AUTOMATIC EXTRACTION OF ROADSIDE TREES FROM MMS DATA USING MINIMUM SPANNING TREE

T. Michikawa [a, b, *], K. Moriwaki [c], N. Yabuki [d], T. Fukuda [d], A. Motamedi [d], K. Hara [a], S. Kurimoto [a]

[a] Center for Environmental Innovation Design for Sustainability, Osaka University, Japan
- (michikawa, hara, kurimoto)@ceids.osaka-u.ac.jp
[b] Photonics Control Technology Team, RIKEN, Japan
[c] Division of Sustainable Energy and Environmental Engineering, Osaka University, Japan - kirkland1739@gmail.com
[d] Division of Sustainable Energy and Environmental Engineering, Osaka University, Japan
- (yabuki, fukuda, motamedi)@see.eng.osaka-u.ac.jp

KEY WORDS: Mobile Mapping System, Point clouds, Roadside tree, Segmentation, Minimum spanning tree

ABSTRACT:

This paper presents a method for extracting roadside trees from point clouds acquired by Mobile Mapping Systems (MMS). Our method first extracts pole-like object such as trees, utility poles and traffic signs from point cloud data based on conventional methods. Our contribution is to introduce a metric for classifying them into roadside trees and other artificial objects. The metric is defined by the length of minimum spanning tree of the point set projected onto horizontal plane. From our observation, the tree length for natural trees is longer than that for other artificial objects and the metric is efficient for classification. Indeed, experimental results show about 87 % of trees can be extracted from MMS data of streets by our method. In addition, we demonstrate its applications to urban planning and management including building tree inventory and evaluation of tree intervals.

* Corresponding author

1. INTRODUCTION

Roadside trees planted alongside streets play an important role for environmental improvement including landscape preservation, reduction of noises generated by cars, improving air quality, relaxation of heat island effect, and CO2 absorption (McPherson et al., 1999). Along with the global trend of adding roadside trees for such reasons, the number of roadside trees is increasing the past few decades in Japan. According to the report (Kurihara et al., 2014), over six million trees have been planted alongside streets and highways in Japan.

The major issue with roadside trees is their maintenance. This is because roadsides are considered severe environment due to high density of exhaust gas from cars which makes roadside trees vulnerable. Additionally, these trees can easily fall down when natural disasters such as typhoons and earthquake happen. In such incidents, infrastructures such as transportation and electricity supply may be damaged or blocked off by these trees. Thus, roadside trees are recognized as a risk factor for infrastructure management and their maintenance is an important issue for local governments.

Tree management procedure is introduced in resources such as Mattheck and Breloer (1994). However, shortage of human resource is a major problem for tree management. Tree management is generally conducted by professionals called tree doctors. They first roughly check all trees, and the selected trees are then examined carefully. The main problem of this approach is that it requires on-site examination which is time-consuming. In addition, examination results are often recorded in papers, that makes them easy to lose and difficult to use the data for analysis such as to track the growth of trees. Some studies resolve this problem efficiently by introducing IC-tags (Yabuki et al., 2011), however they still require on-site examination which it is difficult to cover all trees considering limited human resources.
Main objective of this research is to establish an efficient method for roadside tree management. This paper presents an automatic extraction method for data of trees from a point cloud data acquired by Mobile Mapping Systems (MMS). MMS is a 3D scanning system that uses a car, equipped with laser scanner, Global Positioning System (GPS) and Inertial Measurement Unit (IMU), and scans point cloud data of the surrounding environment while moving.

Our method consists of two major steps, extraction of all pole-like objects and classification of trees from the pole-like objects. In the first step, we extract pole-like objects as separate clusters based on an observation criterion that the trunks of trees can be approximated to cylindrical surfaces. For that, the points on the surfaces are used as initial seeds of pole-like object regions. Points neighboring to the pole-like objects are then merged using region growing technique. Since the first step extracts not only trees but also other artificial objects including traffic signs, utility poles and sign boards, in the second step we classify each cluster into trees and other artificial objects. The main contribution of this paper is to introduce a new metric based on the distribution of points projected on a horizontal plane. Distribution is defined by the sum of lengths of edges of Minimum Spanning Tree (MST) (Sedgewick, 2002) of the projected points. This metric gives an opportunity for clear classification of natural and artificial objects. Using this method, our experiment showed 87% accuracy for MMS data gathered in the city of Sapporo, Japan.

