# 3-D Reconstruction and Visualization of Laser-Scanned Trees by Weighted Locally Optimal Projection and Accurate Modeling Method

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**Abstract:** This paper presents a method to reconstruct 3-D models of trees from terrestrial laser scan (TLS) point clouds. This method uses the weighted locally optimal projection (WLOP) and the AdTree method to reconstruct detailed 3-D tree models. To improve its representation accuracy, the WLOP algorithm is introduced to consolidate the point cloud. Its reconstruction accuracy is tested using a dataset of ten trees, and the one-sided Hausdorff distances between the input point clouds and the resulting 3-D models are measured. The experimental results show that the optimal projection modeling method has an average one-sided Hausdorff distance (mean) lower by 30.74% and 6.43% compared with AdTree and AdQSM methods, respectively. Furthermore, it has an average one-sided Hausdorff distance (RMS) lower by 29.95% and 12.28% compared with AdTree and AdQSM methods. Results show that the 3-D model generated fits closely to the input point cloud data and ensures a high geometrical accuracy.

**Key words:** light detection and ranging(LiDAR); point cloud; weighted locally optimal projection (WLOP); 3-D reconstruction; AdTree

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## 0 Introduction

Trees have a fundamental function in the natural ecosystem[1]. The digital representation of objects is necessary for scientific tasks such as urban landscape visualization, cultural heritage, environmental monitoring, mapping, and modeling. The geometrical models are commonly used to interpret complex surface structures visually. Temporal changes are detectable and thus used as a foundation for various environmental monitoring documentation and maintenance applications.

Light detection and ranging (LiDAR) technology has been widely used in forestry-related analysis and studies. As measurements from LiDAR can achieve a millimeter level of details from objects, it has become possible to capture 3-D information directly and rapidly estimate tree attributes. Accurate 3-D tree modeling improves the scientific approach to forests and vegetation, satisfying environmental goals that heavily rely on vegetation mapping and monitoring[2]. Trees' models have a wide range of applications, including urban landscape design, ecological simulation, forestry management, and virtual entertainment. While landscape design and visualization only require modeling virtual trees, other applications relevant for ecological modeling and forestry management require accurate estimation of tree parameters (e.g., height and stem thickness).

The traditional way of measuring trees is to conduct fieldwork manually, which is usually expensive and time-consuming[3]. Accurate tree modeling

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provides promising approaches to managing vegetation and forests scientifically, which in return, contribute to ecosystem protection and resource preservation[4].

## 1 Related Work

Surface reconstruction using Delaunay techniques[5] produces a mesh with rough geometry when the input points are noisy. To better deal with outliers and delicate surface structures, Lipman et al.[6] developed a highly effective, parameterization-free projection operator, i.e., locally optimal projection (LOP). LOP takes as an input a point cloud with noise or outliers, generating as an output a set of points that adheres to the underlying shape. LOP works with raw data without depending on the local parameterization of points, but it can fail to converge, oscillating near a solution instead. Therefore, it may not work well when the distribution of the input points is highly non-uniform[7].

Huang et al.[7] improved LOP[6] by incorporating locally adaptive density weights, as LOP may not work well when the input point distribution is highly non-uniform. The weighted locally optimal projection (WLOP) yields better convergence and a more locally regular point distribution.

Point cloud consolidation could clean up raw data input, remove various data artifacts, and provide essential geometric attributes to facilitate subsequent processing.

For tree topology reconstruction and branch information extraction[8], existing solutions can be divided into two categories: (1) point cloud segmentation; and (2) skeleton extraction.

Based on point cloud segmentation, a tree point cloud is divided into small clusters, and then these clusters are programmatically connected to reconstruct the branch topology[9]. Geometric elements such as cylinders and spheres are used to reconstruct the 3D model on the existing topological relations. Raumonen et al.[10] used a local method to segment the point cloud on the tree surface into small connected cover sets to identify the branches' topology relationship and used a cylinder to reconstruct the tree in three dimensions, which can efficiently establish the topological relationship of tall trees and the acquisition of basic parameters.

Yan et al.[11] extracted the topological structure of a tree based on the variational $k$-means clustering algorithm. Bucksch et al.[12] organized the input point cloud data according to the octree structure and reconstructed a tree based on the skeleton lines of trees generated from octree cells. Hackenberg et al.[13] developed a hierarchical cylindrical structure to describe the parent-child relationship between tree branches, which can effectively extract different tree components, such as branch topology, length, and the number of branches.

