Filtering(CSF) was developed by Zhang(Wuming, Z, 2016), which was initially utilized to discriminate the ground and non-ground point clouds from ALS. As shown in figure 2, the algorithm simulate the process of a cloth falling on the target terrain with the impact of gravity. Every piece of the cloth keeps dropping before it sticks to target surface. Meanwhile, every piece would be constrained by the internal force of the cloth. Finally, the terrain could be obtained by the cloth model.

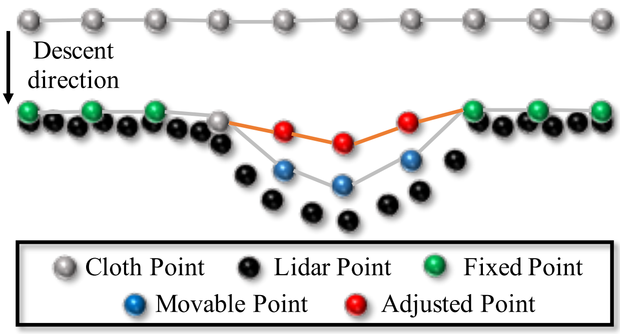


Figure 2 the process of terrain simulation by cloth model; Cloth

The cloth model is a network(see figure 3), which constitutes of a set point with constraint force. It is featured with three aspects: First, every point in the network is constrained by gravity(major force) and force from adjacent points, both of which are independent. Second, every point moves only in vertical direction with gravity in the process of dropping. A point would be fixed once it have fallen onto the surface. Third, a point is constrained by three types of forces, which comprises: four structural forces, four shear forces and eight curve forces. The algorithm is executed by setting only three parameters in terms of maximum iteration, hardness and resolution of the cloth. It thus widely used in various terrain scenarios.

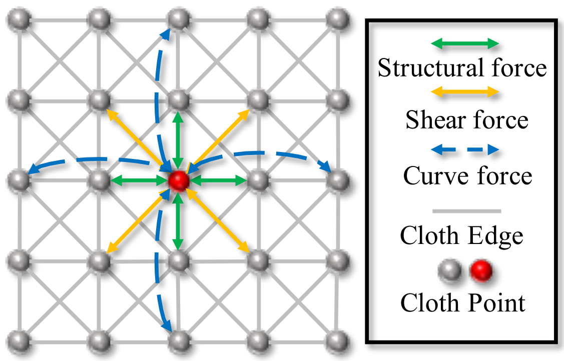


Figure 3 A cloth network and three types of force within a node; the green double arrowhead lines represent structural force; the red double arrowhead lines stand for shear force; the gray lines are cloth edges; the gray and the red points are cloth point

2.3 Minimum Weighted Undirected Graph

Graph cuts algorithm is based on graph theory(West, D.B., 1996), which was initially used to solve image segmentation[23-24]. It works on a connected graph. As figure 4 depicts, a undirected weighted graph is defined as G={V,E}, where V is a set of nodes representing each point in a set of point cloud and E is a set of edges connecting each point. Each edge in the graph is nondirectional.

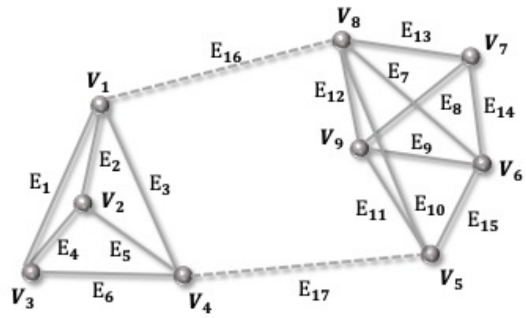


Figure 4 a undirected weighted graph; gray point is the node set (V=$\{V_1, \ldots, V_n\}$) of a graph; gray line represents the edge set (E = $\{E_1, \ldots, E_n\}$).

