COMPARISON OF SINGLE AND MULTI-SCALE METHOD FOR LEAF AND WOOD POINTS CLASSIFICATION FROM TERRESTRIAL LASER SCANNING DATA

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ABSTRACT:

The classification of leaf and wood points is an essential preprocessing step for extracting inventory measurements and canopy characterization of trees from the terrestrial laser scanning (TLS) data. The geometry-based approach is one of the widely used classification method. In the geometry-based method, it is common practice to extract salient features at one single scale before the features are used for classification. It remains unclear how different scale(s) used affect the classification accuracy and efficiency. To assess the scale effect on the classification accuracy and efficiency, we extracted the single-scale and multi-scale salient features from the point clouds of two oak trees of different sizes and conducted the classification on leaf and wood. Our experimental results show that the balanced accuracy of the multi-scale method is higher than the average balanced accuracy of the single-scale method by about 10% for both trees. The average speed-up ratio of single scale classifiers over multi-scale classifier for each tree is higher than 30.

1. INTRODUCTION

Terrestrial laser scanning (TLS) provides a revolutionary way of quantifying individual tree characteristics, with details and accuracy that satellite laser scanning (SLS) and airborne laser scanning (ALS) cannot match (Tao et al., 2015). Significant progress has been made using TLS data to calculate diameter at breast height (DBH), leaf area index (LAI), plant biomass, virtual projections, gap fraction, etc. (Dassot et al., 2011). The inventory measurements and canopy characterization of trees help ecologists and botanists build more accurate models for large amount of fine-scale research.

The retrieval of many parameters of tree from TLS data requires the classification of leaf and wood points to improve accuracy and reduce complexities. The classification of tree point clouds into leaf and wood points is a challenge. According to Wang et al. (2017), two types of methods have emerged for this problem. The first-type method uses intensity information of returned laser pulse (Pfeifer et al., 2007; Pfennigbauer and Ullrich, 2010; Béland et al., 2014). The assumption of this approach is that there are significant differences among the optical properties of different components of a tree at the operating wavelength of the laser system (Tao et al., 2015; Wang et al., 2017). Trees of different species may respond similarly to the laser wavelength , meaning that the intensity-based approach cannot be used for some tree species. In addition, the intensity values need an instrument specific radiometric calibration before it can be used for leaf and wood classification (Pfennigbauer and Ullrich, 2010; Calders et al., 2017). According to Hakala et al. (2012), multi-wavelength scanners have huge potential for improved accuracy and efficiency in comparison with traditional monochromatic laser scanners. However, this type of scanners are still in an early development stage and are not available from commercial manufacturers. The second-type method is referred to as the geometry-based method, which uses three dimensional

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coordinates of objects captured by a laser scanner (Tao et al., 2015; Wang et al., 2017). Tao et al. (2015) proposed a geometry-based method that focuses on leaf and wood classification of TLS data. Their method extracts the skeleton of trees and then separates the leaf and wood points. Ma et al. (2016) developed a method based on the Lalonde’s framework that used the spatial distribution patterns of the manually selected training points of each class to drive the Gaussian mixture model (GMM) for leaf and wood classification (Lalonde et al., 2006). Yun et al. (2016) presented another method based on Dey’s method, which calculated the shape, normal vector distribution, structure tensor of tree point clouds and used the semi-supervised support vector machine (SVM) classifier to separate leaf and wood points (Dey et al., 2012). Recently, Li et al. (2017) proposed the normal difference method based on the differences in the structures of leaf and non-leaf components of trees. To find better machine learning classifiers and salient features, Wang et al. (2017) examined four geometry-based machine learning classifiers and many salient features that were widely adopted in other classification tasks (Brodu et al., 2012; Weinmann et al., 2013, 2015, 2017) and found that machine learning classifiers and several salient features could efficiently separate leaf and wood points from TLS data with high accuracy.

