STREET-SCENE TREE SEGMENTATION FROM MOBILE LASER SCANNING DATA

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ABSTRACT:

Our work addresses the problem of extracting trees from mobile laser scanning data. The work is a two step-wise strategy, including terrain point removal and tree segmentation. First, a voxel-based upward growing filtering is proposed to remove terrain points from the mobile laser scanning data. Then, a tree segmentation is presented to extract individual trees via a Euclidean distance clustering approach and Voxel-based Normalized Cut (VNCut) segmentation approach. A road section data acquired by a RIEGL VMX-450 system are selected for evaluating the proposed tree segmentation method. Qualitative analysis shows that our algorithm achieves a good performance.

1. INTRODUCTION

Mobile laser scanning (MLS), a widely used technology since year 2003 when the first MLS system was developed, has attracted much attention for mainly transportation-related surveys (Jacobs, 2005; Toth, 2009). It is a data revolution. With an MLS system, mobile mapping engineers can drive on a highway, rural road, and railroad, or along the shoreline of a river or lake. Along the way, the system captures trees, bridges, streetlights, buildings, power lines, other street-scene small objects (e.g. cracks, road markings). The collected data are a totally immersive three-dimensional (3D) view of the objects and surroundings (Rybka, 2011).

An MLS system, integrated with a navigation solution, laser scanner(s), high-resolution camera(s), and even more powerful computer systems, has been commercially available for several years (Stauth and Olsen, 2013). MLS systems are capable of working on all-day and all-weather conditions without the consideration of environmental illuminations. In addition, the acquired 3D point cloud data are with real-world coordinates, thereby providing accurate 3D geospatial information of roadways. Thus, studies on MLS as a reliable and cost effective alternative, is worthwhile for carrying out road-scene object inspections along route corridors.

In the case of urban areas, the detection and quantification of vegetation is important for road-scene feature inventory (for example, in safety studies and noise modelling) and environmental and ecological analysis. As an important component of urban vegetation, street trees play an important role in maintenance of environmental quality, aesthetic beauty of urban landscape, and social service for inhabitants. Most developed tree detection methods were applied to terrestrial laser scanning (TLS) point clouds. These methods range from 3D Hough transform, mathematical morphology to skeleton approaches by fitting free-forms.

Based on research achievement, Wu et al., (2013) presented a new step-wise Voxel-based Marked Neighbourhood Searching (VMNS) method for efficiently identifying street trees and deriving their morphological parameters from MLS data. The presented tree detection method included voxelization, calculating voxel values, searching and marking neighbourhoods, extracting potential trees, deriving morphological parameters, and eliminating pole-like objects. Shen et al. (2008) adopted the minimum spanning tree method for extracting objects (including trees) from scattered MLS points.

Rutzinger et al., (2010) segmented initially point clouds into planar regions using a 3D Hough transform and surface growing algorithm. A connected component analysis was further used to merge the remaining small segments. Some object statistics were calculated to obtain tree clusters by removing non-vegetation objects and temporary objects, such as cars and pedestrians. Finally, the classified tree points were thinned by deriving the vertices forming the 3D alpha shape of point clouds. A sphere with a certain radius (alpha value) was passed iteratively from the outside towards the points. Finally, the values of model parameters (describing only the outer shape of the tree.) were derived from the extracted single tree point clouds.

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Saarinen et al., (2013) used multi-temporal MLS data sets to detect the change of riverine vegetation. The proposed method first placed a 2 m × 2 m grid over the study area, and derived metrics describing vegetation density and height to predict the variables in the nearest-neighbour (NN) estimations. According to the training data obtained from aerial images, the vegetation cover type was classified into the following four classes: bare terrain, field layer, shrub layer, and canopy layer. The workflow combining detection and modelling was applicable on single trees scanned by TLS and also on larger areas acquired by MLS. The overall shape of the tree originates from the length of the primary branches and their position on the trunk.

This paper propose a two step-wise tree segmentation method, which includes (1) road point removal based on voxel-based upward growing filtering, and (2) tree segmentation based on a voxel-based normalized cut (VNCut) segmentation method. The remainder of this paper is organized as follows. Section 2 describes the used MLS data. Section 3 introduces the proposed tree segmentation method. Section 4 demonstrates the experiment results and discussion. Finally, concluding remarks are given.

