Deep learning with 3D laser data to identify tree species

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1. Introduction

The 3D laser technology is commonly available for automatic driving system to detect collision on the road. The rapid 3D sensor development enables us to monitor trees along the road if the sensor can identify trees. To identify trees, a fast laser processing technique is required. In image processing, a semantic segmentation has been developed to classify rough sketch of objects (cars, buildings, and vegetation) on 2D landscape images. However, the vegetation has not been classified more by species name. The species identification by laser can play an important role for urban tree recognition. The mobile mapping systems only cover a portion of canopy or one side of stems. The technique to identify species from the limited view of a tree is needed to develop an accurate species identification system.

Deep learning (DL) is one of the most powerful machine learning techniques automatically identify unique features of objects based on training samples. DL has been extensively used for classification in remote sensing. The native species was identified in Spanish savanna to get more than 90% accuracy compared to 70% accuracy of conventional object-based classification (Guirado *et al.*, 2017). Individual palm trees in Malaysia were identified and segmented over densely populated stands from Quickbird (Digital Globe Inc.) high resolution images to reach 90% accuracy (Li *et al*., 2017). However, high accuracy needs a large number of training samples. To reduce collecting samples, the transfer learning has been proposed to borrow the network built from different training samples (Carranza-Rojas *et al.*, 2017). But it is still challenging to collect samples efficiently and the DL accuracy relies on the number of training data. This study proposes a way to generate 2D images of different view angles from a 3D tree virtually as an efficient way to provide 2D training samples for DL processing.

2. Methodology

2.1 Study site and field data

The study site was located at Shinjuku Gyoen National Park in downtown Tokyo, Japan. The park has 58.3 ha area and trees has been preserved since 1591. The five tree species were selected and used for this study (Figure. 1), Italian stone pine (*Pinus Pinea*), Himalayan cedar (*Cedrus deodara*), black pine (*Pinus thunbergii*), London planetree (*Platanus x acerifolia*), cherry blossom (*Prunus spp.*)。 The 10 trees were sampled from each species and the total 50 trees were scanned by terrestrial laser scanner. The reason to choose these species was to have unique shapes and the bigger size among trees in the park. We conducted fieldwork between August to November in 2020. The terrestrial laser scanner used for this study was LMS511 (SICK Inc.). A tree was scanned from two vantage points to cover the front and the back of a tree to get an entire shape. LMS511 laser scanner has 905mm wavelength, 4.7 mrad, 40 m max. distance, and -60°to 90°vertical angle range. The field data was tree height, diameter at breadth height (DBH), crown width, the lowest height of branch and stem. We only used tree height and DBH for the validation of the laser scanner coverage.

2.2 Methodology

The software named cloud compare was used to merge 3D data taken from the two scanning locations (the front and the back of a tree). During the process, the objects such as a fence and shrub were removed only to extract a tree. To create input images for DL processing, the 2D images were generated from

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Technische Universität Wien, 2021. DOI: 10.34726/wim.1861
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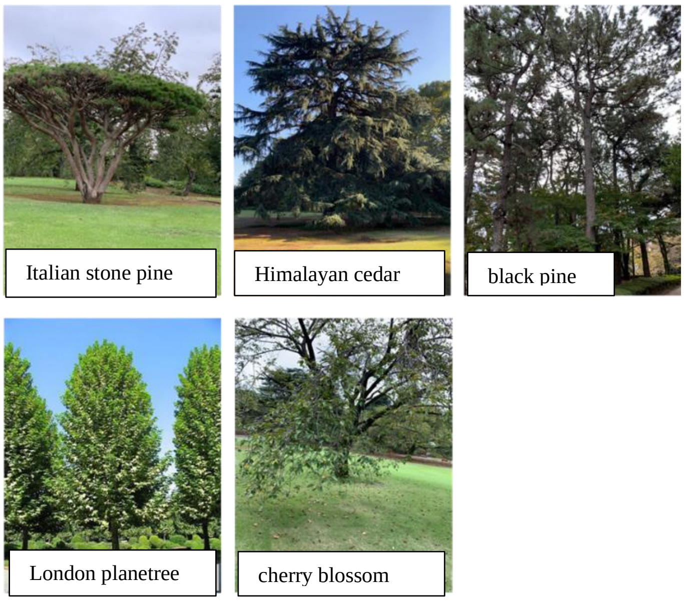

Figure 1: Tree species used for this study.

various viewpoints of a 3D tree virtually. The 3D data was coloured by height and was viewed from different vertical and horizontal angles to create 2D images. For this study, we set the vertical angles for 0°, 30°, 60°, and 90° and horizontal angles for 0°, 90°, 180°, and 270°. The total 16 images were generated from one tree (Figure. 2). DL processing used for this study was Visual Recognition of IBM Watson Studio (IBM Inc.) to identify tree species. The 70% of entire samples was used as training dataset and the rest 30% was used as validation dataset. The total images generated by this method were 5 (species) x 10 (trees) x 16 (images) = 800 (images).