The extracted point clouds of trees can be used for various applications in policy management of roadside trees. This paper investigates some applications including building inventory of trees and tree interval evaluation. In addition, the paper discusses new potential applications for point cloud data of roadside trees.

This paper consists of six sections, Section 2 reviews related work, Section 3 describes the proposed method, Section 4 shows experimental results, Section 5 shows applications and discusses the future directions and Section 6 summarizes the paper.

2. RELATED WORK

Extraction of roadside trees from point cloud data can be considered as segmentation problem. Several methods have been proposed for extracting road assets, such as utility poles and traffic signs, mainly used for their maintenance.

One major approach is to extract local geometric features by Principal Component Analysis (PCA) or covariance matrix, because pole-like objects must have larger variance in single direction. Manandhar and Shibasaki (2001) introduced a method for extracting various types of features acquired by MMS. Given point cloud data, their method classifies man-made objects and natural objects by analyzing standard deviation in three directions.
Yokoyama et al. (2013) introduced a method for classifying objects by PCA. Their metric is based on PCA to point cloud with
smoothing. However, the metric is difficult to distinguish natural and other pole-like objects. Recently, Bremer et al. (2013) used covariance matrix analyses with different scales for decomposing the point clouds into features such as pole-like objects and ground. They also introduced a method for classification of pole-like objects' point clouds by analyzing the number of hierarchy levels of the graph created from their points. Their method achieves good results for trees without leaves.

The other approach is to use machine learning. Since various feature values/vectors can be extracted from point cloud data, they are used for classification by Support Vector Machine (SVM), random forest (Golovinskiy et al., 2009, Zhu et al., 2010, Ishikawa et al., 2013, Fukano et al., 2014). However, major bottleneck of machine learning approaches is preparing training data, or they are usually used segmented point clouds. Although Fukano and Masuda (2015) introduced a method for generating training data by creating an artificial 3D environment and simulating laser scanning in that virtual environment. environment. However, the classification accuracy is low.

3. TREE EXTRACTION FROM POINT CLOUD

3.1 Overview

Given an input point cloud acquired from an MMS, the proposed method extracts individual trees as separate clusters of point cloud data. Our challenge is to extract only roadside tree data from point cloud data of urban environment that includes many artificial objects such as cars, building and other roadside objects. Figure 1 shows an overview of our method.

In order to find them efficiently, we apply some pre-processing methods to remove unnecessary points (such as the road (Figure 1(a)) prior to applying the proposed method. The proposed method consists of two major steps. In the first step pole-like objects are extracted from the input point cloud (Figure 1(b)). Since trunks can be approximated to cylindrical surfaces, we use them as clues for finding pole-like objects. We use RANSAC algorithm (Fischler and Bolles, 1981) for extracting cylindrical surfaces. Second step is to classify pole-like point sets by using minimum spanning tree (Figure 1(c)). Our method evaluates the sum of edge length of minimum spanning tree of projected points. We describe the details of the method in the following subsections.