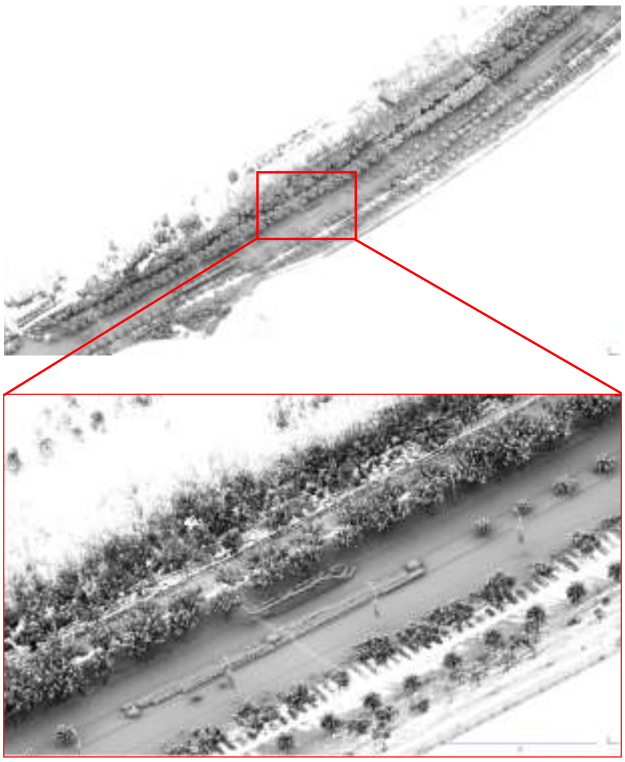


Figure 1. A road section of MLS data collected along Huandao Road in Xiamen, China.

2. MOBILE LASER SCANNING TEST DATA

The data were acquired on 23 April 2012 by a RIEGL VMX-450 system. The surveyed area is in a tropical urban environment, located in the City of Xiamen, southeast China. A complete survey was carried out, once in a forward direction and once in a reverse direction, on Huandao Road from Xiamen University to International Conference and Exhibition Center (ICEC), at a driving speed of approximately 50 km/h. This two-directional-four-lane Huandao road is separated by a median. This is a typical subtropical urban road area with high buildings, dense vegetation, and traffic signposts on both sides of the road. The surveyed road was quite busy; the average driving speed ranged from 30 ~50 km/hour. The buildings (e.g., high-rise residential apartments and commercial buildings) are located along this typical urban road.

This survey kept 30 m and 30 km/hour for target distance and ground speed, respectively. The point density for MLS data strongly relies on the nominal distance to the target where the point spacing is measured as well as the incidence angle. Accordingly, at the vehicle speed of 30 km/hour, the values of point density are estimated as 286.44 points/ m^2. Figure 1 shows a road section of the collected Huandao-Road points.

3. METHODOLOGY

The proposed method is two step-wise strategy: (1) the separation of terrain points and non-terrain points via a voxel-based upward growing filtering, and (2) individual tree segmentation based on a Euclidean distance clustering approach and a voxel-based Normalized Cut appraoch.

3.1 Terrain Point Removal

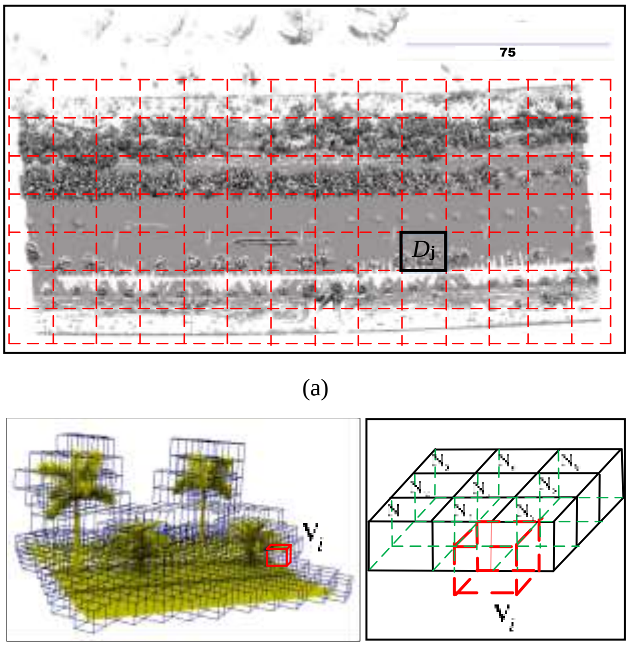
MLS systems collect very dense data close to the scanner path and less dense data farther away from the scanner path. Points belonging to road surface account for a great portion of the collected MLS data. Thus, the established filtering algorithms are unsuitable for filtering non-terrain points from MLS data. To improve computational efficiency, we develop a rapid and effective method, namely voxel-based upward growing filtering method, for removing terrain points. This method is implemented as follows:

1) Grid the entire point cloud into a set of data blocks, D_j (j = 0,1,…, N, where N is the number of data blocks), with a block size of w_b in the XY plane, as shown in Figure 2(a). The block size is determined by terrain fluctuations of the study areas of interest.

