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CLASSIFY TREE SPECIES FROM POINT CLOUDS GENERATED BY DIFFERENT LASER SENSORS: A MULTI-VIEW PROJECTION STRATEGY

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ABSTRACT

Accurately classifying forest tree species is crucial for monitoring forest resources and carbon storage. Light Detection and Ranging (LiDAR) is an emerging active remote sensing technology that provides higher spatial resolution and superior penetration capabilities for complex forest terrain and vegetation structures. Airborne laser scanning (ALS), uncrewed aerial vehicle (UAV)-borne laser scanning (ULS), and terrestrial laser scanning (TLS) are important methods for acquiring three-dimensional forest data. To address the issue of disorderliness inherent in directly using point cloud data for tree species classification, as well as the need to extract and select many key diagnostic features from a vast amount of lidar data for feature-based classification, this study employs a multi-view projection strategy and utilizes weighted average depth integration to incorporate depth information. The ResNet18/4 model is employed to extract and fuse features from depth images obtained from ALS, TLS, and UAVLS point cloud data for tree species classification. The research results demonstrate that the multi-view projection method achieves comparable or better results than the more complex state-of-the-art PointNet++ method, while being only half the size of PointNet++ and exhibiting better datasets generalization.

Index Terms—light detection and ranging (LiDAR), tree species classification, deep learning, point cloud.

1. INTRODUCTION

Obtaining accurate forest species information is a crucial ecological monitoring indicator for characterizing forest biodiversity and quantitatively assessing the stability of forest ecosystems. Light Detection and Ranging (LiDAR) is an active remote sensing technology that enables the precise and rapid acquisition of coordinates and reflection intensity of the target under study. The LiDAR technology can gather information about forest trees from multiple perspectives, and its usefulness in forest resource surveys and research is becoming more widely acknowledged.

Common laser scanning systems used in forest surveys include airborne laser scanning (ALS), unmanned aerial vehicle-borne laser scanning (UAVLS), and terrestrial laser scanning (TLS)[1]. ALS can quickly obtain point clouds of large-scale forest scenes. Compared with ALS, ULS has a lower flight altitude, higher point density and better penetration capability. However, due to flight time and speed restrictions, the coverage area of ULS is limited. TLS has fine spatial resolution, but cannot collect data over larger areas[2]. In forest parameter extraction and tree species classification research, data from laser sensors on different platforms serve distinct purposes.

The unordered nature of point cloud data is one of the challenges in using point cloud data for tree species classification[3]. The most popular approach currently is feature-based classification. This approach involves extracting and selecting numerous key diagnostic features from a large amount of lidar data, relying on profound prior knowledge, and then using them as input to traditional machine learning classifiers. Furthermore, the use of deep learning techniques for the swift and precise classification and identification of tree species within individual tree point clouds is a novel direction in forest resource assessment applications. The ResNet model tackles the issue of gradient vanishing that arises in deep neural networks by incorporating skip connections across layers, thereby greatly improving the learning capacity of deep networks [4]. In recent years, researchers have started to pay attention to tree species classification using LiDAR data[5], with the development of point cloud deep learning techniques such as the PointNet++ model[6]. These methods continuously explore the potential of point cloud and image classification, providing innovative perspectives for the classification of individual tree species.

This study focuses on tree species classification based on multi-view projection of point cloud data. First, six different direction projections and weighted average depth are used to solve the problem of information loss during the conversion of three-dimensional point cloud data into two-dimensional projection images, and at the same time solve the disorder of point cloud data. Secondly, the lightweight model

ResNet18/4 is used to extract and fuse features from depth images and classify tree species. Finally, the method is compared with the popular point cloud deep learning model PointNet++. Experimental evaluations are conducted using point cloud data obtained from ALS, TLS, and UAVLS, aiming to further explore the effectiveness and potential of deep learning methods in differentiating tree species within various types of lidar data.

2. MATERIALS

tsWeiser datasets: This paper evaluates the performance of tree species classification using single-tree point clouds provided by Weiser et al[7]. The dataset was obtained by scanning 12 forest plots of about 1 hectare each with three different platforms (airborne, UAV-borne and terrestrial) under leaf-on and leaf-off canopy conditions in 2019 and 2020. To balance the sample size of different tree species, we ignored some tree species with fewer trees. Table 1 provides a summary of the information for six tree species, including ALS, TLS, UAVLS-leaf-on (ULS-on) and UAVLS leaf-off (ULS-off). Figure 1 shows some of the single tree point clouds.

Table 1 Tree species and number of individual trees in the tsWeiser dataset.