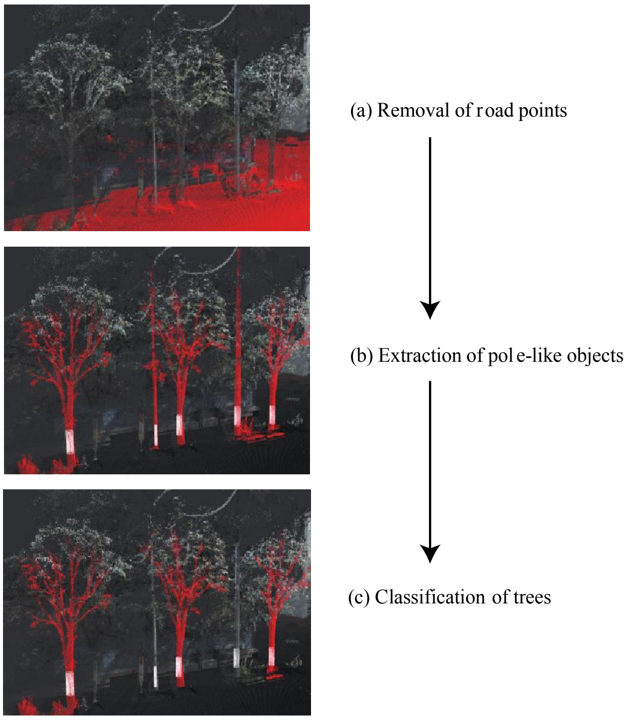


Figure 1: An overview of our method

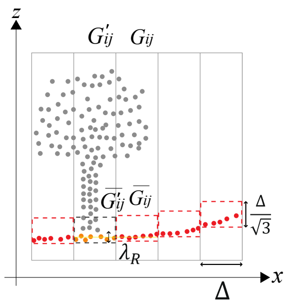


Figure 2: Extraction of road points

3.2 Removing road points

We first remove road points from the input data. The road points are distributed horizontally with small vertical variance (Figure 2). We detect these points and remove them in order to decompose point cloud into pole-like objects more easily. In order to remove the road points, we first decompose the input cloud by uniform grids of $n \times m$ size, and we evaluate distribution of points in each cell $G_{i,j}$. The points of the road have the lowest z-coordinates. We can define bounding box where the road points exist. The upper bound of z-coordinate of the bounding box can be defined by using the gradient of the road. The candidate point set in the bounding box are selected using Equation 1:

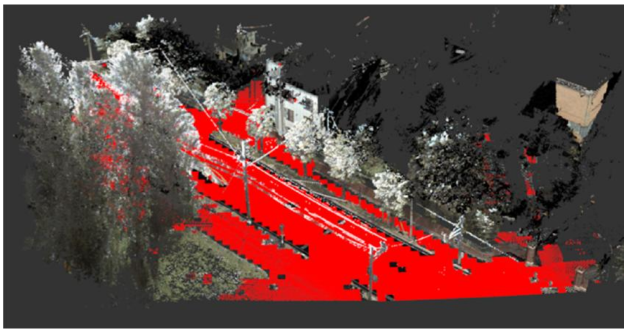
$$\overline{G_{i,j}} = \{p_k | p_{k.z} - z^0 < \Delta \tan\theta\,,\ p_k \in G_{i,j}\}, \qquad (1)$$

where $p_{k.z}$ denotes z-coordinate of p_k, z^0 denotes minimum z-coordinate in $G_{i,j}$, Δ denotes grid size and θ denotes gradient of the road respectively. In this paper we set $\theta = 30$[deg] for all examples. We evaluate $\overline{G_{i,j}}$ as road region when both Equations 2 and 3 are satisfied:

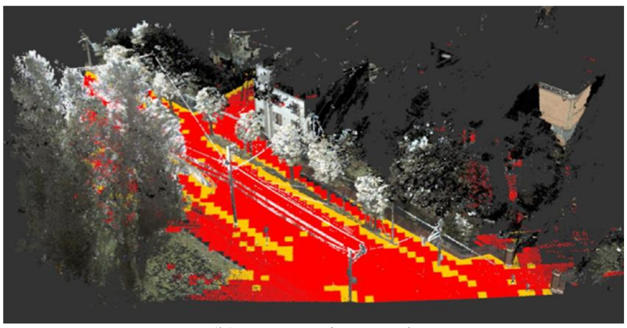
$$\lambda_0 \leq \tau, \qquad (2)$$
$$|\langle \overline{\mathbf{v}_0}, (0,0,1)^T \rangle| \leq \cos\,\theta, \qquad (3)$$

where λ_0 and $\overline{\mathbf{v}_0}$ denote the minimum eigenvalue and normalized corresponding eigenvector of the variance-covariance matrix of $\overline{G_{i,j}}$, and τ is a user-defined parameter (we use $\tau = 0.05$ [m] for all examples). Equation 2 evaluates variance in normal direction and Equation 3 distinguishes road and other flat points such as walls.

Figure 3(a) shows an initial result for classification. In the figure, road points are drawn in red and some of regions are not classified as road region yet. This is because the subset regions include obstacles such as tree roots and cars and they prevent to satisfy conditions in Equations 2 and 3. In order to detect these points as road points, we propagate the road regions to neighboring regions.



