Int J Appl Earth Obs Geoinformation 69 (2018) 64–77

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

journal homepage: www.elsevier.com/locate/jag

Automatic extraction of street trees' nonphotosynthetic components from MLS data

Sheng Xu[a], Shanshan Xu[a,*], Ning Ye[a], Fa Zhu[b]

[a] College of Information Science and Technology, Nanjing Forestry University, Nanjing, China
[b] School of Computer Science and Engineering, Nanjing University of Science and Technology, Nanjing, China

ARTICLE INFO

Keywords:
Nonphotosynthetic components
Stem
Individual tree
MLS
Urban environment
Clustering

ABSTRACT

This paper aims to propose a cluster-based approach for trees' nonphotosynthetic components extraction from mobile LiDAR point clouds. The presented algorithm uses a bottom-up hierarchical clustering strategy to combine clusters belonging to nonphotosynthetic components. The combination process depends on the dissimilarity between two clusters. The measure in the proximity matrix calculation consists of a distance term using the Euclidean distance and a direction term based on the principal direction, respectively. The main contribution of this paper is to solve the optimization of cluster combination by minimizing the proposed energy function and to extract nonphotosynthetic components through a hierarchical clustering process automatically. Performance of the proposed nonphotosynthetic components extraction shows that we achieve the completeness of 94.0%, the correctness of 98.9% and the *F*-score of 0.96 on the experimental urban scene. Besides, we succeed to achieve promising results on the stem detection and individual tree segmentation based on the extracted nonphotosynthetic component.

1. Introduction

Roadside vegetation is an important component of the urban environment and ecosystem, especially the street tree which plays a significant role in the pollution reduction and urban landscape. The nonphotosynthetic component of an individual tree refers to its main stem and branches, which is critical to retrieve the biophysical parameters, e.g. the biomass productivity (Edson and Wing, 2011) and carbon storage (Yun et al., 2016), and monitor the tree growth, e.g. the diameter at the breast height (DBH) (Kwak et al., 2007; Yao et al., 2012) and plant density (Korpela et al., 2010). Nowadays, the light detection and ranging (LiDAR) technique succeeds to collect 3D information of objects using high-density point clouds, which provides a chance for mapping 3D tree structure accurately. The following is a brief discussion of the related work on the nonphotosynthetic component extraction, including the stem detection and individual tree segmentation, from mobile laser scanning (MLS) data and terrestrial laser scanning (TLS) data.

The stem detection refers to the extraction of the main structural axis of a tree, which includes points between the ground and the first leaf branch. Lehtomäki et al. (2010) develop a method for the extraction of pole-like objects from MLS data. Their framework requires the segmentation work to split each scan line, the clustering process to merge the region of interest points, and the refinement step to combine clusters from the same pole and recognize each pole-like object. The problem is the low robustness to outliers, i.e. when there are scattered points around stems, trunks are difficult to be detected. Hetti Arachchige (2013) proposes a geometric-feature-based method for the tree stem segmentation from MLS data in urban environments. Their idea is to filter points from stems based on the principal direction feature which is calculated by exploring the variance of a point's neighborhood. This method does not need any priori knowledge of the tree, e.g. the size or height, and can be used for various kinds of tree structures. However, the performance of the stem growing is degraded by the break or hole on the stem caused by occlusion or data incompleteness. Liang et al. (2014) propose a method for mapping large forest plots with MLS data. They establish a local coordinate system to detect points on a vertical planar first and then use a series of 3D cylinders to describe stem sections. They achieve a high performance in the experimental forest, where stem points are from pole-like objects. Xia et al. (2015) propose a method to detect the stem of bamboos from TLS data. They succeed to distinguish neighboring stems and merge the thin structure stems from the same bamboo without a cylinder fitting process. However, a complex classification process is required before the stem detection to classify stem points. Xu et al. (2018) propose a stem detection method based on the dynamic programming technique

* Corresponding author.
E-mail address: shanshanxus@gmail.com (S. Xu).

https://doi.org/10.1016/j.jag.2018.02.016
Received 21 December 2017; Received in revised form 22 February 2018; Accepted 26 February 2018

with MLS data. The key steps include the detection process to extract candidate trees and the optimization process to achieve optimal stems. Their method works well in incomplete trees caused by the data collection and occlusion, but the detection performance highly relies on the circle fitting process, which incurs problems in the mix scene of trees and other pole-like objects.