Species	Species ID	No. of trees			
		ALS	TLS	ULS-on	ULS-off
Fagus sylvatica L.	FagSyl	397	46	366	509
Picea abies (L.) H. Karst.	PicAbi	205	30	200	331
Pseudotsuga menziesii (Mirb.) Franco	PseMen	189	38	140	164
Pinus sylvestris L.	PinSyl	158	36	103	79
Quercus petraea (Matt.) Liebl.	QuePet	156	33	152	262

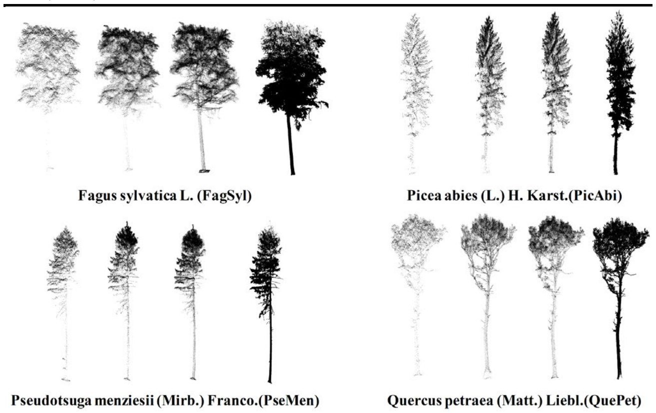

Figure. 1. Samples of individual tree from tsWeiser. (From left to right: ALS, ULS-on, ULS-off, TLS datasets).

tsAllen datasets: Due to the limited amount of tsWeiser-TLS data, the proposed method was tested using the TLS dataset provided by Allen et al[8]. The datasets were acquired by scanning 38 forest plots measuring 30m × 30m in central Spain in July 2018. Detailed information about the tsAllen datasets can be found in Table 2, and Figure 2 illustrates some examples of individual tree point clouds. The dataset can be accessed at https://zenodo.org/record/6962717.

Table 2 Tree species and number of individual trees in the tsAllen datasets.

Genus	Species	SpeciesID	Number
Quercus	*Quercus ilex*	QUEILE	364
	Quercus faginea	QUEFAG	1116
Pinus	*Pinus pinaster*	PINPIN	140
	Pinus sylvestris	PINSYL	277
	Pinus nigra	PINNIG	581

Figure. 2. Samples of individual tree from tsAllen. (*Quercus ilex, Quercus faginea, Pinus pinaster, Pinus sylvestris, Pinus nigra*).

3. METHODS

3.1 Multi-View Projection Architecture

Multi-view Projection: uniformly scaled to fit within the range [-1, 1] in all three dimensions. Six directional views are projected at 1.4 units. The coordinate axes are defined by the internal coordinate system of the scanner, where the z-axis is vertical, and the x and y axes have no fixed orientation. The camera's field of view (FOV) is set to 90° (consistent with Goyal et al. [9]), and the image resolution is set to 256×256.

Generating Depth Images from Point Clouds: Given a simplified view of a single tree point cloud, the projection onto six orthogonal planes is used to create sparse depth images. Depth is defined as the minimum distance from the axis to a pixel where a point exists; otherwise, it is set to zero. The pixel values are linearly mapped to the depth, preserving some structural information of the point cloud along the axis-aligned directions. Assuming (x, y, z) is the coordinate of a point in the single tree point cloud, the point p is obtained by perspective projection with a depth of z in 2D coordinates $(\boldsymbol{x_1} = x/z, \boldsymbol{y_1} = x/z)$. Multiple points may be projected onto the same discrete position on the image plane. To generate depth values at image positions, we conducted ablation experiments using a weighted average depth, where points closer to the plane are given higher weights $(1/z)$.

Deep learning classification: To make the number of parameters comparable to point-based methods, we use ResNet18 with quarter filters as the backbone (ResNet18/4)[9]. It is half the size of PointNet++. The six images are passed forward through ResNet18/4, and then six sets of output features (values of the penultimate layer) from the network are fused in series, and finally classified. The specific process is shown in Figure 3.

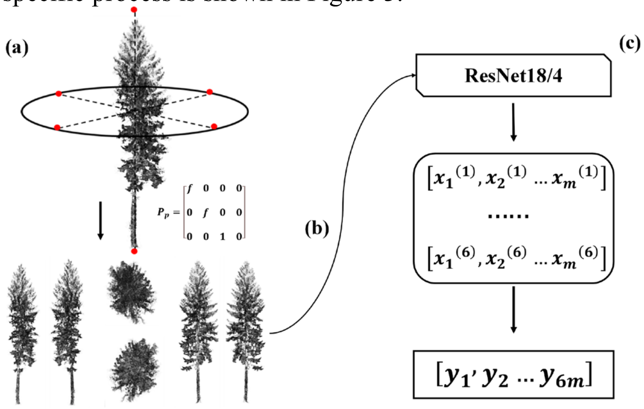

Figure. 3. Multi-View Projection technology roadmap.