The algorithm implements the partition procedure by cutting the weighted connected graph into sub-graphs, and the weight of each edge triggers the procedure. Equation (1) demonstrates that graph cuts occurs when the weight value lower than the threshold, which is preset according to the prior knowledge.

$$\mathrm{Cuts} = \min \mathrm{W_{ij}} \tag{1}$$

Equation (2) defines the weight parameter in the algorithm. $\boldsymbol{W_{ij}}$ is determined by $\boldsymbol{F_{(n)}}$, $\boldsymbol{\sigma_I^2}$ and $\boldsymbol{X_{(n)}}$ (here, n = i, j). $\boldsymbol{F_{(n)}}$ is the input feature of the a edge; $\boldsymbol{X_{(n)}}$ stands for the spatial position of node i and node j. $\left\|\boldsymbol{X_{(i)}} - \boldsymbol{X_j}\right\|_2^2$ represents the Euclidean distance of i and j. r is the searching radius in each time.

$$w_{ij} = e^{-\frac{\|F_{(i)}-F_{(j)}\|_2^2}{\sigma_I^2}} * \begin{cases} e^{-\frac{\|X_{(i)}-X_{(j)}\|_2^2}{\sigma_I^2}} & \boldsymbol{if\ ,\ \|X(i)-X(j)\|_2<r} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Self loop is not allowed in the algorithm. In equation (3), the weight of edge is zero when the two end of a single edge is the same node. this would improve computational efficiency.

$$\begin{cases} W_{ij}\ , & if, i \neq j \\ 0\ \ , & if, i = j \end{cases} \tag{3}$$

3. EXPERIMENT AND PERFORMANCE EVALUATION

3.1 Study material description

A coniferous forest region was selected the study area(see figure 5), which covers about 1 $\mathbf{km^2}$. In the region, forests are unevenly distributed. Meanwhile, terrain condition is comparatively complexed with the maximum difference reaches 6 m. Point cloud data was derived from airborne laser scanner, and the average distance among point clouds is 1 meter.

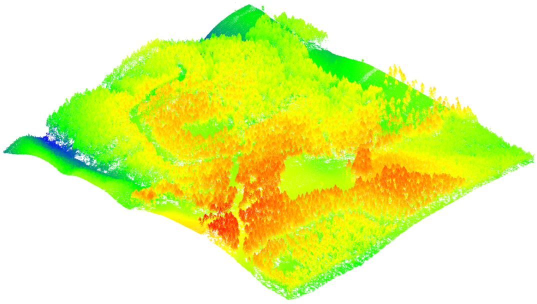
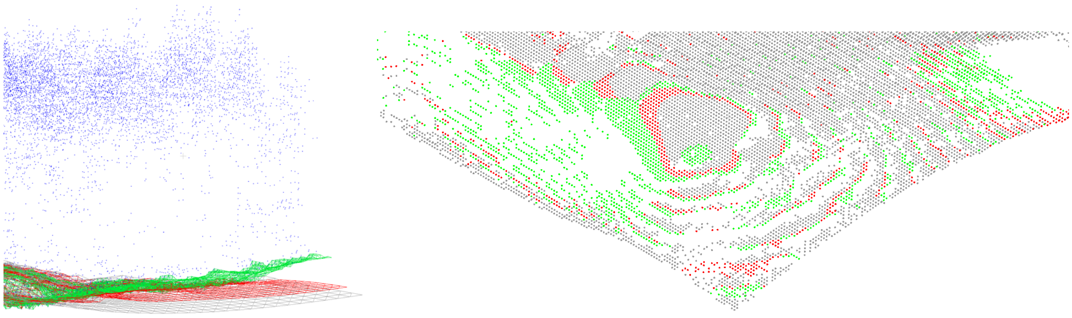


Figure 5 study area(coniferous forest).