In Wang’s experiments, he only uses single-scale salient features to training classifiers. However, the surfaces of trees are heterogeneous and their distinctive properties are seldom defined at one specific scale. Therefore, using multi-scale salient features in this problem holds huge potential for improved accuracy (Brodu et al., 2012). The lack of comparative studies on the abilities of single-scale and multi-scale salient features to characterize the spatial patterns calls for further research on how single-scale and multi-scale salient features affect the classification accuracy and efficiency.

In this study, we examine the accuracy and efficiency of single- and multi-scale leaf and wood classification methods to find better classification strategy based on the Brodu’s framework.

2. MATERIALS

The study site is located at the Jigong Mountain National Nature Reserve (114°02' E, 31°50' N), Henan Province, China. The TLS data of two oak trees of different sizes were acquired from four scan positions by Leica ScanStation P40 in April, 2016. The Registration and Edit module of Leica Cyclone 9.1.4 software are used to preprocess tree point cloud. The acquired point cloud was further manually cleaned, as the point cloud of other trees and ground should be removed. The cleaned point cloud for tree 1 and tree 2 contains 3,065,470 and 11,373,009 points, respectively. The average distance between two adjacent points is ~3mm. To assess the classification accuracy of single- and multi-scale methods, we manually identified leaf and wood points of the two trees. For tree 1, 1,948,299 and 1,117,171 points belong to leaf and wood, respectively. For tree 2, 6,799,597 points belong to leaf and 4,573,412 points to wood. The original data of tree 1 and tree 2 are shown in Figure 1(a) and Figure 2(a), respectively.