(a) Initial extraction result



(b) Propagation result

Figure 3: A result for road points removal

Propagation process is applied to regions that are neighboring the road regions $G'_{i,j}$ neighboring to $G_{i,j}$. We extract pseudo road points $\overline{G'_{i,j}}$ by Equation 4:

$$\overline{G'_{i,j}} = \{p_k \,|\, |p_{k.z} - \mathrm{avg}(\overline{G_{i,j}})_z| < h,\ p_k \in G'_{i,j}\}, \quad (4)$$

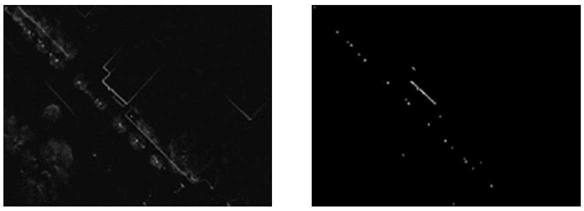
where $\mathrm{avg}(\overline{G_{i,j}})_z$ and h denote average z-coordinate of $\overline{G_{i,j}}$ and a user-defined threshold respectively. We set $h = 0.1$[m] in all examples. This value is decided based on the average difference between elevation of roadways and sidewalks. If the number of points in $\overline{G'_{i,j}}$ is larger than 50% of that of $G'_{i,j}$, we propagate to neighboring cells. We repeat this procedure until propagation stops. Figure 3(b) shows the propagation results in yellow. The result shows most of road points are extracted correctly.

3.3 Extraction of pole-like objects

Extraction of pole-like objects can be considered as cylindrical surface fitting problem. RANSAC (Fischler and Bolles, 1981) is a popular solution approach for this problem. However, RANSAC requires many tests for finding proper parameters for cylinders, and applying it to a large point cloud is time-consuming. Our method enhances processing by reducing unnecessary points (that clearly do not belong to pole-like objects) using projected images (Livny et al., 2010). The method first creates a density image by projecting the points onto horizontal plane. Each pixel (x, y) stores density value $\rho_{x,y}$ of the points $I_{x,y}$ defined by Equation 5:

$$\rho_{x,y} = \sum_{p_u \in I_{x,y}} w(p_{i.z} - z^0)\ , \quad (5)$$

where $w(h)$ is a binarization function that returns 1 if $w(h) \leq H_d$ and 0 otherwise. A density image is shown in Figure 4(a)
is shown in Figure 4 (a). Since trees are usually grow vertically, the density of projected points at trunks are higher than of leaves. We apply a simple binarization with a threshold ϵ to the density image in order to extract points around pole-like objects as shown in Figure 4(b). This enables us to extract only walls and pole-like objects and drastic decrease in the number of points.



(a) Density image (b) Binarization result

Figure 4: Point projection onto a 2D image

Parameter estimation for the fitted cylinder is computed by selecting two random points and using their position and normal vector values (Schnabel et al., 2007). Fitting score is defined by the number of points that their distance to the fitted cylinder are less than the user-defined threshold λ_c . In our experiment, we used $\lambda_c = 0.015$[m] . We consider pole-like objects exist where cylinder with high sore is identified. Figure 5 shows the fitting result. Wireframe cylinders denote the fitted result. However, this approach may pick large objects as pole-like entities (Figure 5 (b)) because the large number of points in these objects may fall under the above mentioned criteria. We can eliminate this problem by evaluating the ratio of points fitted onto the cylinders.

(a) (b)

Figure 5: Fitting result

Using RANSAC output, segmentation of the point cloud is performed. The final step is to extract pole-like points using cylinder fitting result. We first build *k*-nearest neighbor graph which connects close points. Then, region growing for the graph is applied with points near the cylinder as initial seeds. Since the road points are removed in the first step, most of trees can be extracted clearly. In case of overlapping or connected trees, they are segmented from an intermediate surface. Figure 6 shows the result of segmentation.