On the other hand, skeleton extraction-based methods directly obtain the skeleton lines from the original input point cloud and then perform 3-D reconstruction work. Wu et al.[8] successfully extracted the skeleton of a corn plant through a Laplace transform-based algorithm. Although some existing skeleton extraction methods do not require a high point cloud quality, most models only extract skeletons and do not extract tree parameters.

Du et al.[9] proposed the AdTree method to accurately reconstruct tree branches from individual tree point clouds, using the minimum spanning tree (MST) algorithm to extract the main skeleton. The AdTree method reconstructs the 3-D model by cylinder fitting. The novelty of this method is that the initial tree skeleton is reconstructed based on the intrinsic spatial distribution of points. Its simplification strategy keeps the tree branches' topological structure, maintaining the tree's topological fidelity with good geometrical accuracy. Compared to other open-source tree cylindrical modeling methods, TreeQSM[10], SimpleTree[13], and PypeTree[14], the tree stem and branches generated from AdTree have higher geometric accuracy with distances between the input point and the output model of less than 10 cm.

There is a class of models called quantitative structural model (QSM), which is a typical method for point cloud segmentation with a great potential to obtain tree structure parameters[10-13,15]. It can quantitatively describe the tree's basic topology (branch structure), geometry, and volume properties. These attributes include the total number of branches, branches order, parent-child relationship, branches lengths, the volume and angle of a single branch, and the branch size distribution.

Models such as SimpleTree[13], PypeTree[15], and TreeQSM[10] all belong to the category of QSM. TreeQSM has been used to estimate above-ground biomass (AGB) of different tree species[16]. QSM has also been used in tree species identification[17] and forest radiation transmission simulation[18]. In addition, QSM performed well in extracting structural parameters such as tree diameter at breast height[19] and crown width[14].

Fan et al.[20] proposed the AdQSM method, a novel, accurate and detailed method for AGB estimation. This model is based on AdTree. It can effectively and non-destructively estimate AGB from TLS point clouds, which is essential to monitor trees' growth, health, economic value, and ecological benefits.

This research studies how the WLOP method could refine an unorganized tree point cloud to reconstruct a 3-D model of a tree accurately. Based on the literature review of the existing methods, it is decided to use the AdTree method for tree topology reconstruction. AdQSM is based on AdTree, but its approach is on AGB estimation. Our study will measure the distances between the model and the point cloud by a suitable error metric, such as the widely used one-sided Hausdorff distance[21]. This distance is measured from the input point cloud to the output model and it is used to compare the 3-D reconstruction accuracy of the proposed WLOP-AdTree with AdTree and AdQSM methods.

## 2 Methodology

The ground laser scanner is used to generate the raw data of trees. The terrestrial laser scan (TLS) of trees are collected at Nanjing University of Aeronautics and Astronautics. Scanned trees are manually segmented to get one point cloud of each tree, creating a data set for our experiment.

### 2.1 Point cloud consolidation

Given an unorganized set of points $\boldsymbol{P}=\left\{\boldsymbol{p}_j\right\}_{j\in J}\subset\boldsymbol{R}^3$, LOP[6] defines a set of projected points $\boldsymbol{X}=\left\{\boldsymbol{x}_i\right\}_{i\in I}\subset\boldsymbol{R}^3$ onto the set $\boldsymbol{P}$ by a fixed-point iteration.

WLOP incorporates locally adaptive density weights and propose $\eta(r)=-r$ as the repulsion term, achieving both better convergence and a more locally regular point distribution.

The projection for the point $\boldsymbol{x}_i^{k+1}$ is

$$\boldsymbol{x}_i^{k+1}=\sum_{j\in J}\boldsymbol{p}_j\frac{\alpha_{ij}^k/v_j}{\sum_{j\in J}\alpha_{ij}^k/v_j}+\mu\sum_{i'\in I\setminus\{i\}}\boldsymbol{\delta}_{ii'}^k\frac{\omega_{i'}^k\beta_{ii'}^k}{\sum_{i\in I\{i\}}\omega_{i'}^k\beta_{ii'}^k}\tag{1}$$

$$v_j=1+\sum_{j'\in J\setminus\{i\}}\theta\left(\left\|\boldsymbol{p}_j-\boldsymbol{p}_{j'}\right\|\right)\tag{2}$$

$$\omega_{i'}^k=1+\sum_{i'\in I\setminus\{j\}}\theta\left(\left\|\boldsymbol{\delta}_{ii'}^k\right\|\right)\tag{3}$$

