INDIVIDUAL TREE SPECIES CLASSIFICATION BASED ON TERRESTRIAL LASER SCANNING USING CURVATURE ESTIMATION AND CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT:

In this paper, we propose a new method for specifying individual tree species based on depth and curvature image creation from point cloud captured by terrestrial laser scanner and Convolutional Neural Network (CNN). Given a point cloud of an individual tree, the proposed method first extracts the subset of points corresponding to a trunk at breast-height. Then branches and leaves are removed from the extracted points by RANSAC -based circle fitting, and the depth image is created by globally fitting a cubic polynomial surface to the remaining trunk points. Furthermore, principal curvatures are estimated at each scanned point by locally fitting a quadratic surface to its neighbouring points. Depth images clearly capture the bark texture involved by its split and tear-off, but its computation is unstable and may fail to acquire bark shape in the resulting images. In contrast, curvature estimation enables stable computation of surface concavity and convexity, and thus it can well represent local geometry of bark texture in the curvature images. In comparison to the depth image, the curvature image enables accurate classification for slanted trees with many branches and leaves. We also evaluated the effectiveness of a multi-modal approach for species classification in which depth and curvature images are analysed together using CNN and support vector machine. We verified the superior performance of our proposed method for point cloud of Japanese cedar and cypress trees.

1. INTRODUCTION

Terrestrial laser scanner (TLS) is commonly used in forestry community to capture dense point cloud of individual trees in forest. Comparing with aerial laser scanning, the advantage of TLS is the detailed and precise measurement of individual trees so that shape parameters, such as height and breast height diameter, can be accurately estimated using point cloud. Although tree species is one of the important attribute for forest inventory, they are manually specified by skilled workers visually to date. The number of such skilled workers is decreasing in Japan, and training workers is costly expensive. Therefore, the method for accurately and automatically classifying tree species is required for efficiency and cost saving of forest inventory.

1.1 Related works

Many works have been reported for tree species classification using aerial or satellite images (Corgan, 2012, George, 2014, Krahwinkler, 2013). However, trees species classification using TLS has not been well studied and few works have been reported to date.

The common approach for tree species classification based on laser scan is to extract features by evaluating point cloud and then to use them for machine learning such as Support Vector Machine (SVM) or Random Forest. For example, Guan *et al*. (2015) extracted features by evaluating the point distribution along the vertical direction and used them in SVM classification. Lin *et al*. (2016) computed various shape parameters of an individual tree related to stem, branch, and crown shapes, and then used them for SVM classification. However, these methods assume that an entire tree can be scanned without occlusions. As for Japanese planted forest, trees are densely standing in general as shown in Figure 1 and occlusion is unavoidable in the scanning process. Therefore, such methods cannot be directly used for our data set.

Figure 1. Our test site.

Othmani *et al*. (2013) proposed a method that creates a depth image by applying smoothing for the patch which is a subset of points corresponding to trunk and then by subtracting from the original patch. The depth image is then binarized and multiple features are extracted from the image. Extracted features are finally used for Random Forest classification. This method focuses on five species whose trunk shape clearly vary, and cannot be directly used for our data set, *e.g*., Japanese cedar and cypress shown in Figure 2, in which trunk shapes are both cylindrical.

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Figure 2. Comparison of bark texture (Left: Japanese cedar, Right: Japanese cypress)

Recently, CNN gained much attention in image processing and computer vision fields, and outperforming results are reported. This technique is also used for tree species classification using RGB images. Carpentier *et al*. (2018) presented the method for evaluating bark texture in deep learning which focus on 23 different species. Sun *et al*. (2017) presented another method for evaluating leaf and crown shapes clearly in RGB images using deep learning. They both achieved classification accuracy higher than 90%. However, the inside of forest is dark, and thus the bark and leaf shape cannot be captured clearly in RGB images. In addition, it is difficult to capture crown shapes individually since those of neighbouring trees are intersected in dense Japanese planted forest.

1.2 Our Objective and Overview of Our Proposed Method

In this paper, we propose an improved version of previous method by Mizoguchi *et al*. (2017). Here we briefly review the overview of the method. Given a point cloud of an individual tree, the method first detects a subset of points at beast height. The second step removes points corresponding to branches and leaves included in the extracted points by RANSAC-based circle fitting. Then for the remaining trunk points, a cubic polynomial surface is fitted globally in the least squares sense. Depth is computed at each point as a distance to the fitted surface and points are converted to the depth image representations. Finally, depth images are used for CNN to specify tree species.