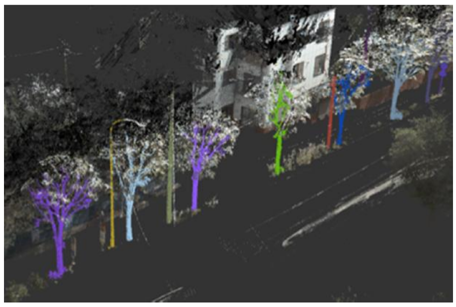
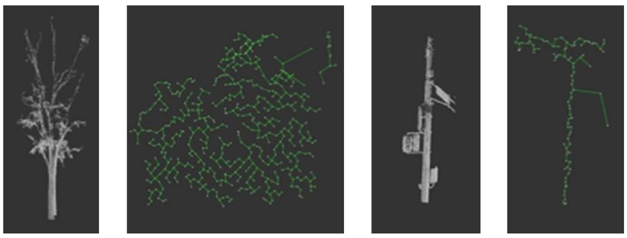
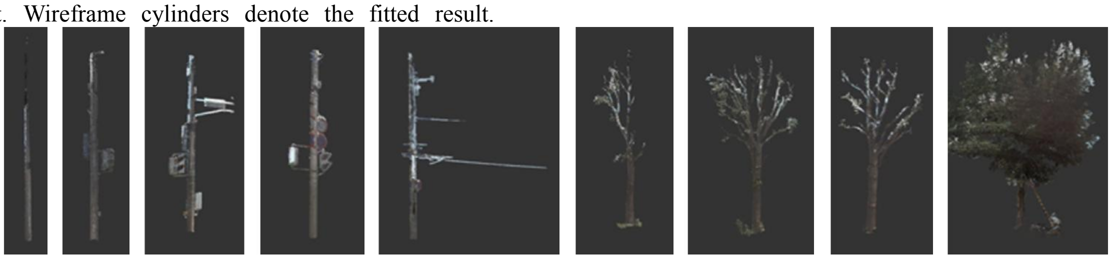


Figure 6: Segmentation result.



(a) Tree (b) Utility pole

Figure 7: Classification by Minimum Spanning Trees of projected points



PLO	92	81	61	62	52	53	63	63	36
MST	3	8	12	15	32	36	42	62	170

Figure 8: Comparison of our metric with PLO metric

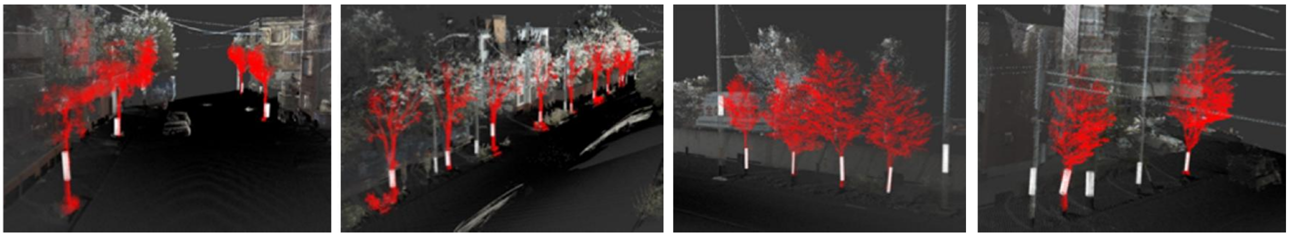


Figure 9: Results

3.4 Classification of pole-like objects

Extracted pole-like points are not only trees but also other artificial objects such as utility poles and traffic signs. This step distinguishes tree from other artificial objects.

From our observation, we found out that there is a significant difference in the distributions of points for different pole like objects. Distribution of artificial objects is non-uniform, whereas natural objects is uniformly distributed. In order to evaluate their distributions, we introduce a new metric by using Minimum Spanning Tree (MST) of the graph G. Our metric is defined by the total length of edges of MST of the points projected onto horizontal plane as described in Equation 6:

$$L_{mst}(G) = \sum_{e_j \in G} \|e_j\|, \qquad (6)$$

where $\|e_j\|$ denotes the length of edge e_j. Figure 7 shows examples of the MSTs of two point clouds. We can confirm the total length of MST of the tree is longer than that of artificial objects. Additionally, we evaluated the MST length (L_{mst}) for various pole-like objects. Figure 8 shows the Pole-Like Object (PLO) metric results introduced by Yokoyama et al. (2013). Analyzing two different metrics shows that MST is capable of distinguishing trees from other pole-like objects more clearly.