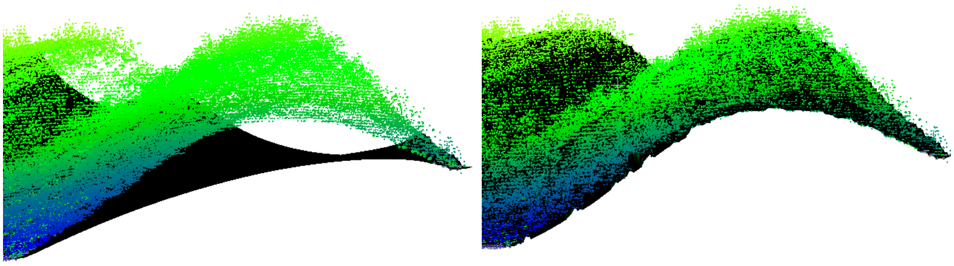
3.2 Data processing

The data processing was based on a workstation with GTX1080 GPU, Intel(R) Xeon(R) E-2186G CPU and 64G RAM, Python 3.6 and Anaconda Spyder IDE. The original LiDAR data was firstly processed through ground filtering to acquire the ground and non-ground point clouds. Then the DEM, the DSM and the CHM were obtained and then used as the complementary data for further analysis. In the first stage, parameter comparison test was conducted to select the optimal parameter combination. According to the input parameters of the code repository, cloth resolution, cloth hardness and slop processing were tested. Figure 6a is the results for cloth resolution test. It shows that with the growth of cloth resolution, the cloth model performs better to simulate the terrain. Figure 6b shows the terrain simulation differences when hardness value varies. when the hardness value is higher, the simulation result is better. Figure 7 is the comparison on the slop processing, which shows that slop processing facilitates the terrain simulation, especially for large terrain fluctuation.



(a) (b)

Figure 6 Comparison of cloth resolution (DTM data) and cloth hardness; In (a), the resolution of green, red and gray respectively are 1m, 2m, 3m; In (b), the red, green and gray respectively represents the hardness value:1, 2, 3



(a) (b)

Figure 7 comparison test on slop processing; (a) is the output without slop processing; (b) is the result through slop processing; the green points are LiDAR point clouds; The curved surface is simulated cloth model.

Based on the comparison result, the optimal parameter combination of CSF was determined. The details are listed in table 1. Thus, the ground and non-ground point clouds were discriminated(see figure 8). Ground point clouds were used to generate DEM and DSM through inverse distance weighting(Lu, G.Y, 2008), while non-ground point cloud data was used for treetop extraction based on the present method.

Table 1 optimal parameters used in the CSF ground filtering

Parameter	Cloth Hardness	Cloth Resolution	Classification Distance	Maximum Iteration	Slop Processing
Value	3	0.5 m	1.5 m	150	yes

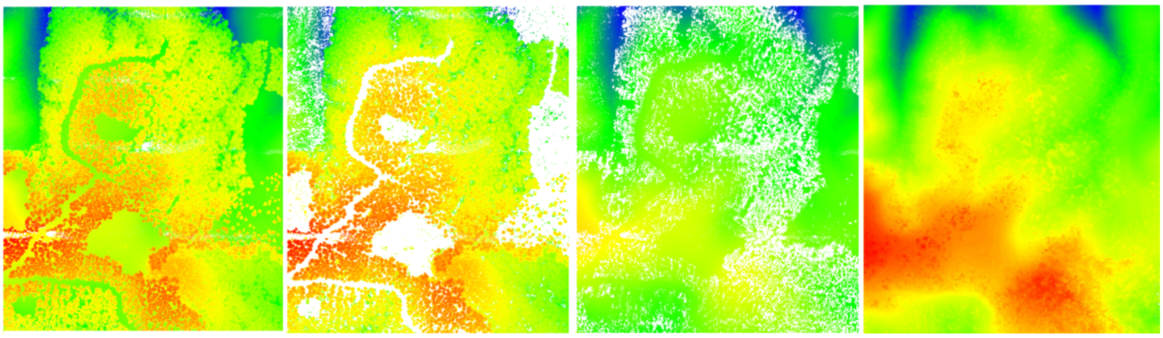


Figure 8 the result of ground filtering through CSF;(a) is original ALS data; (b) is ground points; (c) is non-ground points;(d) is the DEM generated from ground point

CHM was generated from DEM and DSM through raster subtraction. Both CHM and non-ground point clouds were normalized by DEM. The normalized point cloud was then used as the input data for treetops extraction and normalized CHM was used in comparison test.