This method achieved the high accuracy, i.e., approximately 90%, for Japanese cedar and cypress data set. However, it tends to fail to classify species in the case that trees are slanted or many branches and leaves are attached to the trunk. The reason is that branches and leaves cannot be removed by RNSAC-based circle fittings and thus the least squares surface cannot be tightly fitted to the trunk point.

In this paper, to solve the above problem, we propose to use curvature estimation on point cloud for species classification based on CNN. Our proposed method computes maximum and minimum principal curvatures at each scanned point by local quadratic polynomial fitting. Curvatures represent surface roughness involved by split and peeling of bark. Then maximum and minimum curvature images which are both gray scales are created for each tree, and they are used in CNN for tree species classification. Since curvatures are computed locally at each scanned point, the computation is stable for slanted trees with many branches and leaves where the previous method (Mizoguchi, 2017) failed to represent their bark shapes in the resulting depth images, and can create curvature images in which bark shapes are captured. We compared the classification results using depth and max/min curvature images from various experiments. We also evaluated the effectiveness of multi-modal approach (Gupta, 2014) by comprehensively analysing the three kinds of images with CNN and SVM.

We note that it is possible to use 3D CNN, such as VoxNet (Maturana, 2015), for tree species classification by voxelizing point cloud. But this method can deal with only small size of voxel data, e.g., 32×32×32, therefore, detailed texture of bark cannot be well captured in the voxel model. We prefer the method in which point cloud is expanded to its 2D image representation where relatively large size., e.g., 227×227 pixels, can be used and thus bark shape can be clearly captured.

1.3 Classification Criteria

We focus on Japanese cedar and cypress which cover the large part of domestic planted forest. As for the classification criteria, several candidates can be considered, such as leaf, bark and crown shapes (Othmani, 2016). Among the candidates, we selected bark texture since they clearly represent unique characteristics of each tree and do not change their appearance under seasonable variation and aged deterioration. Figure 2 shows the examples of bark texture of Japanese cedar and cypress. Both barks are split in strips, but their shapes are different and the bark of cypress is relatively wider than that of cedar. In addition, the bark of cedar is tightly stuck to the trunk, and in contrast that of cypress is peeled off in places. The trunk shapes of the Japanese cedar and cypress are almost cylindrical and the difference appear only in thin bark tightly attached to the trunk. Our challenge is to detect such small different characteristics of bark from point cloud and represent them in the resulting depth and curvature images.

1.4 Data Preparation

We used FARO Focus3D scanner in this work. The angular pitch was set to 0.018deg for both horizontal and vertical directions. Single scan contains about 50,000,000 points, and its scanning time is approximately 7 minutes. Spatial resolution is about 5mm at 10m distance. Many trees with different ages are included in our data set from 33 to 90 years, thus shape parameters vary greatly, *e.g*., breast-height diameter between 0.2m to 1.0m.

2. OVERVIEW OF OUR PROPOSED METHOD

Given a point cloud of an individual tree, our proposed method classifies its species by the following four steps. An overview of the method is shown in Figure 3. The first and second steps follow the previous work of Mizoguchi *et al*. (2017), and depth image is created from a subset of points extracted from a part of trunk. Then in third step, curvature image creation is newly integrated, and in the last step, they are used combined with depth image for tree species classification by CNN and SVM.

2.1 Patch extraction (step1)

The first step of our proposed method follows the method in (Mizoguchi, 2017). After expanding point cloud to its image representation, a patch is extracted which is a point subset of trunk at breast height. We extract point within 256×256 pixels to use them for CNN in the classification step. With this method, the extracted portion of point cloud varies depending on the scanning distance as shown in Figure 4, where curvature images are shown as examples. As for the horizontal direction, the number of pixels containing points is larger for trees closer to the scanning position. And as for the vertical direction, height range is smaller for the trees closer to the scanning position. The height range is approximately 2m for the trees at 15m scanning distance.