In our implementation, Kruskal algorithm (Kruskal, 1956) is used for building MST. We compute MST on a 2D image, created by projecting the original point cloud. This method removes the effect of the density of the point cloud on the MST score.

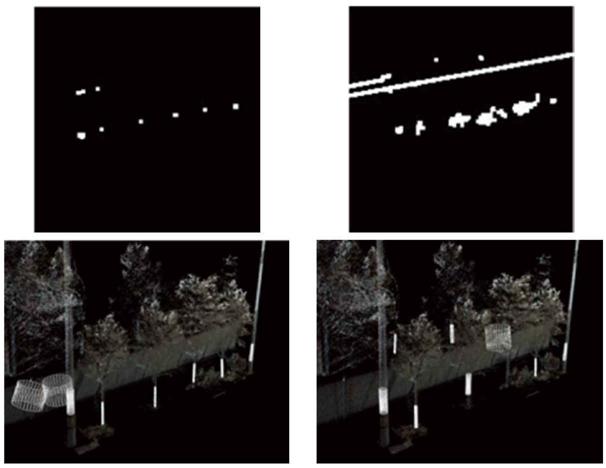
4. RESULTS AND DISCUSSION

We implemented above algorithms using Point Cloud Library and OpenCV, and applied to MMS data of Sapporo city, Japan. Figure 9 shows the results of extraction. In each figure, white wireframe shows the cylindrical fitting results and tree data are drawn in red. We can confirm that our metric can effectively distinguish roadside trees from other artificial objects. Table 1 summarizes the extraction result. The input data contains 123 trees in total confirmed by the authors. Our method extracted 121 separate clusters identified as trees where 108 of those were correctly detected. Among those, 13 non-tree objects were extracted as trees and 15 trees are failed to be extracted. As a result, 87.8% of the tree can be extracted from the MMS data.

Ground truth (confirmed by the authors)	123
Extracted clusters as road side trees	121
True positive	108
False positive	12
# missed trees	15

Table 1: Statistics

There are two main reasons for the error. First reason is related to the process of binarization for creating projected images in Equation 5. As shown in Figure 10, it is difficult to extract all pole-like with a single threshold, this is because the density of the original point cloud varies due to scanning conditions. Hence, when projected on 2D surface they do not reach the density required by binarization. As a result, defining an optimum threshold is difficult and is specific to each point cloud input set. The other reason is related to the placement configuration of some utility poles. As shown in Figure 11, the utility poles are installed close to each other. Hence, it is difficult in our current implementation to decompose them, and it extracts them as a single object. Additionally, the MST metric for this object becomes relatively large and the method identifies it as a tree.



$\epsilon = 50$ $\quad\quad$ $\epsilon = 15$

Figure 10: Difficulty of threshold control (Top: Binarization image, Bottom: Fitting result)

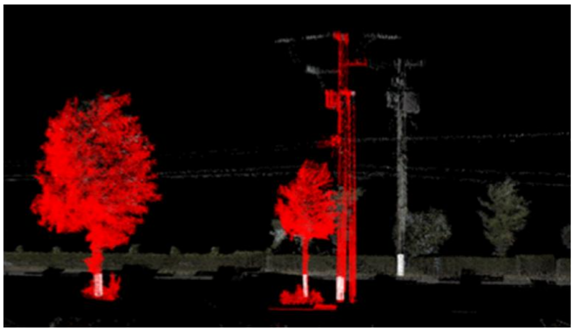


Figure 11: An example of misrecognition

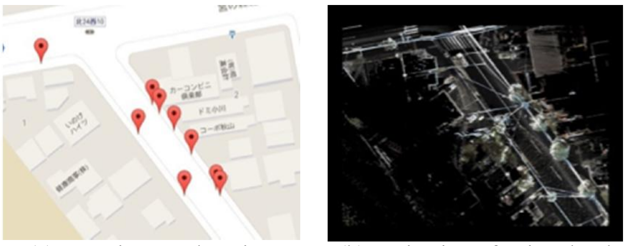
Computation time for our dataset was about 150 seconds on a common desktop PC with Intel Core i7-4770k (3.50 GHz) CPU and 16GB RAM. The main bottleneck is MST computation by Kruskal algorithm in which the most time is spent. Improving performance is promising since their computations are independent from each other and it is easy to parallelize.