3.3 CSF filtering and MWUG cuts

To implement CSF algorithm ,the normalized non-ground point clouds were firstly inverted in Z direction. After that, CSF was applied on the inversed data to filter out the potential point clusters(see figure 9a). To extract each cluster and store them as an independent unit, the Minimum weighted undirected graph cut was conducted on the clusters to divide the whole graph into sub-graphs(see figure 9b). Here, the searching range was set as 2m, and the threshold was 1.4m. furthermore, connectivity analysis was implemented to explore the range of a sub-graph, and extract them as an independent unit.

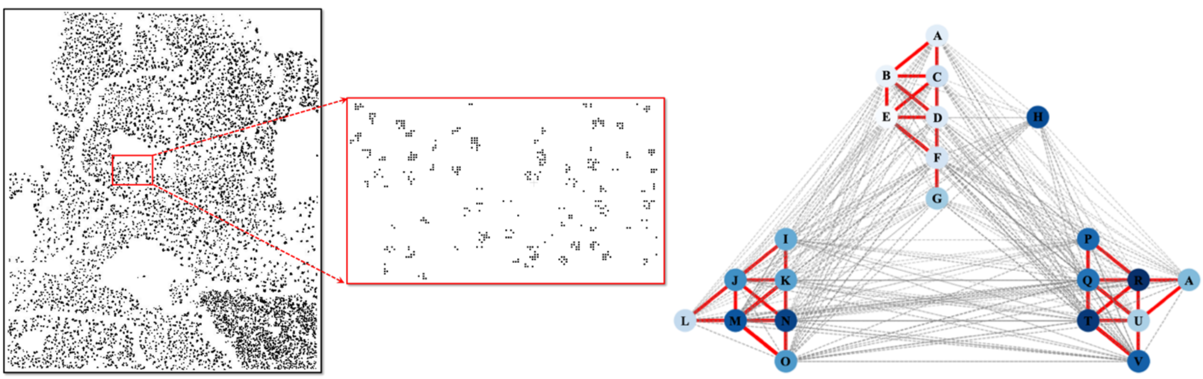
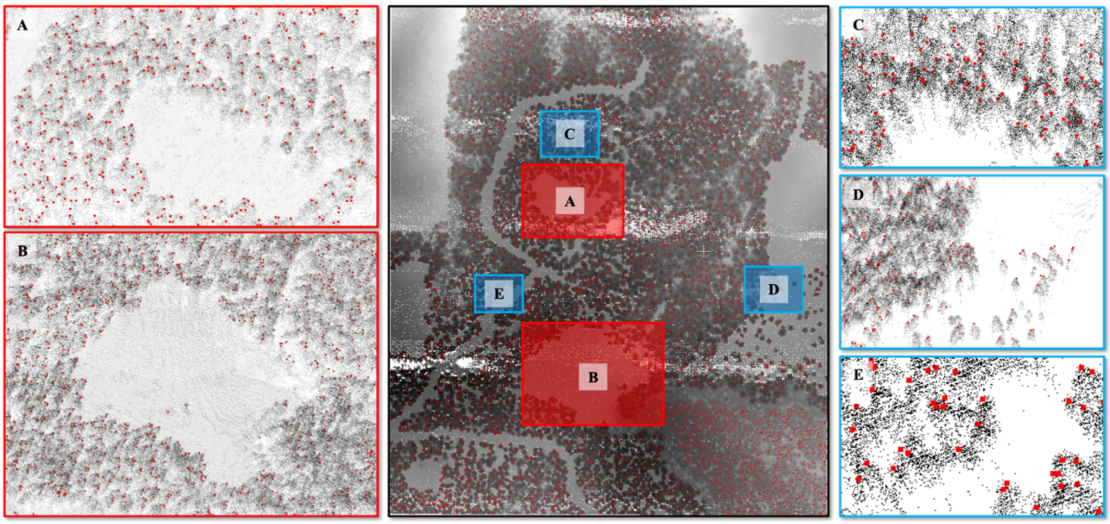


Figure 9 the result of potential point cluster extraction; (a) demonstrates the filtering results by CSF; (b) shows a local figure for minimum weighted graph cut; In (b), points labeled with alphabets are the nodes; the gray dashed lines are the edges needed to be cut and red lines are the retained edges

3.4 Treetop extraction and assessment

There are points with the same Z maximum in a single extracted united. It means false treetop points would exist. In order to extract true tree tops, two conditions were used. We assume that the true treetop should have following characteristics. Vertically, the true top must be the highest in the Z direction; Horizontally, the true top should be nearest to the centroid of the corresponding unit in the XOY. Based on the two constraints, the final result was achieved, which is displayed in figure 10.