2) Organize each data block, D_j, into an octree partition structure with a spacing of w_v to generate a set of voxels, v_i (i = 0,1,…, M, where M is the number of voxels), as shown in Figure 2(b). The voxel size is empirically determined based on the point density of the acquired MLS point clouds and the computational efficiency of the proposed terrain removal method.

3) Each voxel, v_i, grows upward to its nine neighbors, N_1 to N_9, which are located above the voxel, as shown in Figure 2(c). Then, each neighbor continues to grow upward to its corresponding nine neighbors. The upward growing process stops when no more voxels can be reached. Finally, a voxel, v_e, with the highest elevation within the grown region is determined to justify whether voxel v_i contains terrain points or non-terrain points based on the following criteria:
   (a) If the elevation of v_e lies below a pre-defined terrain threshold, H_{thresh} label all points in voxel v_i as terrain points, which are further removed.
   (b) Otherwise, label all points in voxel v_i as non-terrain points, which are retained.

The proposed voxel-based upward growing filtering method has the advantage of rapidly and effectively handling large scenes with strong terrain fluctuations.



(a)

(b) (c)

Figure 2. (a) Gridding raw points of a road section into data blocks in the XY plane, (b) octree partition structure for block D_j, and (c) nine upper neighbors (N_1 to N_9) for each voxel v_i.

3.2 Tree Segmentation

To rapidly group non-terrain points into separated clusters representing individual objects, we use a Euclidean distance clustering approach, which clusters discrete points based on their Euclidean distances. Theoretically, an un-clustered point is grouped into a specific cluster if and only if the shortest Euclidean distance to the points in this cluster lies below a pre-defined threshold, d_t. Otherwise, a new cluster is created to contain this point. Such a Euclidean distance clustering approach starts at an un-clustered non-terrain point and then iteratively processes each un-clustered point until all non-terrain points are grouped into specific clusters. Through Euclidean distance clustering, most separated objects are successfully segmented. However, by using the Euclidean distance clustering approach, some adjacent or overlapped objects cannot be well segmented.

Before tree classification, individual trees must be separated from the clusters that contain multiple objects. In our previous study (Yu et al., 2015), we propose a voxel-based normalized cut (VNCut) segmentation method, which effectively segments point cloud clusters, containing multiple adjacent or overlapped objects, into separated objects. Thus, in this letter, we use the VNCut segmentation method to segment individual trees.

First, a cluster containing multiple overlapped objects is voxelized using the octree partition strategy with a voxel resolution w_s. Then, the generated voxels are organized into a complete weighted graph $\boldsymbol{G} = \{\boldsymbol{V}, \boldsymbol{E}\}$, where the vertices $\boldsymbol{V}$ are formed by the voxels, and the edges $\boldsymbol{E}$ are connected between each pair of voxels. The weights on the edges function to measure the similarities between the two connected voxels. Such a weight is computed based on the geometric features of the associated voxels as:

$$w_{ij} = \begin{cases} \exp\left(-\dfrac{\left\|p_i^{\mathrm{H}} - p_j^{\mathrm{H}}\right\|_2^2}{\sigma_{\mathrm{H}}^2}\right) \cdot \exp\left(-\dfrac{\left|p_i^{\mathrm{V}} - p_j^{\mathrm{V}}\right|^2}{\sigma_{\mathrm{V}}^2}\right), & \text{if } \left\|p_i^{\mathrm{H}} - p_j^{\mathrm{H}}\right\|_2 \le d_{\mathrm{H}} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where w_{ij} = the weight on the edge connecting voxels i and j
$p_i = (x_i, y_i, z_i)$ = the centroid of voxels i
$p_j = (x_j, y_j, z_j)$ = the centroid of voxels j
$p_i^{\mathrm{H}} = (x_i, y_i)$ = the coordinates of the centroid of voxels i on the XY plane
$p_j^{\mathrm{H}} = (x_j, y_j)$ = the coordinates of the centroid of voxels j on the XY plane
$p_i^{\mathrm{V}} = z_i$ = the z coordinate of the centroids of voxels i
$p_j^{\mathrm{V}} = z_j$ = the z coordinate of the centroids of voxels j
σ_{H}^2 = the variances of the horizontal distributions
σ_{V}^2 = the variances of the vertical distributions
d_{H} = a distance threshold restraining the maximum valid horizontal distance between two voxels

The centroid of voxel i is computed as:

$$p_i = \frac{1}{m_i} \sum_{k=1}^{m_i} p_k^i \tag{2}$$

where m_i = the number of points in voxel i;
p_k^i = a point in voxel i.