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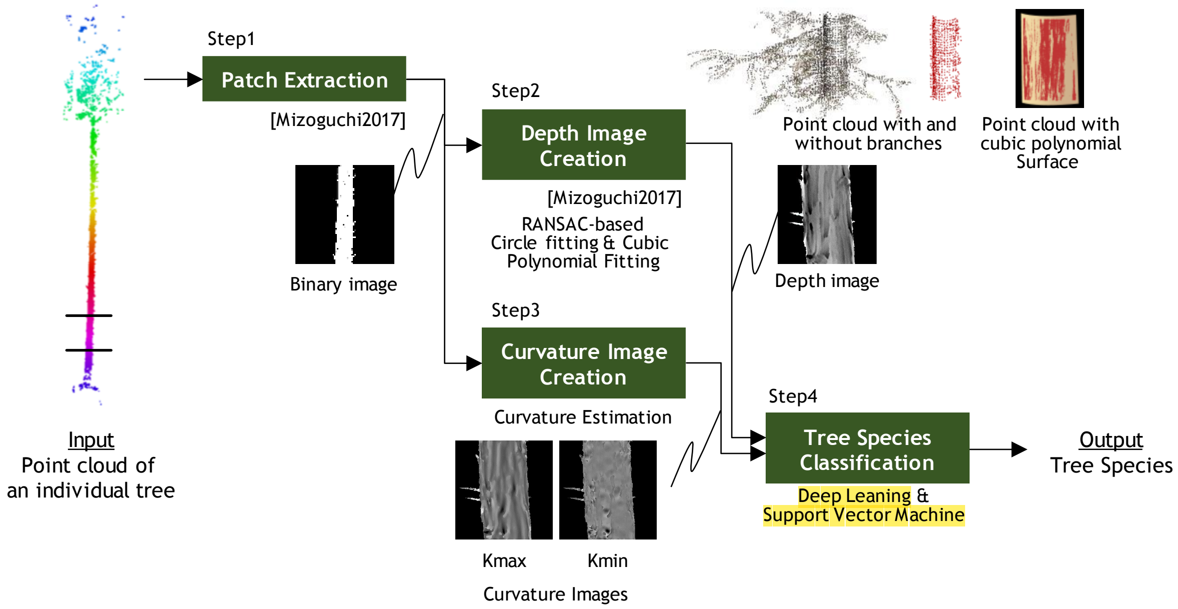

Figure 3. Overview of our proposed method

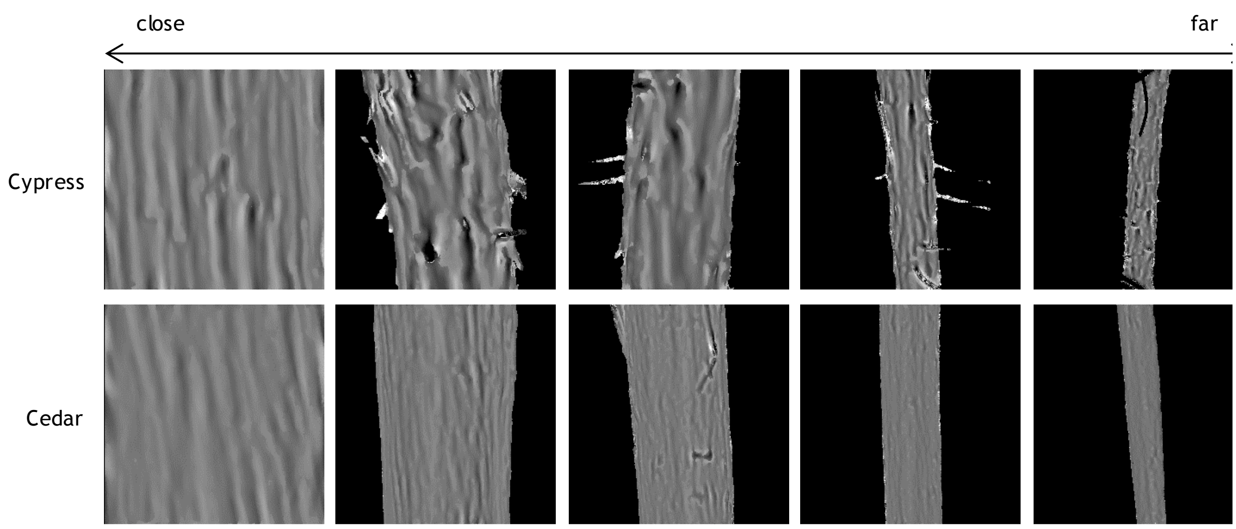

Figure 4. Difference of created curvature images depending on the scanning distance

2.2 Depth image creation by RANSAC-based circle fitting and global cubic polynomial surface fitting (step2)

Next, as presented in (Mizoguchi, 2017), the method creates a depth image in which bark texture is clearly captured by globally fitting a cubic surface in the least-squares sense to trunk points. The subset of points extracted in the first step may include points corresponding to branches and leaves. A surface cannot be tightly fitted to trunk points with them, and the bark texture cannot be well represented in the image. Therefore, to remove branches and leaves, the method first projects the points to xy-plane. Assuming upward vertical direction corresponds to +z direction, projected trunk points distribute on a circle. Therefore, RANSAC-based circle fitting is applied to the projected points, and trunk points are detected. Points which do not distribute on a circle correspond to branches and leaves. For the trunk points without branches and leaves, a surface can be tightly fitted and the depth image is created by computing the depth as the distance at each scanned point to the fitted surface. Examples of depth images are shown in Figure 5.