3.2 Comparison with other methods

PointNet++ extends PointNet's pioneering role in point cloud deep learning by applying it recursively to the point set's nested partitions. It adeptly manages the uneven density of collected point cloud data through multi-scale feature integration. This research utilizes PointNet++ as a control algorithm for comparative experimentation.

4. EXPERIMENTS

Based on the tsWeiser dataset, single-tree classification was performed on four groups of datasets: ALS, TLS, UAVLS-on, and UAVLS-off, using the Multi-View Projection method and the PointNet++ model. The hyperparameters used for training the model were kept consistent with the tsWeiser dataset through experiments conducted on the tsAllen dataset. Throughout the entire process, a stratified systematic sampling method was employed, with random selection proportions of 70%, 15%, and 15% for training, validation, and testing, respectively. During training, weighted sampling with replacement was used to balance the dataset, ensuring equal representativeness for each species. Table 3 summarizes the hyperparameters used in the experimental model configurations. The evaluation metrics for the classification results include the confusion matrix and overall accuracy (OA).

Table 3 Hyperparameters for PointNet++ model and Multi-View Projection model training.

Parameter	PointNet++	Multi-View Projection
Batch Size	12	128
Number of points	2048	/
Epochs	200	200
Optimizer	Adam	Adam
Learning Rate	0.001	0.001
Weight Decay	0.0001	/

The deep learning framework used in the experiment is PyTorch 1.12.1 + CUDA 11.3. The device is running on Windows 11 operating system and is equipped with an Intel® CoreTM i7-13700KF CPU @ 3.80 GHz, 32 GB of memory, and an NVIDIA GeForce RTX 4090 (24GB) graphics card.

5. RESULTS AND DISCUSSION

5.1. tsAllen datasets results

The tsAllen validation dataset was used to classify tree species using the Multi-View Projection model and the PointNet++ model. The OA of the PointNet++ model was 0.801, while the Multi-View Projection model achieved 0.804. The confusion matrix for this classification result is shown in Figure 4. It can be observed that the PointNet++ model misclassified 36% of PINPIN as PINNIG. In contrast, the Multi-View Projection model reduced the misclassification between PINPIN as PINNIG to 5%. Therefore, the Multi-View Projection model outperforms the PointNet++ model. The PointNet++ model performance in classifying other species within the same genus was relatively weak. The Multi-View Projection model exhibited good robustness both within the same genus and across different genera. From a subordination perspective, PointNet++ model exhibits higher accuracy for PINNIG and QUEFAG, while the Multi-View Projection model demonstrates a more balanced performance. This can be attributed to two reasons: firstly, the Multi-View Projection model achieves better dataset balance. Secondly, the three-dimensional structures of species within the same genus are similar, making it challenging for purely point-cloud-based deep learning methods to distinguish between them.

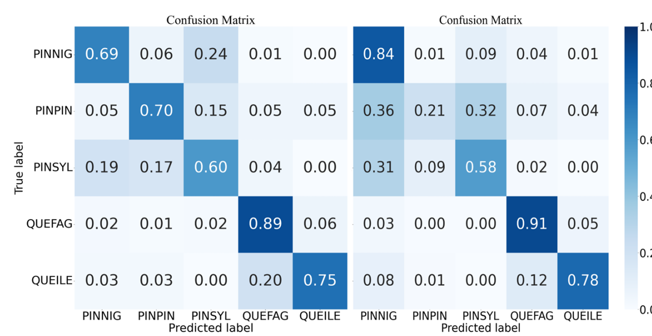

Figure. 4. Confusion matrix for tree species classification of the validation dataset (left: Multi-View Projection model, right: PointNet++ model).

5.1. tsWeiser datasets results

The tree species classification was performed using the Multi-View Projection model and PointNet++ model on the four validation sets of tsWeiser. The average OA were 0.9018 and 0.8935, respectively, indicating that the Multi-View Projection model outperforms the PointNet++ model, as shown in Table 4. In the two experiments using UAVLS data, there was little difference between the Multi-View Projection model and the PointNet++ model under deciduous and non-deciduous conditions. Compared to UAVLS data and ALS data, ALS data exhibited higher accuracy in tree species classification. The classification results of the four experiments demonstrate that the Multi-View Projection model possesses strong capabilities in tree species classification. It achieves comparable or better results than the advanced methods on PointNet++, while being only half the size of PointNet++ and exhibits superior dataset generalization.