where $v_j$ and $\omega_{i'}^k$ are the adaptive density weights, $\alpha_{ij}^k=\dfrac{\theta\left(\left\|\boldsymbol{\xi}_{ij}^k\right\|\right)}{\left\|\boldsymbol{\xi}_{iJ}^k\right\|}$ and $\beta_{ii'}^k=\dfrac{\theta\left(\left\|\boldsymbol{\delta}_{ii'}^k\right\|\right)\left|\eta'\left(\left\|\boldsymbol{\delta}_{ii'}^k\right\|\right)\right|}{\left\|\boldsymbol{\delta}_{ii'}^k\right\|}$. $\theta(r)=\mathrm{e}^{-r^2/(h/4)^2}$ is a smooth weight function which decreases rapidly, the radius $h$ defines the size of the influence neighborhood $h=4\sqrt{d_{\mathrm{bb}}/m}$, where $d_{\mathrm{bb}}$ is the diagonal length of the boundary box of the model, and $\eta(r)$ is a decreasing function which penalize points $\boldsymbol{x}_i$ that get too close to other points in $\boldsymbol{X}$. Thus, the attraction of point clusters in the given set $\boldsymbol{P}$ is relaxed by the weighted local density $v(2)$, and the repulsion force from points in dense areas is strengthened by the weighted local density $\omega$ (3).

This study proposes the separate application of WLOP on the tree point cloud, segmenting it into two parts: the main trunk and the rest of the tree, as shown in Fig.1. It will be carried out as follows: A tree point cloud is the input to this process, then the point cloud will be segmented into two point-clouds the main trunk and rest of the tree. The iterative application of WLOP algorithm will separately consolidate this segmented point clouds, and then the resulting point clouds will be merged.

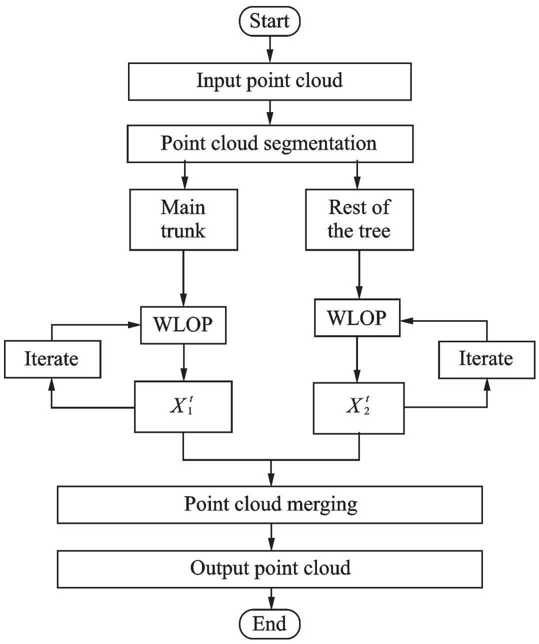


Fig.1 Flowchart of WLOP algorithm

### 2.2 3-D model reconstruction

AdTree method will be used to reconstruct tree branches using as an input point cloud the output of the previous stage. Fig.2 shows the main steps of AdTree method.

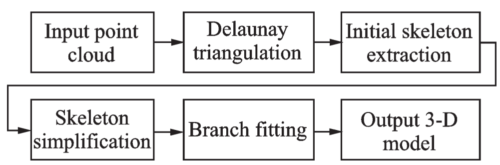


Fig.2 Main steps of AdTree method

Delaunay algorithm triangulates the input points, and the initial skeleton is extracted by the minimum spanning tree MST algorithm.

The initial skeleton is simplified by iteratively retrieving and merging adjacent vertices close enough.

Cylinder fitting is used to reconstruct the 3-D model over input points, the non-linear least squares method is used to obtain the radius of the main trunk, and the subsequent branches' radius is derived from the main trunk geometry.

### 2.3 Measurements

Given two finite point sets $A = \boldsymbol{a}_1, \boldsymbol{a}_2, \cdots, \boldsymbol{a}_n$ and $B = \boldsymbol{b}_1, \boldsymbol{b}_2, \cdots, \boldsymbol{b}_n$, two-side Hausdorff distance $H(A, B)$ is defined as[22]

$$H(A,B) = \mathrm{Max}\left(\boldsymbol{h}(A,B), \boldsymbol{h}(B,A)\right) \tag{4}$$

$$\boldsymbol{h}(A,B) = \underset{a \in A}{\mathrm{Max}}\ \underset{b \in B}{\mathrm{Min}} \left\| \boldsymbol{a} - \boldsymbol{b} \right\| \tag{5}$$

where the function $\boldsymbol{h}(A, B)$ is called the one-sided Hausdorff distance. This metric measures the proximity between the 3-D model and the point cloud (less is better). This metric is more tolerant towards the perturbations of point locations than shape comparison.