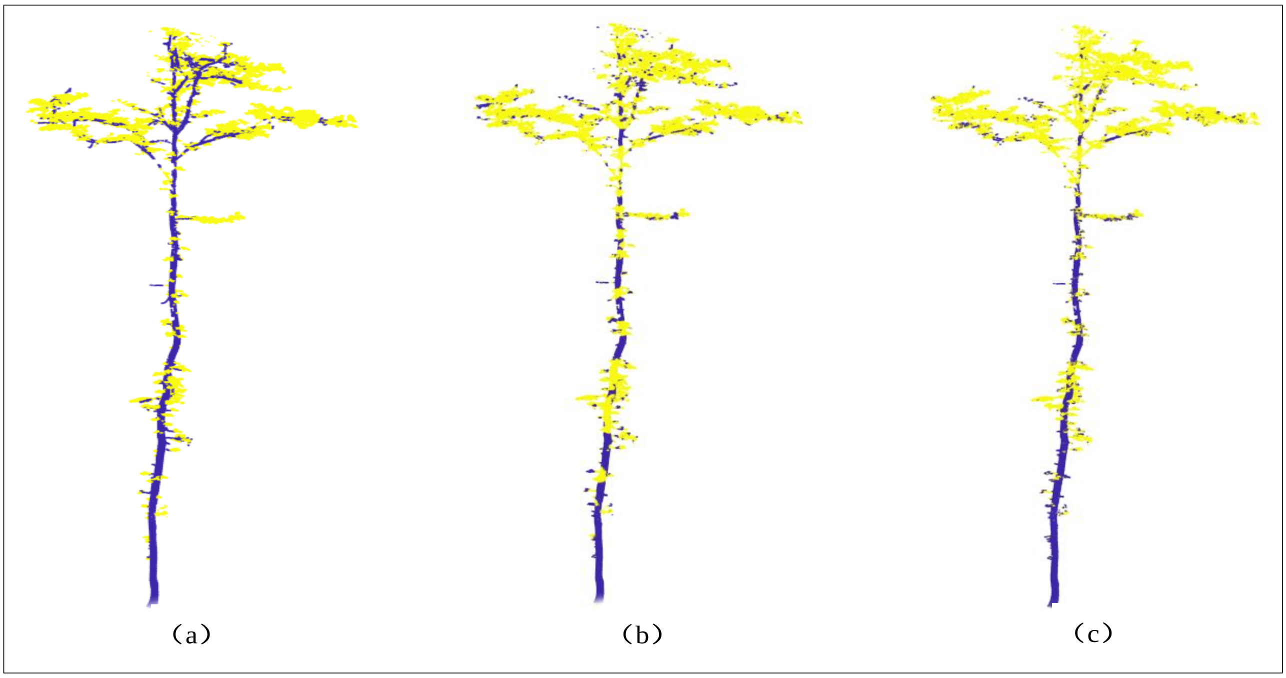

Figure 1. The point cloud of tree 1. (a) the manually classified point cloud; (b) the classification result of single-scale method (r = 0.3m); (c) the classification result of multi-scale method (r = 0.02m-1m).

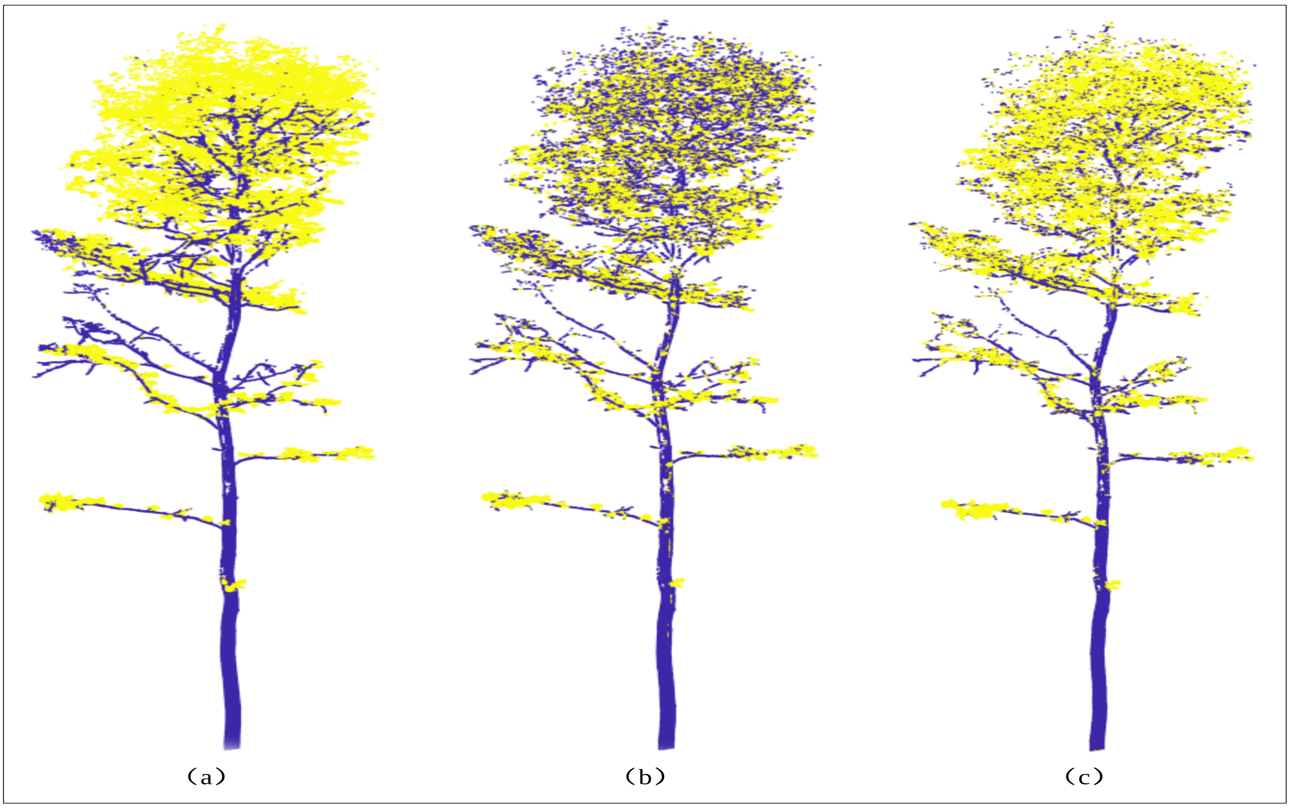

Figure 2. The point cloud of tree 2. (a) the manually classified point cloud; (b) the classification result of single-scale method (r = 0.14m); (c) the classification result of multi-scale method (r = 0.02m-1m).