Thus, if the horizontal distance between two voxels exceeds d_{H}, the weight on the edge connecting these two voxels is set to zero. In the standard normalized cut segmentation method (Shi and Malik, 2000), the cost function that partitions graph $\boldsymbol{G}$ into two disjoint voxel groups $\boldsymbol{A}$ and $\boldsymbol{B}$ by maximizing the similarity within each voxel group and minimizing the similarity between two voxel groups is defined as:

$$Ncut(\boldsymbol{A}, \boldsymbol{B}) = \frac{cut(\boldsymbol{A}, \boldsymbol{B})}{assoc(\boldsymbol{A}, \boldsymbol{V})} + \frac{cut(\boldsymbol{A}, \boldsymbol{B})}{assoc(\boldsymbol{B}, \boldsymbol{V})} \tag{3}$$

where $cut(\boldsymbol{A}, \boldsymbol{B}) = \sum_{i \in \boldsymbol{A}, j \in \boldsymbol{B}} w_{ij}$ = the total sum of weights between voxel groups $\boldsymbol{A}$ and $\boldsymbol{B}$
$assoc(\boldsymbol{A}, \boldsymbol{V}) = \sum_{i \in \boldsymbol{A}, j \in \boldsymbol{V}} w_{ij}$ = the total sum of weights of all edges ending in voxel group $\boldsymbol{A}$.

The minimization of $Ncut(\boldsymbol{A}, \boldsymbol{B})$ is accomplished by solving its corresponding generalized eigenvalue problem (Shi and Malik, 2000). After eigenvalue decomposition, graph $\boldsymbol{G}$ can be bipartitioned into voxel groups $\boldsymbol{A}$ and $\boldsymbol{B}$ by applying a threshold to the eigenvector associated with the second smallest eigenvalue.

(a)

(b)

Figure 3. (a) Non-terrain points after terrain removal, (b) detected individual trees after VNCut.

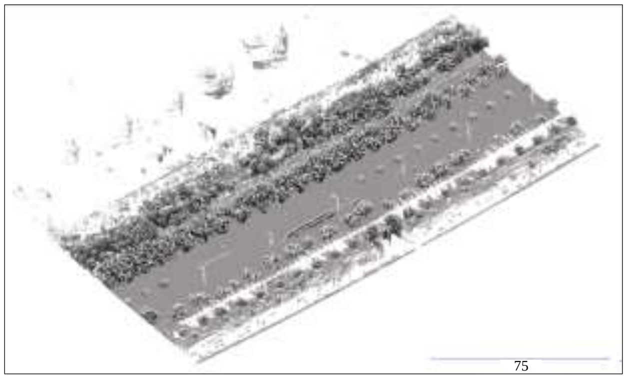
By using the VNCut segmentation method, the clusters that contain more than one object are effectively segmented into individual objects. After segmentation, prior knowledge (e.g. crown size) is used to filter out those non-tree objects such as light poles. Figure 3 shows a visual example of the detected individual trees.

4. RESULTS AND DISCUSSION

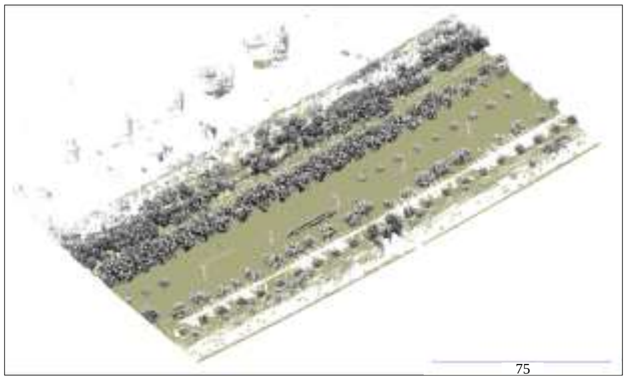
Figure 4 (a) shows a road section selected from the data (shown in Figure 1) for evaluating the proposed tree segmentation performance. This road section is about 60 m long. Some short trees (Sago cycas) are regularly planted in the middle of the road. Along two sides of the road, some trees are very dense and even overlapped with each other.

First, the voxel-based upward growing filtering method was used to classify the MLS data into terrain points and non-terrain points. In this study, the block size (w_b) and voxel size (w_v) were set to 3 m and 5 cm, respectively. The terrain threshold (H_{thresh}) was set to 0.3 m for removing terrain points. As shown in Figure 4(b), road points (rendered by olive colour) are separated well from non-terrain points. Figure 4(c) shows the classified non-terrain points only. After the removal of terrain points, the tree segmentation performed these non-terrain points via the proposed Euclidean distance clustering and voxel-based normalized cut.