Table 4 The Overall accuracy of PointNet++ model and multi-view projection model training.

Datasets	Multi-View Projection	PointNet++
ALS	0.9157	0.9081
ULS-on	0.9065	0.8887
ULS-off	0.8960	0.8738
TLS	0.8889	0.9032

The research results further demonstrate that classification based on automatically extracted learning features can achieve better accuracy while significantly reducing the need for manual inputs during the preprocessing stage, which is comparable to the results requiring additional processing and subjective feature selection as reported by Terryn et al. [10], [11]. The approach proposed by Zou et al. [12] relies on a large amount of segmented leaf data and requires manual data processing by personnel with additional technical expertise, posing significant challenges when using point cloud data in standard forest monitoring. The high accuracy of our classification results and the robustness of the model highlight the importance of applying deep learning methods and represent a significant step towards fully automated forest inventory.

6. CONCLUSIONS

This study validates the feasibility of tree species classification using a multi-view projection approach with ALS, TLS, and UAVLS point cloud datasets, and addresses the unordered nature of point cloud data by integrating depth information through weighted average pooling. The proposed method employs the ResNet18/4 model to extract and fuse features from depth images, thereby improving classification accuracy. Comparable or better results were achieved compared to PointNet++ complex state-of-the-art methods. This research holds significant importance for the quantitative assessment of forest resources and carbon storage. This advancement enables scalable long-term resource management and ecosystem preservation, improves inventory-based carbon stock estimation, and further enhances our understanding of ecological processes.

7. ACKNOWLEDGMENT

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8. REFERENCES

[1] Y. Wang *et al.*, “In situ biomass estimation at tree and plot levels: What did data record and what did algorithms derive from terrestrial and aerial point clouds in boreal forest,” *Remote Sensing of Environment*, vol. 232, p. 111309, Oct. 2019.

[2] L. Terryn *et al.*, “Quantifying tropical forest structure through terrestrial and UAV laser scanning fusion in Australian rainforests,” *Remote Sensing of Environment*, vol. 271, p. 112912, Mar. 2022.

[3] Q. Zhang, Y. Peng, Z. Zhang, and T. Li, “Semantic Segmentation of Spectral LiDAR Point Clouds Based on Neural Architecture Search,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1–11, 2023.

[4] Z. Xi, C. Hopkinson, S. B. Rood, and D. R. Peddle, “See the forest and the trees: Effective machine and deep learning algorithms for wood filtering and tree species classification from terrestrial laser scanning,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 168, pp. 1–16, Oct. 2020.

[5] B. Liu, H. Huang, S. Chen, X. Tian, and M. Ren, “Tree Species Classification of Point Clouds from Different Laser Sensors Using the PointNet++ Deep Learning Method,” in *IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium*, Jul. 2023, pp. 1565–1568.

[6] A. Gupta, J. Byrne, D. Moloney, S. Watson, and H. Yin, “Tree Annotations in LiDAR Data Using Point Densities and Convolutional Neural Networks,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 58, no. 2, pp. 971–981, Feb. 2020.

[7] H. Weiser, J. Schäfer, L. Winiwarter, N. Krašovec, F. E. Fassnacht, and B. Höfle, “Individual tree point clouds and tree measurements from multi-platform laser scanning in German forests,” *Earth System Science Data*, vol. 14, no. 7, pp. 2989–3012, Jul. 2022, doi: 10.5194/essd-14-2989-2022.

[8] M. J. Allen, S. W. D. Grieve, H. J. F. Owen, and E. R. Lines, “Tree species classification from complex laser scanning data in Mediterranean forests using deep learning,” *Methods in Ecology and Evolution*, vol. 14, no. 7, pp. 1657–1667, 2023.

[9] A. Goyal, H. Law, B. Liu, A. Newell, and J. Deng, “Revisiting Point Cloud Shape Classification with a Simple and Effective Baseline,” in *Proceedings of the 38th International Conference on Machine Learning*, PMLR, Jul. 2021, pp. 3809–3820. Accessed: Dec. 22, 2023.

[10] L. Terryn *et al.*, “Tree species classification using structural features derived from terrestrial laser scanning,” *ISPRS Journal of Photogrammetry and Remote Sensing*.

[11] D. Seidel *et al.*, “Predicting Tree Species From 3D Laser Scanning Point Clouds Using Deep Learning,” *Frontiers in Plant Science*, vol. 12, 2021.

[12] X. Zou, M. Cheng, C. Wang, Y. Xia, and J. Li, “Tree Classification in Complex Forest Point Clouds Based on Deep Learning,” *IEEE Geoscience and Remote Sensing Letters*, vol. 14, no. 12, pp. 2360–2364, Dec. 2017.