3. METHODS

3.1 Feature Calculation

Let $q = (x, y, z) \in R^3$ be a point in the three dimensional space. $Q = \{q_i \in R^3 \mid i=1,\ldots,N\}$ denotes the tree point cloud. The scale r in our paper is defined as the radius of the ball centered on a point of interest. For each point in Q, the neighborhood ball is computed at one or more given scale(s). The Principal Component Analysis (PCA) is applied to the points in that ball (Shaw, 2013).

The ordered eigenvalues resulting from the PCA for point q_i are $\lambda_1 \geq \lambda_2 \geq \lambda_3$, which is used to infer the local spatial distribution pattern of this point. Let $P_i = \lambda_i /(\lambda_1+\lambda_2+\lambda_3)$. If $P_1 \gg P_2 \approx P_3$, the points in the ball are primarily distributed in one dimension, as in the case of branches. If $P_1 \approx P_2 \gg P_3$, the points in the ball are primarily distributed in two dimension, as in the case of leaves. Similarly, if $P_1 \approx P_2 \approx P_3$, the points are distributed evenly in three dimension. Then the salient feature (SF) of the given point at the given scale can be defined as the simple combination of P_1, P_2 and P_3.

$$SF = (P_1, P_2, P_3)$$

3.2 Classifier

The famous machine learning classifier Support Vector Machine (SVM) is used in our method (Vapnik et al.,1997). For a binary classification problem, it tries to find a hyper-plane $\boldsymbol{w}\,\boldsymbol{x} + b = 0$, which maximizes the distance of the closest vector in both classes. $\boldsymbol{w}$ is the normal vector to the hyper-plane, and b is the distance of the closest point on the hyper-plane to the origin. For a non-linear classification problem, it uses a kernel function implicitly mapping the vector into a high-dimension space to simplify the classification problem.

3.3 Evaluation

We use the balanced accuracy *(ba)* to assess the accuracy of single- and multi-scale classifiers. With *tl, tw, fl, fw* denotes the number of points *truly(t) / false(f)* classified into the *leaf(l) / wood(w)* class, balanced accuracy is classically defined as $ba = (al + aw) / 2$ with each class accuracy defined as $al = tl / (tl + fw)$ and $aw = tw / (tw + fl)$ (Brodu et al., 2012). The total running time of the processing includes the time consumed by feature extracting, classifier training, and leaf and wood classification. The speed-up ratio is used to assess the efficiency of single- and multi-scale classifier. With *ta* and *tb* denoting the total running time of classifier *a* and *b*, speed-up ratio of classifier *a* over *b* is defined as *ta / tb*.

4. EXPERIMENTS AND RESULTS

Our experiments are conducted on a 64-bit windows 10 with an Intel Core i7-7700k 4.2GHz processor and 16GB RAM. The source code of our method is written in C++ programing language. To reduce the computation load, we calculate the salient features on a subset of the tree point cloud. The number of points in the subset is about 10% of the tree point clouds Firstly, about twenty percent of the aforementioned data is used to train forty single-scale classifiers (r = 0.02m, 0.04m, 0.06m,…, 0.98m, 1m) and one multi-scale classifier (r = 0.02m-1m) for each tree. The reason why we train so many single-scale classifiers is that we want to obtain an optimal average classification accuracy of the single-scale classifier. Then, these classifiers are used to classify leaf and wood points for each tree.