The individual tree segmentation refers to extract independent tree crown points from input data. Pfeifer et al. (2004) propose a method for the reconstruction of individual trees in forests from TLS data. At the beginning, they model local branches of each tree by using the circular cylinder fitting. Then, they capture the axis direction and the axis position by setting a radius for the cylinder fitting. Finally, they track cylinders along branches and reconstruct the entire tree. They achieve a high performance in obtaining individual trees in the forest, where most trees stand vertically. Pu et al. (2011) propose a framework for recognizing different objects from MLS data. It starts with an initial rough classification, including the ground surface, objects on the ground, and objects off the ground. Based on the obtained segments' features, e.g. the size, shape, orientation and topological relationships, the objects on the ground are assigned to more detailed classes such as traffic signs, trees, and building walls. They do not require samples for training in the classification and succeed to recognize points from an individual tree. However, this knowledge-based method highly relies on the parameter setting, especially the vegetation region with various point densities. Raumonen et al. (2013) propose a method for efficiently obtaining the nonphotosynthetic component of individual trees, including trunks and branches, from TLS data. Their idea is to make a flexible cylinder model to reconstruct the surface of trees, after which the branches are modeled as collections of cylinders. They perform well in the nonphotosynthetic component extraction from artificial trees, however, the validation with a large number of trunks in the real scene is unmentioned in their work. Wu et al. (2013) propose a voxel-based method to segment tree crowns from MLS data. Their voxel-based morphological model succeeds to make full use of points' spatial information in the vertical and horizontal directions. They provide an improvement over 2D neighborhood search methods in the split of overlapping tree crowns. However, they detect the multiple-stemmed street tree as several separated trees in the urban scene. Tao et al. (2015) develop a shortest-path algorithm to help segment the overlapping region of trees from MLS data. They first detect trunks based on the assumption that trunks are separated from each other, and then segment crowns based on the fact that vascular plants tend to minimize the transferring distance to the root. They achieve a high accuracy in extracting the roadside trees from both TLS data and MLS data. However, incomplete stems are potential to be missed in their trunks detection. Fan et al. (2016) present a classification method to localize urban trees with MLS data. They organize off-ground points by the voxel technique first, and then localize candidate trees by setting thresholds for the elevation. After this, they extract object features based on the geometric information to classify tree points. They achieve high accuracy in the experimental palm trees, however, the non-adaptive thresholding method is easy to cause problems in a general urban scene with different tree structures. Li et al. (2016) propose a growing strategy to segment tree crowns from MLS data. They first remove artifacts by a coarse classification process to obtain the candidate tree clusters. After that, they select tree seeds for the following trunk points growing. Finally, they propose a dual growing process to separate one tree from others by circumscribing a trunk in a growing radius and segment a crown in the constrained growing region. Their method works well in different street trees, however, their tree growing process fails to deal with the trunk curvature and incompleteness. Zhong et al. (2017) provide a top-down segmentation pipeline for the individual tree segmentation, which includes a connectivity-based spatial clustering, a stem-based segmentation, and a normalized-cut-based refinement. This algorithm performs well in the split of neighboring trees by using their modified node similarity calculation. The problem is that the localization of stems relies on the horizontal histogram of the formulated nodes, which is easy to be affected by the point density.

Both MLS and TLS system succeed to collect the side information of objects using 3D point clouds. TLS system is flexible to collect data in different environments, such as the mountain and forest area. However, TLS data are limited to a small-scale scene, and the collection usually requires multiple scans, which brings the task of the point registration. In comparison, MLS system is easy to provide abundant side information of street trees, e.g. the trunks and branches, in a large-scale region. In MLS data collection, the mean point density along the trajectory is over 750 pts/m^2, which are suitable for the urban tree research. However, due to the fact that scenes in MLS data are more complicated than TLS data, e.g. much contamination generated in the collection and various artifact objects, the accuracy of the tree point extraction is far from being desired.

The objective of this paper is to propose a new bottom-up hierarchical clustering algorithm to the nonphotosynthetic component extraction from MLS point clouds. The clustering process starts with a number of clusters, and then conducts a series of merging operations to combine clusters from the same nonphotosynthetic component. Two main contributions of this paper are: (1) we provide a new clustering approach to the nonphotosynthetic component extraction from MLS point clouds, and (2) we succeed to optimize the cluster combination based on minimizing the proposed energy function. Our cluster combination is automatic and is globally optimal, which provides a better extraction result than methods using the greedy strategy in the grouping of the interest region.

This paper is organized as follows. Section 2 overviews the framework of the proposed nonphotosynthetic component extraction algorithm. Section 3 focuses on the calculation of the dissimilarity between clusters. Section 4 presents the optimization of the cluster combination based on the energy function minimization. Section 5 shows experiments to evaluate the performance of the proposed extraction. The conclusions are outlined in Section 6.

2. An overview of the proposed nonphotosynthetic component extraction algorithm

The process of the nonphotosynthetic component extraction is shown in Fig. 1. The first step is the data preprocessing for the outlier removal and the ground point filtering. The outlier removal is based on the calculation of the mean μ and standard deviation σ of k-nearest neighbors (Rusu et al., 2008). In our work, k is 30 and points between $\mu - \sigma$ and $\mu + \sigma$ are regarded as valid points. To improve the efficiency of data processing, ground points are filtered before the subsequent component extraction. As mentioned in the work of Xu et al. (2018), road points are much denser than off-ground points in MLS data in the urban environment. Since road points are lower than off-ground points, peaks in the elevation histogram can be used to find the elevation threshold for the ground filtering. Points that are lower than the elevation of the achieved peak point are regarded as ground points. Details of optimizing the peak point selection for the ground point removal are shown in Xu et al. (2018).

The second step aims to extract the points from the stems or branches, and merge them into a complete nonphotosynthetic component based on a bottom-top hierarchical clustering strategy. Assume that the input point set is P and the cluster set is C. Each element in C is a cluster containing one or more points from P. The goal is to achieve that each element in C is a point cluster of the complete nonphotosynthetic component of an individual tree. Main steps of the proposed hierarchical clustering are as follows.

(1) Start with a cluster set C and each element contains a point from P.
(2) Formulate the proximity matrix by calculating the dissimilarity between clusters.
(3) Solve the optimal combination solution to merge clusters and