Next, the clusters were created from the extracted non-terrain points based on a clustering threshold (d_t) of 0.15 m. The voxel size (w_s) was set to 5 cm. The thresholds of these parameters were empirically determined based on the point density of the collected MLS data. However, some clusters included several trees and other objects such as light poles because the trees, particularly planted along the road sides, were very dense and even severely overlapped together. Thus, the proposed voxel-based normalized cut was performed to obtain the individual trees. The segmented trees are shown in Figure 4(d). The visual inspection shows that the majority of trees individually segmented and the tree segmentation results are satisfactory.



(a)



(b)

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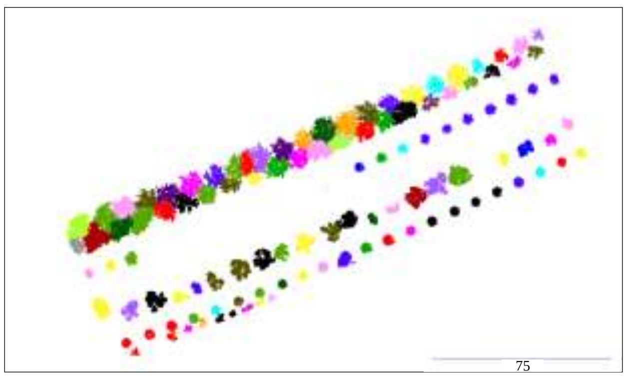

(d)

Figure 4. A test data selected from Figure 1. (a) The raw point cloud, (b) the classified terrain points and non-terrain point, (c) the classified non-terrain points, and (d) the individual tree segmentation results.

5. CONCLUSION

This paper has presented a two step-wise tree segmentation method from MLS data. To efficiently identify trees, the voxel-based upward growing filtering method was first presented to classify MLS data into terrain points and non-terrain points. Next, based on the classified non-terrain points, the Euclidean distance clustering was performed to obtain a set of clusters and then the voxel-based normalized cut method was used to obtain individual trees from these clusters. To evaluate the performance of the proposed tree segmentation, a road section was selected from the MLS data acquired by a RIEGL VMX-450 system. The visual inspection of the experimental results demonstrated the feasibility of the proposed method in segmenting individual trees from MLS data.

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REFERENCES

Guan, H., Yu, Y., Ji, Z., Li, J., Zhang, Q., 2015. Deep learning based tree classification using mobile LiDAR data. *Remote Sensing Letters*, 6(11), pp.864-873.

Jacobs, G., 2005. Uses in transportation in high-definition surveying: 3D laser scanning, *Professional Surveyor Magazine*, vol. April.

Rutzinger, M., Pratihast, A., Oude Elberink, S., and Vosselman, G., 2010. Detection and modelling of 3D trees from mobile laser scanning data. In: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Newcastle upon Tyne, UK, Vol.38, Part 5, pp. 520–525.

Rybka, R., 2011. Autodesk and Bentley systems talk about mobile LiDAR. *LiDAR*, 1(2), pp.41-44.

Shen, Y., Sheng, Y., Zhang, K., Tang, Z., and Yan, S., 2008. Feature extraction from vehicle-borne laser scanning data. In: *The International Conference on Earth Observation Data Processing and Analysis (ICEODPA)*, Wuhan, China, Vol.7285.

Shi, J., Malik, J. 2000. Normalized cuts and image segmentation, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(8), pp.888–905.

Stauth, D. and Olsen, M., 2013. Mobile LiDAR technology expanding rapidly, http://oregonstate.edu/ua/ncs/archives/2013/mar/mobile-lidar-technology-expanding-rapidly. [Accessed 04 January 2016].

Toth, C., 2009. R&D of mobile lidar mapping and future trends. ASPRS Annual Conference, Baltimore, Maryland, USA.

Wu, B., Yu, B., Yue, W., Shu, S., Tan, W., Hu, C., Huang, Y., Wu, J., and Liu, H., 2013. A voxel-based method for automated identification and morphological parameters estimation of individual street trees from mobile laser scanning data. *Remote Sensing*, 5, pp.584–611.

Yu, Y., Li, J., Guan, H., Wang, C., and Yu, J., 2015. Semiautomated extraction of street light poles from mobile LiDAR point-clouds. *IEEE Transactions on Geosciences & Remote Sensing*, 53(3), pp.1374–1386.