The classified leaf and wood points of tree 1 and tree 2 are shown in Figure 1 and Figure 2, respectively. Owing to the limitation of space, we only plot one single-scale classifier classification result for tree 1 and tree 2 in Figure 1(b) and Figure 2(b),as they has the highest balanced accuracy. Similarly, the classification result of the multi-scale classifier for tree 1 and tree 2 is presented in Figure 1(c) and Figure 2(c), respectively.

The classification accuracies are shown in Figure 3. The highest balanced accuracy of the single-scale classifier ($r = 0.3m$) for tree 1 is 0.78, which is lower than that of the multi-scale classifier by about 4%. The highest balanced accuracy of the single-scale classifier (r = 0.14m) for tree2 is 0.82, which is very close to that of multi-scale classifier. However, the mean balanced accuracy of the single-scale classifiers for each tree is close to 0.7, which is lower than that of the multi-scale classifiers by about 10%. It is worth noting that the balanced accuracies of each classifier for tree 1 and tree 2 are lower than those reported in Yun et al. (2016), Ma et al. (2016) and Wang et al. (2017) by about 10%-15% because different tree point clouds, salient features and classifiers are used. Because the purpose of our study is to study the abilities of single-scale and multi-scale features to characterize the local spatial patterns of points in point clouds, we only build a classifier as simple as Brodu’s method.

The speed-up ratios of each single-scale classifier over the multi-scale classifier for both trees are shown in Figure 4. The mean speed-up ratios for tree 1 and tree 2 are up to 49.90 and 32.77, respectively. So more attention should be paid to reducing the computation load if we want to use multi-scale features to improve classification accuracy in the future.

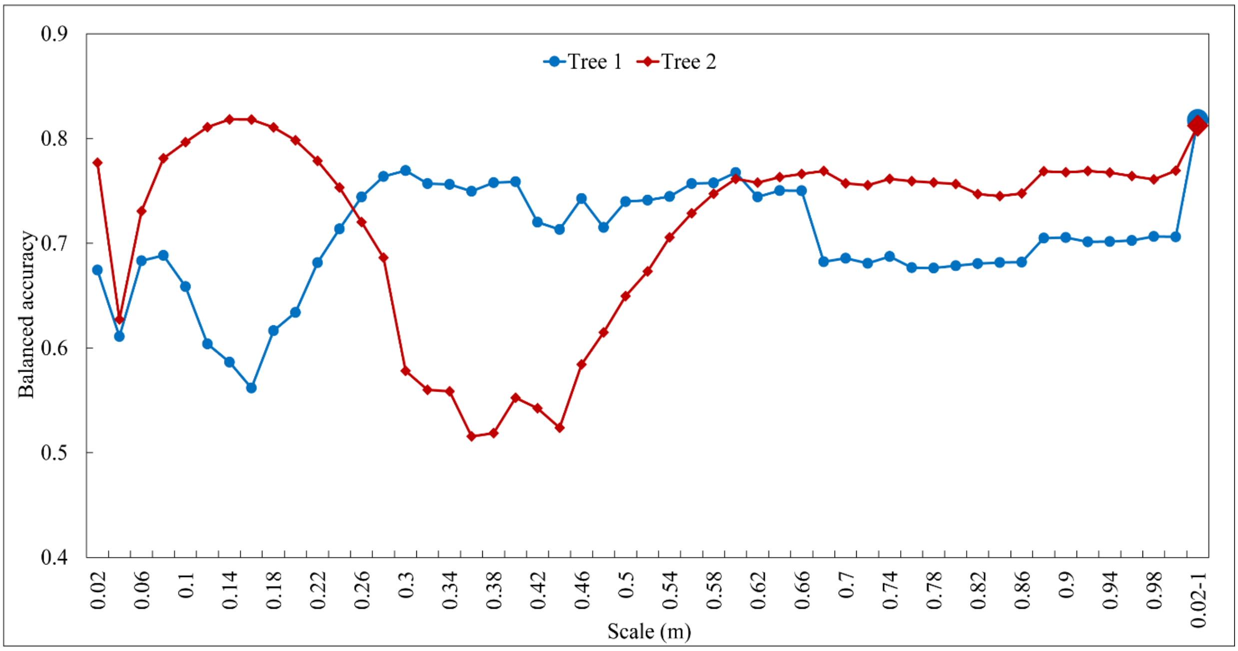

Figure 3. The balanced accuracy of each classifier for each tree. The balanced accuracy of multi-scale classifier is shown in the last column.