## 3 Experimentation, Results and Analysis

TLS data: We preprocess the raw data by removing the ground points. As shown in Fig. 3, only point clouds of trees are used in this study.

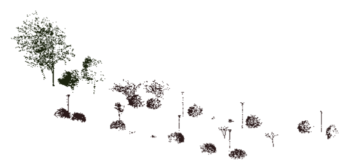

Fig.3 Complete TLS

Trees segmentation: Raw data is manually segmented into ten individual trees point clouds; the bounding box of segmented trees shown in Fig.4 denotes that each tree conforms to the resulting dataset.

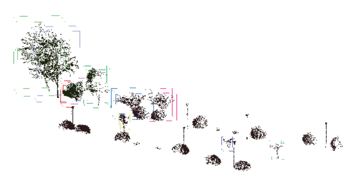

Fig.4 Segmented trees from TLS

### 3.1 Point cloud consolidation WLOP

WLOP is carried out for each tree point cloud of the dataset. The WLOP algorithm is used to consolidate the segmented point clouds, in which the repulsion term is set to $0 \leqslant \mu < 0.5$ and the number of iterations is set to 50. The default value h defines the size of the influence neighborhood.

Fig.5(a) shows the tree point cloud which is the input to this process. Then the point cloud will be segmented into two point-clouds: The main trunk (Fig.5(b)), and the rest (Fig.5(c)). Consolidated point clouds shown in Fig.5(d) and Fig.5(e) will be merged resulting in a tree point cloud Fig.5(f).

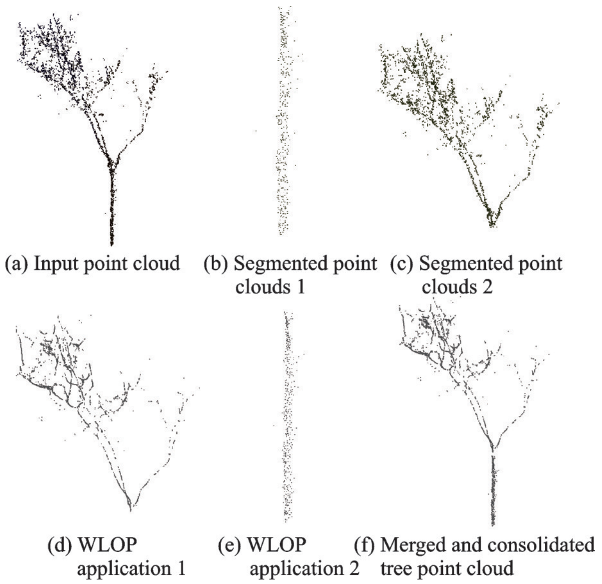


Fig.5 Point cloud processing WLOP

### 3.2 3-D model reconstruction

Fig.6(a) shows the consolidated tree point cloud from the previous stage. The initial tree skeleton is extracted Fig.6(b) by the Delaunay algorithm. This algorithm triangulates the input points by the minimum spanning tree MST algorithm, the initial skeleton shown in Fig.6(c) is extracted. The initial skeleton Fig.6(c) is simplified by iteratively retrieving and merging close enough adjacent vertices. The result is shown in Fig.6(d). Cylinder fitting is used to reconstruct the 3-D model, shown in Fig.6(e) over input points.

The non-linear least squares method is used to obtain the radius of the main trunk, and the subsequent branches' radius is derived from the main trunk geometry.

### 3.3 Results and analysis

Tables 1, 2 show the one-sided Hausdorff distance between two layers in mesh units, sampling one of the two layers and finding the closest point over the other mesh for each sample. The mesh whose surface is sampled is used as the input point cloud, and the target mesh is the 3-D model.