The efficiency of our method largely depends on the result of cylindrical fitting, for example having enough scanned points from cylindrical part of trees (i.e., their trunk). For instance, using our proposed method, it is difficult to extract trees occluded by
walls. In addition, our method is designed to extract roadside trees and other approaches will be required for extracting other types of roadside plants.

5. APPLICATION TO POLICY MANAGEMENT

The extracted tree data is a promising information source to be used for various applications in policy management related to roadside tree maintenance. This section shows two applications and discusses a future direction of the use of point cloud data for tree maintenance.

First application is an automatic creation of tree inventory. Roadside trees are usually managed by local governments using physical logs. The inventory includes information of each tree such as position, height and diameter of the trunk. These information is usually acquired by stationary measurement devices such as total stations. The use of stationary instruments provides more precise information, however they are inefficient for measuring a large number of trees in a geographically large area. Whereas the use of MMS is less precise, however they can process large number of trees on streets in one data collection round. Figure 12 (a) shows a simple example of tree inventory implementation on Google Maps. This example computes tree location from MMS data and adds red location pins on the maps. Projected image of original input point cloud is shown in Figure 12 (b) for comparison.



(a) Mapping tree location (b) Projection of point cloud

Figure 12: An application to tree inventory

Second application is the evaluation of tree planting interval. Local governments usually have their guidelines for planting as shown in Table 2 (Koto-city committee on roadside trees, 2010). These type of guidelines are mainly developed to promote unified landscape design that both beautifies the city and improves the environmental health factors. However, these guidelines may be updated based on the new requirements corresponding to the growth of the city. The MMS data will enable us for rapid evaluation of existing tree intervals.

Width of road [m]	Tree height [m]	Interval [m]
>3.0	>5.0	8.0
2.5-3.0	2.5-3.0	6.0

Table 2: A guideline for tree intervals of Koto city (Tokyo)

This research has developed an interval evaluation system based on the criteria given by the user (Figure 13). In the experiment, the desired interval is set to 8.5 ± 1.0 [m] and invalid interval is visualized in red. The center of fitted cylinders are used for computing interval between trees. Once trees are extracted, these kind of evaluation is easy to implement. Additionally, parameter survey by changing valid intervals is also possible which is useful for decision making.

As shown in above examples, the main advantage of MMS scanning is to efficiently collect data of a large area in a short time period, comparing to stationary scanners. This enables us to roughly grasp trends and estimate basic indices such as location and height. On the other hand, detailed analysis of condition and health factors of tree is still difficult to perform using low density data gathered by an MMS. Hence, these is still need for diagnosis by human for certain applications.

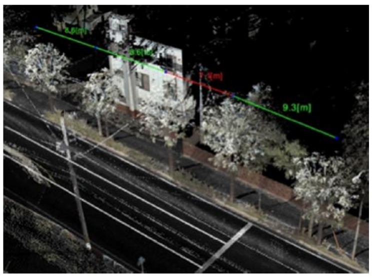


Figure 13: Computer-aided design of tree interval

Another possible application of MMS data is tracking the changes of shapes and parameters of trees over time. As natural objects grow by time, their overall shape changes per each scanning interval as well as seasonally. Since, the main purpose for gathering MMS data is mainly to acquire information about artificial objects such as civil structures and roadside poles, the scanning usually repeated in large time intervals. However, if roadside trees could be scanned by MMS in short term intervals such as per season, some other additional knowledge can be acquired by analyzing changes.

6. SUMMARY AND FUTURE WORK

This paper has presented an automatic method for extracting roadside tree from urban point cloud data scanned by MMS. The proposed method classifies the extracted pole-like objects using MST-based metric. This method is efficient for classifying roadside trees and artificial objects. Our case study showed 87.8% accuracy on tree extraction. In addition, the paper investigated two applications using the extracted trees, and discussed other possible applications for the use of MMS for tree maintenance.