2.3 Curvature image creation by curvature estimation on point cloud (step3)

The next step estimate principal curvatures at each point in the subset of points by locally fitting a quadratic polynomial surface to its neighboring points. Curvatures measures the surface concavity and convexity on 3D geometry, and widely used in computer graphics (Ohtake, 2004) and digital engineering (Vieira, 2005).

First, for each point p_i, its neighboring points $N(p_i)$ within the specified distance r is extracted. We set r=30mm from various experiments and reasonable results are obtained. Next, a quadratic polynomial surface $f(u,v)$ in equation (1) is fitted to $N(p_i)$ in the least squares sense.

$$f(u,v) = a_0u^2 + a_1uv + a_2v^2 + a_3u + a_4v + a_5 \tag{1}$$

Here, (u,v) is a planar parameterization of each point which is

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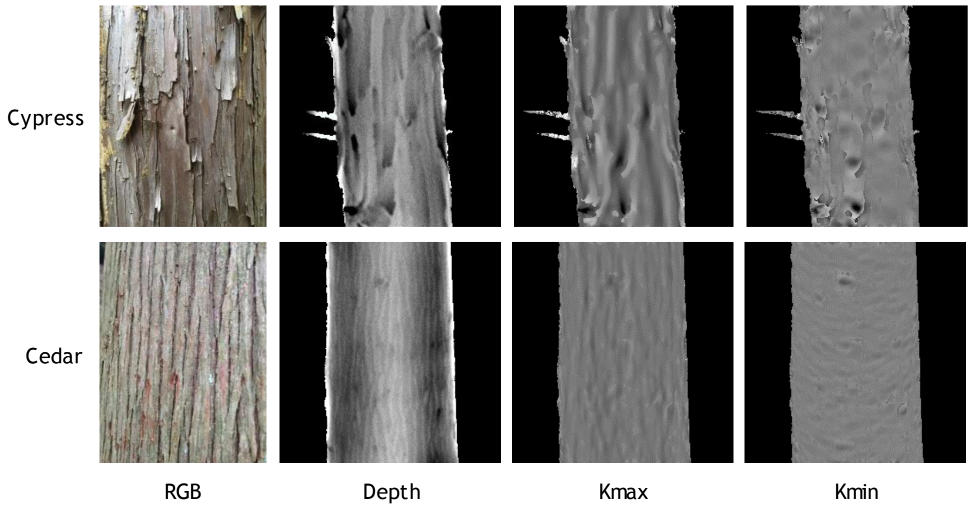

Figure 5. Examples of created depth and curvature images

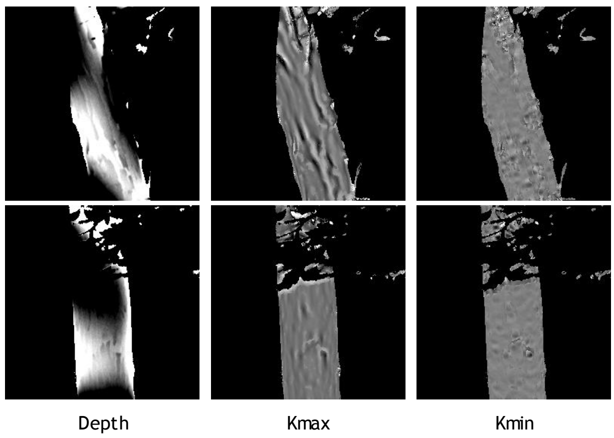

Figure 6. Stable creation of curvature images (top: cedar, bottom: cypress)

computed through plane fitting to $N(p_i)$. Finally, maximum and minimum curvatures $k_{\max}$, $k_{\min}$ are computed by analyzing surface $f(u,v)$ (Ohtake, 2004, Vieira, 2005).