The results in Tables 1 and 2 determine how close the generated 3-D model is to the input point cloud. It is considered that while the distance is shorter, the error is smaller, which is evident in the

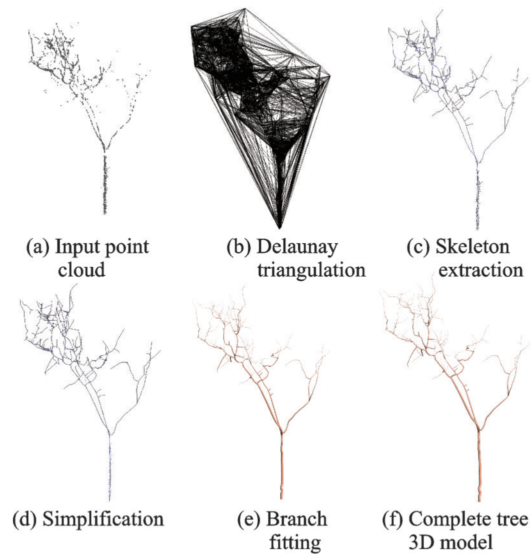


Fig.6 AdTree 3D model reconstruction

**Table 1 One-sided Hausdorff distance (Mean)**

| Point cloud | AdTree | AdQSM | WLOP-AdTree |
|---|---|---|---|
| tree_nuaa_1 | 0.020 197 | 0.010 907 | 0.016 064 |
| tree_nuaa_2 | 0.022 844 | 0.016 695 | 0.017 755 |
| tree_nuaa_3 | 0.008 045 | 0.006 133 | 0.004 706 |
| tree_nuaa_4 | 0.006 489 | 0.006 291 | 0.003 423 |
| tree_nuaa_5 | 0.007 956 | 0.005 381 | 0.004 702 |
| tree_nuaa_6 | 0.034 394 | 0.024 62 | 0.025 182 |
| tree_nuaa_7 | 0.023 026 | 0.024 552 | 0.017 298 |
| tree_nuaa_8 | 0.025 491 | 0.018 073 | 0.015 133 |
| tree_nuaa_9 | 0.014 901 | 0.008 492 | 0.009 416 |
| tree_nuaa_10 | 0.013 656 | 0.009 87 | 0.008 915 |

**Table 2 One-sided Hausdorff distance (RMS)**

| Point cloud | AdTree | AdQSM | WLOP-AdTree |
|---|---|---|---|
| tree_nuaa_1 | 0.031 478 | 0.023 877 | 0.026 419 |
| tree_nuaa_2 | 0.038 001 | 0.034 874 | 0.033 308 |
| tree_nuaa_3 | 0.012 65 | 0.013 014 | 0.007 48 |
| tree_nuaa_4 | 0.009 593 | 0.011 795 | 0.005 128 |
| tree_nuaa_5 | 0.016 977 | 0.013 211 | 0.016 945 |
| tree_nuaa_6 | 0.085 164 | 0.055 895 | 0.046 293 |
| tree_nuaa_7 | 0.050 425 | 0.053 315 | 0.045 496 |
| tree_nuaa_8 | 0.070 646 | 0.044 451 | 0.032 699 |
| tree_nuaa_9 | 0.030 278 | 0.023 34 | 0.025 47 |
| tree_nuaa_10 | 0.028 339 | 0.024 564 | 0.022 453 |

bar graphs in Fig.7 and Fig.8. Smaller distance denotes less errors. As shown in Fig.7 and Fig.8, the result of WLOP-AdTree has the best accuracy compared with AdTree and AdQSM.

Fig.9 shows a sample of the 3-D models generated using AdTree, AdQSM and WLOP-AdTree methods. The measurements show that the one-sided Hausdorff distance (mean) of WLOP-AdTree is on average lower by 30.74% and 6.43% compared with AdTree and AdQSM methods, respectively, and the one-sided Hausdorff distance (RMS) of WLOP-AdTree is on average lower by 29.95% and 12.28% compared with AdTree and AdQSM methods. These results show that the 3-D models generated fit closely to the input point cloud data.

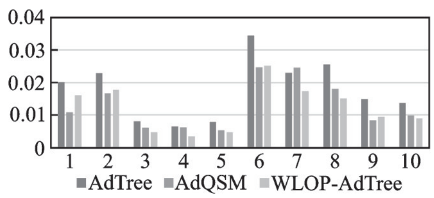


Fig.7. Bar chart of one-sided Hausdorff distance (mean)

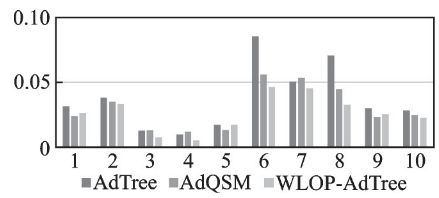


Fig.8 Bar chart of one-sided Hausdorff distance (RMS)