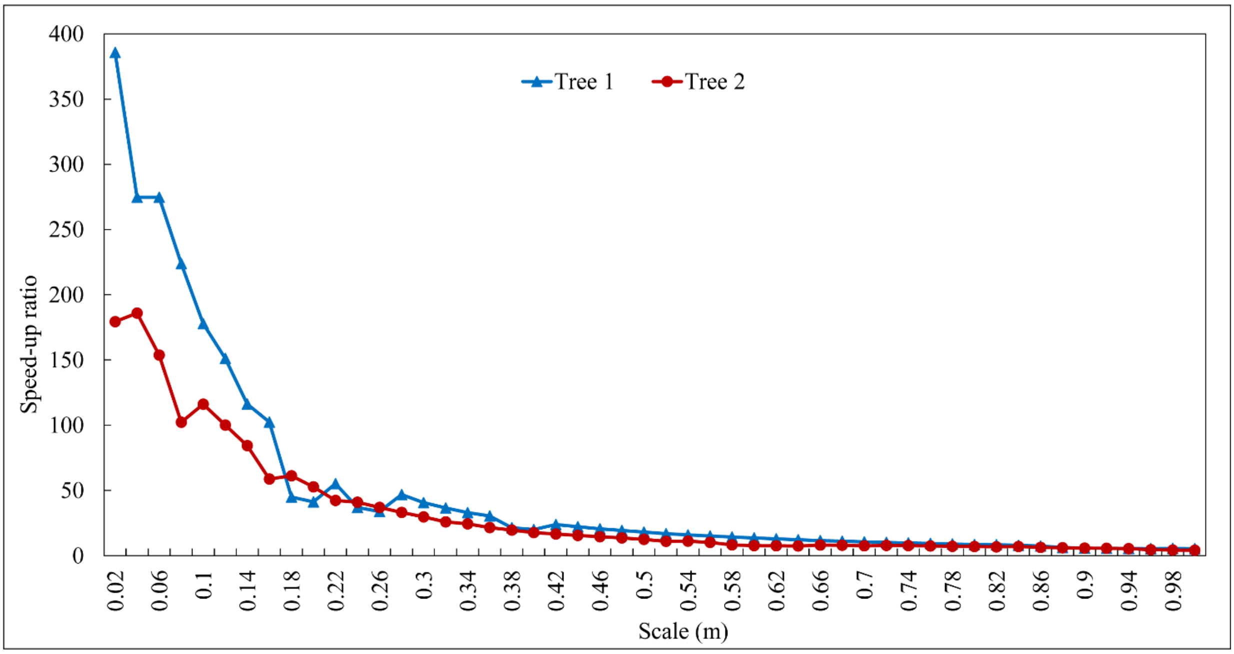

Figure 4. The speed-up ratio of each single-scale classifier over multi-scale classifier for each tree.

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5. CONCLUSION

In this study, we assess how single-scale and multi-scale features affect the classification accuracy and efficiency of leaf and wood. Two oak trees of different sizes and complexities are used to evaluate the accuracy and efficiency of the classifiers. Experimental results show that multi-scale features can achieve higher balanced accuracy. On average, the balanced accuracy of the multi-scale method is higher than that of the single-scale method by about 10%. However, the mean speed-up ratio of single scale classifiers over multi-scale classifier is higher than 30. In the future, we will employ more optimization strategies to reduce the processing time of the multi-scale method.

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