Curvatures are normalized to create curvature images by setting appropriate thresholds. Examples are shown in Figure 5. Both maximum and minimum curvatures represent surface roughness involved by split and peelings of bark. Although maximum curvature image is blurred compared to depth images, they well measure the bark shape including the split and peelings.

Comparing cedar and cypress, the bark of cedar is tightly stuck to the trunk, and in contrast that of cypress is peeled off in places. Therefore, curvature is relatively smooth on cedar images, and large curvature value can be found in places on cypress images at the portions with large surface roughness.

Figure 6 show examples of created images. In depth images, bark texture cannot be captured by the method (Mizoguchi, 2017) since trees are slanted or leaves are included in patch. In contrast, curvature images can stably capture bark texture in both cedar and cypress images, which show the computational stability of curvature estimation to slanted tree with branches and leaves.

2.4 Tree species classification using Convolutional Neural Network (CNN) and Support Vector Machine (SVM) (step4)

In the final step, created depth and curvature images are used for CNN to classify tree species. We selected AlexNet for CNN architecture which includes five convolutions, three pooling and three fully connected layers (Krizhevsky, 2012). For multi-modal classification, we used the combinatorial approach of CNN and SVM which is common in image recognition tasks (Gupta, 2014; Girshick, 2016). In this method, multiple kinds of images are fed into CNN individually as shown in Figure 7. We computed 4,096 degrees features from first fully convolutional layer for each image, and then combined the features to use in SVM classification as in (Gupta, 2014). We note that it is possible to implement similar classification process using only CNN as in (Eitel, 2015).

Figure 7. Our multi-modal classification stream

3. EXPERIMENTAL RESULTS AND DISCUSSION

This chapter describes the experimental result of the proposed method. We used 2,500 images for depth, kmax, and kmin respectively for training, and 389 cedar and 359 cypress images for validation. Results are shown in Table 1.

Table 1(a) – (c) presents results where single channel images of depth, kmax, and kmin are used in CNN individually. The experimental results show that the highest accuracy 91.3% was obtained when kmax images are used in CNN. This is because curvature can be estimated locally at each point, and the bark texture can be stably captured in the resulting curvature images rather than depth images.

Table 1 (d) and (e) show the results of multi-modal classification where depth and kmax, and depth, kmax, and kmin images are comprehensively evaluated using CNN and SVM. It is expected that multi-modal approach enables higher accuracy than the single use of image. However, the accuracy was lower than single use of kmax image. This is probably because the units of depth and curvature are different, and they could not be adjusted well in their normalization step of image creation.

Table 1. Classification results of tree species

(a) Depth images with CNN

		classification results		recall
		cedar	cypress	
actual	cedar	341	48	87.7%
	cypress	28	331	92.2%
	precision	92.4%	87.3%	89.8%

(b) Kmax images with CNN

		classification results		recall
		cedar	cypress	
actual	cedar	353	36	90.7%
	cypress	29	330	91.9%
	precision	92.4%	90.2%	91.3%

(c)Kmin images with CNN

		classification results		recall
		cedar	cypress	
actual	cedar	310	79	79.7%
	cypress	66	293	81.6%
	precision	82.4%	78.8%	80.6%

(d)Depth and Kmax images with CNN and SVM

		classification results		recall
		cedar	cypress	
actual	cedar	362	27	93.1%
	cypress	45	314	87.5%
	precision	88.9%	92.1%	90.4%

(e)Depth, Kmax and Kmin images with CNN and SVM

		classification results		recall
		cedar	cypress	
actual	cedar	363	26	93.3%
	cypress	43	316	88.0%
	precision	89.4%	92.4%	90.8%

One of the main factors of misclassification is the individual difference of trees. There exists cedar with large split and peeling-off of bark and thus they look like cypress, and vice versa. Another criterion must be added in addition to bark texture for correct classification of them.

4. CONCLUSION AND FUTURE WORK

In this paper, we proposed a method for tree species classification based on image creation from point cloud and CNN. We demonstrated the effectiveness of our proposed method from various experiments. Curvature estimation enabled stable creation of images in which bark textures are well represented, and they improved the classification accuracy than using depth images (Mizoguchi, 2017). Unfortunately, multi-modal approach could not achieve the higher accuracy than single uses of image in our experiments.

As for future work, we will extend this technique for species classification of broad-leaved trees in mixed forest. There exist more than 100 species in Japan. Evaluating only bark texture from TLS point cloud is not sufficient for classification of such trees. We consider that integration of multi-sourced data from multiple platform, such as UAV, is essential.

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