Efficient individual tree identification from multiple source point cloud

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Abstract. Detection and identification of individual trees are becoming increasingly important for forest related applications. Current, researches mostly concentrate on the segmentation of canopy height models (CHMs), which only produce rough tree delineation and numbers. Considering that different trees have changeable economic value and growing speed, this approach proposed a robust workflow that detects not only the location and shape of single trees but also the basic tree type. First, the multiple source point clouds are combined and classified to build the CHMs, based on the geometric information. Then, the tree tops are extracted based on the mathematical morphology operations. The tree delineation are then grown based on the tree tops and the competition among adjacent tress is considered. Finally, a multi-view projection based classification network was developed to identify the tree type, which meanwhile indicate the connecting trees that are hardly separated in CHMs. Experiments results on various data source demonstrate that the proposed approach can produce significant improvements on the detection results than existing researches.

1. Introduction

Trees are the most frequent considered elements in the forest related applications in recently researches[1-2]. Generally, most methods concentrate on the detection and delineation of trees based on the aerial LiDAR point cloud or the canopy height models (CHM) extracted from them [3]. Those information are important factors that indicate the biological characteristics and ecological functions of the forest. For instance, in the filed of electric transmitting, a precision estimation will not only benefit the planning of power network but also the safety of electric fluxlines.

Traditional approaches extract the tree information based on the top of the crown [4-5], which means the point with the extreme height in local, and the delineation of trees are grown from the peak point with certain constraints, i.e., the spatial connection and the absolute height in CHM. Such methods often face difficulties in separating connected trees, especially when not all the peak points are found. To deal with the issues, RANSAC based approaches was used in work of [6], which consider the surface of the crown as cones with vertical axis. The problem is that the some type of trees will be omitted when the shapes is not that regular or the thresholds are not properly set. Another limitation for current researches is that the information we try to extract are not enough for the corresponding applications. For instance, when consideration the safety of electric line, we care not only the tree height or its distance to the electric line, but also the type of the tree, since different trees have changeable growing speed [7-8]. In some applications, we want to reconstruction the whole...
scene and require more detailed structures, other than the center peak. Those information are sometimes not clear or even unavailable in single data source. As such, we need to make full use of the point cloud from various view or data source to fully understand the whole scenes.

In this work, an efficient approach to identify individual trees was proposed. The scene considered includes not only the urban street but also the forest areas. The tree points are first found, then separated into single trees, and finally classified into typical types. Experimental results on various data source shown that the proposed approach can extract detailed and precise information of individual trees from various data source.

2. Method

2.1. Overall workflow

The overall workflow of the proposed approach are provided in figure 1. The method starts with the registration of point clouds from different data source. Then a deep learning network is used to classify and extract the high vegetation points. Based on those points, the canopy height model can be constructed. Next, the mathematical morphology approach is adopted to find the local tree peak, followed by a region growing algorithm to detect the tree delineation and the corresponding tree point clouds. Finally, a projection based deep network is adopted to do the tree type classification, result in all the necessary information which can be further used in the forest related application.

2.2. Point cloud registration

Unlike tradition approaches that consider mostly the aerial point clouds, the data used in our approaches contain both aerial and vehicle points, with changeable view and stations. Such a solution makes it possible to evaluate the trees with more detailed and complete structure, while meanwhile bring much trouble to the registration procedure. The difficulties come from various factors, such as inconsistent details, varied point density and noisy, which makes traditional approaches like the ICP algorithms rather hard to properly work. Besides, we also need to consider the efficiency when dealing with multiple stations. In this work, we adopted the method in our earlier researches [8], and a graph structure is adopted to deal with the relations among different data sources and stations, and search for the best solution to merge all related points.
2.3. Construct of CHM
Once the point clouds are registered and merged, the vegetation points are classified and we use them to create the canopy height models within the area. The classification of the point clouds is based on the RandLA-Net [9], which is fast and robust for large area and high density data. The canopy height models (CHM) convert the unordered point clouds into a raster structure that are free from the influence of the up and down of the terrains. The mesh structure is first built based on the vegetation and ground points, and the isolate points or noise are filtered. The CHM values of the grid is then calculated by interpolation on the mesh, decreased by the ground height.

2.4. Local peak and tree delineation
Similar to the work of [10], the detection of the tree in CHM starts with the finding of local crown peaks. The mathematical morphology approach from OpenCV are used to found the convex areas and the peak points are the pixel with the maximum height inside. A advantage of the proposed approach here is that we use multiple view point clouds, and some of the tree trunks are available. This makes it possible to separate connected trees when some peak points are omitted. Such a work is realized by a extra step that extras the tree trunks via the tensor voting algorithms, since the trunk points have strong linear tensor features and are easily extracted.