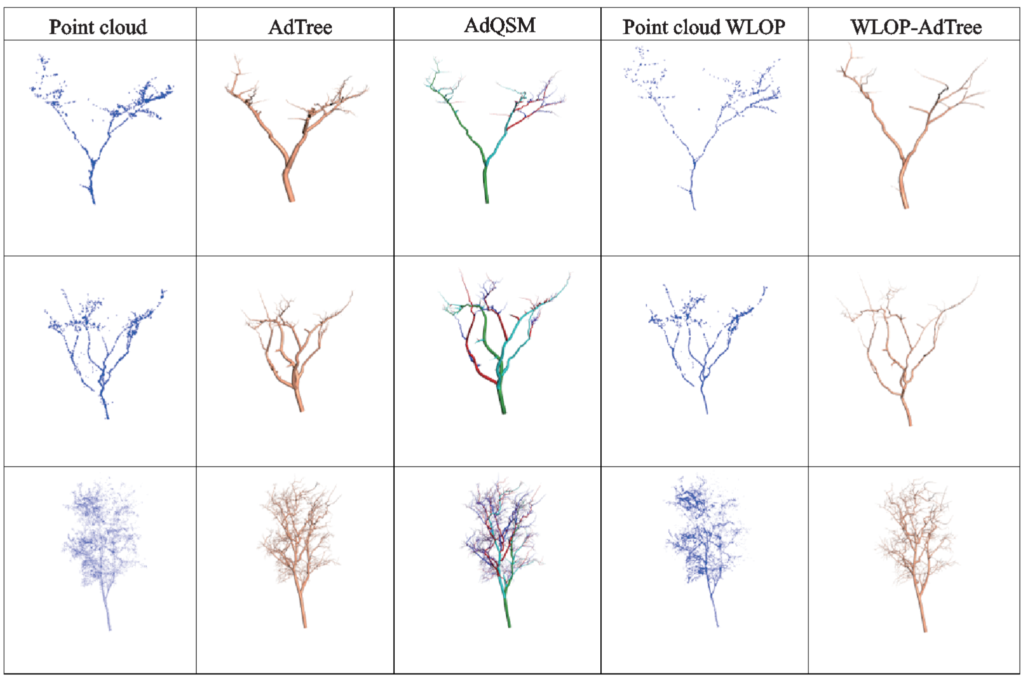


Fig.9 3-D reconstructed models

## 4 Conclusions

This paper has presented the WLOP-AdTree method to accurately reconstruct detailed 3-D tree models. In order to consolidate the point cloud and improve its 3-D representation accuracy, WLOP algorithm is introduced, its reconstruction accuracy is tested using a data set of ten TLS segmented trees point clouds, and its one-sided Hausdorff distance between the input point cloud and the resulting 3-D reconstruction model is measured. Experimental results show that the 3-D model generated with WLOP-AdTree method fits more closely to the input point cloud data than AdTree and AdQSM methods, thus ensuring high geometrical accuracy.

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**Author contributions** Mr. **TAMAYO Alexis** conducted the study and wrote the paper. Dr. **LI Minglei** contributed to the algorithm design and revision of the study. Ms. **LIU Qin** and Dr. **ZHANG Meng** contributed to the discussion of the algorithm, conclusion and background. All authors commented on the manuscript draft and approved the submission.

**Competing interests** The authors declare no competing interests.

(Production Editor: CHEN Jun)

# 基于加权局部最优投影和精确建模的激光扫描树木三维重建与可视化研究

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**摘要:**本文提出了一种从地面激光扫描(Terrestrial laser scan, TLS)点云重建树木三维模型的方法。该方法使用加权局部最优投影(Weighted locally optimal projection, WLOP)和AdTree方法来重建精细的三维树木模型。为了提高表示精度,方法引入了WLOP来合并点云。本文在包含10棵树的数据集上进行了实验,以输入点云和重建的三维模型之间的单边Hausdorff距离来衡量重建精度。实验结果表明,相比于AdTree和AdQSM,最优投影建模方法得到的的单边Hausdorff距离的平均值分别降低了30.74%和6.43%,均方根值分别降低了29.95%和12.28%。证明了本文方法生成的三维模型与输入的点云数据拟合程度好,拥有较高的几何精度。

**关键字:**激光雷达;点云;加权局部最优投影(WLOP);三维重建;AdTree