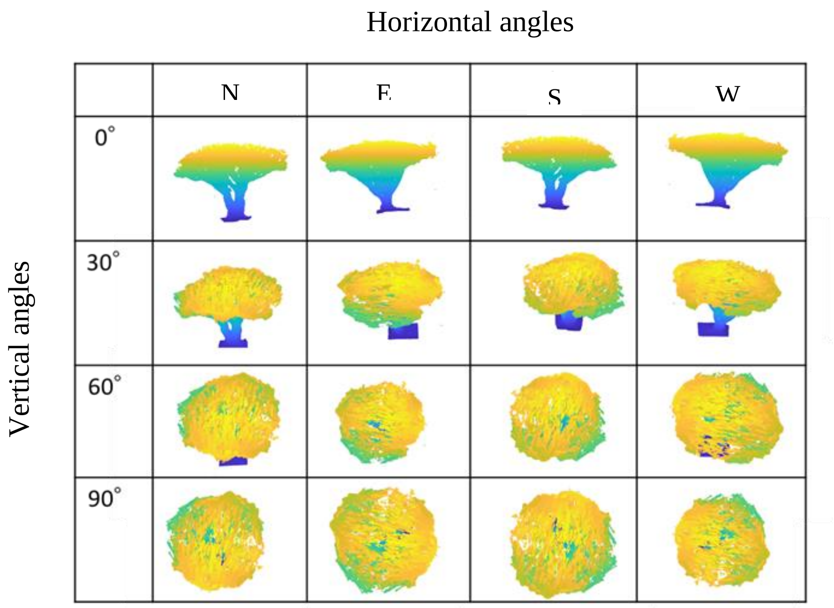

Figure 2: Generating different view angle 2D images from a 3D tree for DL processing.

3. Results and Discussion

Tree height and DBH had good relation between field and laser measurement. Tree height had 0.94 of R^2 value (p < 005) and DBH measurement had 0.7 of R^2 value (p < 005). The sensor used for this study has enough capability to cover the upper height vertically and reach enough depth inside canopy horizontally. And tree hight and DBH were the most trustable parameters from field data to validate this sensor capability.

DL result showed the listed species with ratio. The highest number of the ratio was used as the species identified from DL. Furthermore, the training and validation data was separated by vertical angle to obtain each accuracy by angle (Table 1). The overall accuracy was derived by all data (Table 2) . From Table 1, London planetree had similar shapes within the same species samples and Italian pine was the most unique shape different from the other species. They were identified accurately. Cherry blossom, black pine, and Himalayan cedar had more irregular and diverse shapes from various looking angles. It was difficult to find the common feature during DL process among training dataset. Thersefore, the within-species variance was more than the among-species variance. Black pine and Himalayan pine were misclassified each other by 40%. From Table 1 and 2, overall accuracy had the lower accuracy than each angle accuracy. From Table 1, 60° view angle had the best accuracy to identify species through this method.

To improve the accuracy for irregular shape trees, stem, leaves, and branching structure can be separately trained (Joly et al., 2014). Then the weighted score among separated components can be used to find the best identification result from DL. This 2D image generation approach helps simplify classifying (or labelling) objects from massive 3D data (Xie *et al.*, 2020). The terrestrial laser has been used for DL in the past study for tree species identification (Lin and Herold, 2016). Our approach took a different way to use 2D images generated from 3D data instead of measuring tree parameters from 3D from their approach. Our approach is more efficient way to reduce the cost and time to prepare training samples and a flexible way to provide input images for DL processing.

Table 1. Accuracy assessment separated by angle

	Italian pine	Himalayan cedar	black pine	London planetree	cherry blossom
0	75%	8%	42%	100%	42%
30	92%	25%	8%	100%	0%
60	100%	42%	42%	100%	0%
90	83.30%	16.70%	33.30%	100%	8%

Table 2. Overall accuracy

	Italian pine	Himalayan cedar	black pine	London planetree	cherry blossom
all angles	68.80%	20.80%	12.50%	95.80%	18.80%

References

Carranza-Rojas, J., Goeau, H., Bonnet, P., Mata-Montero, E., and Joly A. (2017) Going deeper in the automated identification of Herbarium specimens, *BMC Evolutionary Biology* 17, 181

Guirado, E. Tabik, S., Alcaraz-Segura, D., Cabello, J., and Herrera F., (2017) Deep-learning versus OBIA for scattered shrub detection with google earth imagery: ziziphus lotus as case study, *Remote Sensing* 9:1220

IBM Watson Studio, https://www.ibm.com/jp-ja/cloud/watson-studio (access date: 2021.6.1)

Joly, A. Goëau, H., Bonnet, P., Bakić, V., Barbe, J., Selmi, S., Yahiaoui, I., Carré, J., Mouysset, E., Molino, J-F., Boujemaa, N., Barthélémy, D. (2014) Interactive plant identification based on social image data, *Ecological Informatics* 23: 22-34

Li, W., Fu, H., Yu, L., and Cracknell, A. (2017) Deep learning based oil palm tree detection and counting for high-resolution remote sensing images, *Remote Sensing* 9: 22

Lin, Y. and Herold, M. (2016) Tree species classification based on explicit tree structure feature parameters derived from static terrestrial laser scanning data, *Agricultural and Forest Meteorology*, 216: 105-114

Xie, Y., Tian, J., and Zhu, X.X. (2020) Linking points with labels in 3D, *IEEE Geoscience and Remote Sensing Magazine* December 2020: 38-59.