(a) (b) (c)

Figure 10 the result of individual treetop extraction and localization in the whole area; the red and blue rectangle in (b) areas correspond to (a) and (c); the areas with red boundaries show the details of the extraction results; the areas with blue boundaries are the sampled test regions for result assessment

For result assessment, three subplots were sampled from the test area(see figure 10b, 10c and figure 11). In each subplot, The output was compared with the result from artificial interpretation. The extracted tree number and the spatial differences between artificial interpretation output and result from the present method were calculated. The statistical details is shown in table 2 where the difference in the XOY plane is the median of the sample site. It shows high consistency of extracted tree number between the output from the present method and the artificial interpretation outcome.

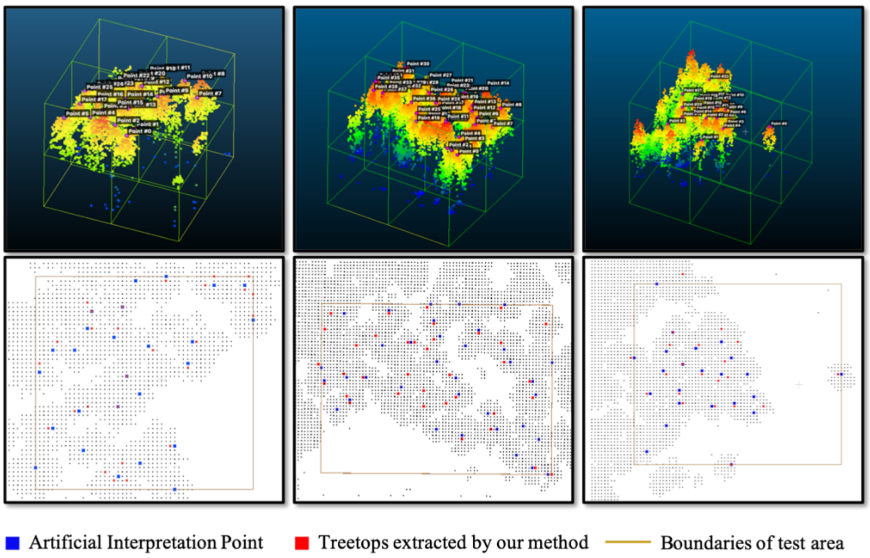


Figure 11 The details of test plots and the results derived from the present method and the artificial interpretation;

Table 2 statistical detail for treetop extraction assessment

Test Plot	Method Name	Extracted Tree Number	Average XOY Difference
Plot #1	The present method	28	1.06 *m*
	Artificial interpretation	27	
Plot #2	The present method	37	1.22 *m*
	Artificial interpretation	39	
Plot #3	The present method	22	1.10 *m*
	Artificial interpretation	23	

4. COMPARISON TEST

The comparison test was conducted to explore the algorithm performance difference between our method and current method. CHM-based mark-controlled watershed approach was selected because it has been widely applied in individual tree extraction, tree top extraction and relevant researches. In the experiment, Two subplots were used as the test area. CHM-based watershed treetop detection was achieved by LiDAR 360 commercial software. Results from the two methods were evaluated based on artificial interpretation.