Once the peak points are found, the tree delineation can be calculated with a growing algorithm. We use similar parameters with [10] while growing, including the searching radio and relative height ratio. The completion between adjacent tree are also considered, which consider both the tree height and the distance to the tree center. The growing algorithm will indicate the region of the target tree, therefore produce the tree delineation.
2.5. Tree classification and verifying
Once the tree points are available, this step further distinguishes the tree type and evaluates the tree with the estimated tree parameters. Point clouds from different views bring much more detailed information than only the aerial point clouds, makes it possible to further identify the tree type. Besides, results from above steps can be verified in this step, aim to distinguish the false classified objects and improve the detection results. Here we use a projection-based deep convolutional neural networks to do the classification. The tree points are projected in to 2D images from different views, forming a feature image, with a band for each view. The depth/relative length are taken as the gray level of the image, the color information can also be merged when available. In this way, the classification of trees can be converted into the issue of feature image labeling. False trees and multiple ones are also taken as unique classes while training, which are used to find the errors in above steps. Finally, we estimate the necessary parameters of the trees, including the type, width, height as well as the expected growing speed, which will be used in other applications.

3. Experiments
This section evaluates the proposed approaches experimentally. Figure 2 gives an overview of the two data sets. One is selected from the campus of the Southwest Jiaotong University (Swjtu), Sichuan, Chengdu, China; another is from the forest in suburban Nanchang (Nanchang), Jiangxi Province, China. Both data have two views: top view of both datasets are the aerial LiDAR point cloud with a density of about 4 pts/m²; ground view of the Swjtu is connected by vehicle LiDAR with the main circle road inside the campus, using the iScan-STM; ground view of Nanchang is connect by tens of fixed stations and one of which is also shown in Figure 2. The common area of the datasets are considered in the experiments.

Figure 3 (top) shows some details of the CHM files generated by the combined vegetation and ground points in common areas, as well as the detected local peak points. Figure 3 (down) are the corresponding LiDAR point clouds extracted based on the CHM files, which can be further processed in the classification procedure. It can be seen that most trees are successfully detected when the trees are sparse in Swjtu, results in a high precision. In the Nanchang data set, due to the limit DEM quality in mountainous regions, as well as the closed trees, the immediate results will face lost of difficulties when only consider the CHM results.
Figure 3. (top) CHM results and the peak points, and (down) corresponding point clouds.

Figure 4 gives examples of two connected trees that share common peak points, which are considered as one by the CHM file. Such situations are easily corrected by the ground view, since their tree trunk are rather clear and are successfully extracted.

Figure 4. Influence of taking ground view into consideration. (left) two trees share same peak points, and (right) results after consider the tree trunks from ground view.

For the tree type classification, only the results of the Swjtu data are available currently, since the corresponding training data are required. The labeled trees include four types: cinnamomum camphora, heteropanax fragrans, slash pine and gingko, each about 50 examples. We took 80% for training and 20% for testing, and a 86.7% overall precision was reported.
4. Conclusion
This work proposed an efficient approach to identify individual tree, using not only the urban street but also the forest areas. The tree points are first found, then separated into single trees, and finally classified into typical types. Experimental results demonstrate that the proposed approach can extract detailed and precise information of individual trees from various data source. The further works are for more precise detection, classification, as well as the modeling of the detailed tree structures.

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References
[1] Li, L., & Liu, C. (2019). A new approach for estimating living vegetation volume based on terrestrial point cloud data. PLoS ONE, 14(8), e0221734.
[2] McDaniel, Matthew N., Takayuki B., Christopher S., Phil I., Karl. (2012). Terrain classification and identification of tree stems using ground-based LiDAR. Journal of Field Robotics. 29. 891-910. 10.1002/rob.21422.
[3] Ayrey, E, Fraver, S, Kershaw, & JA, et al. (2017). Layer stacking: a novel algorithm for individual forest tree segmentation from lidar point clouds. Can J Remote Sens.
[4] Michael F., Alistair S., Andrew H., Paul E. G., Lee V., and Nicholas C.. (2006) Automated estimation of individual conifer tree height and crown diameter via two-dimensional spatial wavelet analysis of lidar data, Can. J. Remote Sensing, Vol. 32, No. 2, pp. 153–161.
[5] Li, W., Guo, Q, Jakubowski, M. K., & Kelly, M. (2012). A new method for segmenting individual trees from the lidar point cloud. Photogrammetric Engineering and Remote Sensing.
[6] Tittmann, P., Shafii, S., Hartsough, B., & Hamann, B. (2011). Tree Detection and Delineation from LiDAR point clouds using RANSAC.
[7] Zhong, R., Wei, J., Su, W., & Chen, Y. F. (2013). A method for extracting trees from vehicle-borne laser scanning data. Mathematical & Computer Modelling, 58(3-4), 727-736.
[8] Ge, X., and Hu H.*, (2020). Object-based incremental registration of terrestrial point clouds in an urban environment. ISPRS Journal of Photogrammetry and Remote Sensing, 161, 218-232.
[9] Q. Hu, B. Yang, L. Xie, S. Rosa, Y. Guo, Z. Wang, N. Trigoni, A. Markham, (2020) RandLA-Net: Efficient Semantic Segmentation of Large-Scale Point Clouds, In: CVPR.
[10] Zörner, J.; Dymond, J.; Shepherd J.; Jolly, B. (2018). PyCrown - Fast raster-based individual tree segmentation for LiDAR data. Landcare Research NZ Ltd.