The main future work for this research is to investigate practical solutions to achieve 100% extraction accuracy. However, we do not envision that this accuracy can be achieved by this method or any future extension to it. We expect the maximum accuracy can be achieved using minimum users input considering the cost function. In addition, we would like to explore additional applications in policy management fields using the extracted data.

ACKNOWLEDGEMENTS

The MMS data is courtesy of Digital Geometry Processing Laboratory at Hokkaido University and Asia air survey Co. Ltd.

REFERENCES

Bremer, M., Wichmann, V. and Rutzinger, M., 2013. Eigenvalue and graph-based object extraction from mobile laser scanning point clouds. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences II-5/W2*, pp. 55-60.

Fischler, M. A. and Bolles, R. C., 1981. Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography. *Commun. ACM* 24(6), pp. 381-395.

Fukano, K. and Masuda, H., 2015. Classification for road side objects based on simulated laser scanning. *in Proceeding of the Second International Conference on Civil and Building Engineering Informatics.*

Fukano, K., Oguri, S. and Masuda, H., 2014. Recognition and reconstruction of roadside objects based on mobile mapping data. *in Proceeding of The 15th International Conference on Precision Engineering (ICPE2014)*.

Golovinskiy, A., Kim, V.G. and Funkhouser, T., 2009. Shape-based recognition of 3D point clouds in urban environments. *in 2009 IEEE 12th International Conference on Computer Vision*, pp.2154-2161.

Ishikawa, K., Tonomura, F., Amano, Y. and Hashizume, T., 2013. Recognition of road objects from 3D mobile mapping data. *International Journal of CAD/CAM* 13, pp.41-48.

Koto-city committee on roadside trees, 2010. A guideline of planting roadtrees in koto-city. *https://www.city.koto.lg.jp/seikatsu/douro/gairoju/gairoju.html* (Retrieved on 16 Feburary, 2015, written in Japanese).

Kruskal, Joseph B., J., 1956.On the shortest spanning subtree of a graph and the traveling salesman problem. *Proceedings of the American Mathematical Society* 7(1), pp.48-50.

Kurihara, M., Takeda, Y. and Kubota, S., 2014. The roadside trees of japan vii. *Technical Report No. 780*, National Institute for Land and Infrastructure Management, Ministry of Land, Infrastructure,Transport and Tourism. (Written in Japanese).

Livny, Y., Yan, F., Olson, M., Chen, B., Zhang, H. and El-Sana, J., 2010. Automatic reconstruction of tree skeletal structures from point clouds. *ACM Trans. Graph*. 29(6), pp. 151:1-151:8.

Manandhar, D. and Shibasaki, R., 2001. Feature extraction from range data. *in Proceedings of the 22nd Asian Conference on Remote Sensing*, Vol.2, pp. 1113-1118.

Mattheck, C. and Breloer, H., 1994.Field guide for visual tree assessment (VTA). *Arboricultural Journal* 18(1), pp. 1-23.

McPherson, E.G., Nowak, D.J. and Rowntree R. A. eds., 1999. Chicago's urban forest ecosystem: results of the Chicago urban forest climate project. *Technical Report NE-186, U.S. Department of Agriculture, Forest Service, Northeastern Forest Experiment Station*.

Schnabel, R., Wahl, R. and Klein, R., 2007. Efficient RANSAC for point-cloud shape detection. *Computer Graphics Forum* 26(2), pp.214-226.

Sedgewick, R., 2002. Minimum spanning trees. *in Algorithm in C*, Addison-Wesley, Oxford, chapter 20, pp. 219-264.

Yabuki, N., Kikushige, Y. and Fukuda, T., 2011. A management system of roadside trees using RFID and ontology. *Computing in Civil Engineering,* pp.307-314.

Yokoyama, H., Date, H., Kanai, S. and Takeda, H., 2013. Detection and classification of pole-like objects from mobile laser scanning data of urban environment. *International Journal of CAD/CAM* 13, pp.31-40.

Zhu, X., Zhao, H., Liu, Y., Zhao, Y. and Zha, H., 2010. Segmentation and classification of range image from an intelligent vehicle in urban environment. *in 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp.1457-1462.