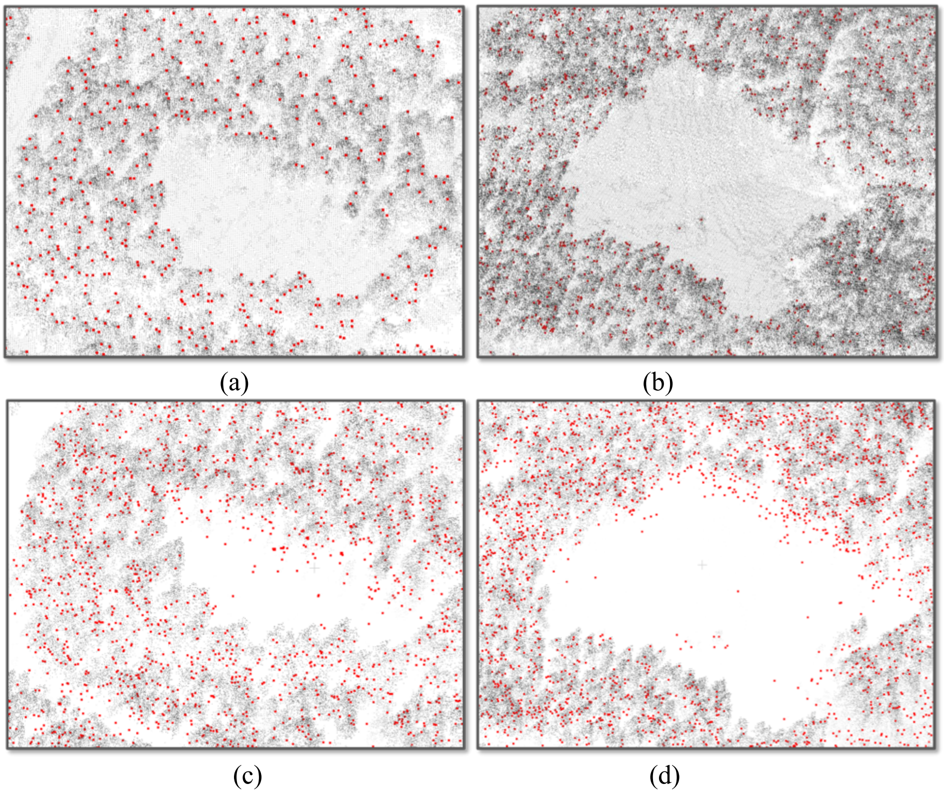


Figure 12 the results of comparison tests; (a)and(c) is the test in the first test plot; (b)and(d)is the result in the second test plot; (a), (b) were achieved by the present method, and (c),(d) were obtained by the CHM-based method; In the four sub-figures, the red point represents the extracted tree points

Figure 12 visualizes detection results from the two methods. Compared with the output from CHM-based marker-controlled watershed method, extracting treetops from the present method is more accurate. More importantly, the present method is capable of discriminating the low vegetation and trees, while CHM-based marker-controlled watershed method mistakenly recognized the top of low vegetation as the treetops, which shows the weakness in discriminating the noise.

5. CONCLUSION AND FUTURE OUTLOOK

In the study, a combination method to extract individual coniferous tree tops was proposed, which used both the CSF and the MWUG cuts algorithms. In the procedure, data pre-processing was firstly conducted to eliminate the impacts from terrain fluctuation and extract non-ground point clouds. Besides, potential point clouds were filtered out by CSF, and independent cluster units were extracted by MWUG cuts and connectivity analysis. Furthermore, two spatial constraints were applied to avoid multi-treetop phenomenon, and true tops were finally detected. The accuracy assessment and comparison test were conducted, both of which shows the good performance of the present method.

In the future, more work would be firstly done in completing the whole procedure of the individual tree segmentation and classification based the treetop detection algorithm in the paper. What's more, further research would be conducted to improve algorithm performance in a more complex condition(e.g. broad-leaf and coniferous mixed forest). Moreover, how to improve the computational efficiency of the algorithm when encountering the big data size of point cloud should also be studied. Beside, the assessment process is quite important for algorithm performance evaluation, in the study, we just assessed the performance by comparing the results with artificial interpretation. This obviously caused errors and uncertainty. To solve the problem, data with ground truth acquired from situ measurement would be used in future study. Meanwhile, more explorations should be conducted to investigate whether the indexes (the number of extracted tree and XOY differences) is enough to reflect the algorithm, and finally a set of scientific assessment index for individual treetop extraction should be established.

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