Issues of Tree Species Classification from LiDAR Data using Deep Learning Model

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Abstract. Trees inventory is an important task for the ecology, calculation of carbon dioxide absorption and city arrangement reasons. But different types of trees have their own characteristics, and the problem of their automatic classification is urgent. Various sensors are currently used to meet this challenge but the most often used is LiDAR. Different classification methods are applied, including deep learning. One of the modern deep learning models for point cloud data is PointNet. Therefore, the authors of this work applied it to classify tree species. Russia has its own specific set of tree species and the authors collected a dataset for the research containing tree species typical for this area and carried out its labeling. The results showed good capabilities of PointNet for tree species classification but revealed the problem of insufficient data for high training accuracy and difficulties with manual marking of instances based on point cloud data. The paper gives recommendation for overcoming these issues.

Keywords: LiDAR, tree species classification, deep learning.

1 Introduction

One of the most discussed and urgent problems at this moment is the problem of ecology. There is a huge number of different factors that affect the state of nature and one of them is the carbon. It is the aggregate of all greenhouse gas emissions that directly or indirectly accompany any activity of a person or organization in terms of carbon dioxide. To limit global warming, compared to preindustrial levels, the Paris Agreement was adopted. It is a legally binding international treaty on climate change entered into force on 4 November 2016. To achieve this long-term temperature goal, countries aim to reach global peaking of greenhouse gas emissions as soon as possible to achieve a climate neutral world by mid-century [1].

Under this agreement, countries are encouraged to take action to implement and support activities related to forest conservation, sustainable forest management and increasing forest carbon stocks in developing countries. [1] That is why it becomes necessary to monitor the situation with forest plantations and how much carbon will be absorbed by this or that part of the forest plantation. Accurate characterization of forest species and their spatial distribution is critical for sustainable forest management and for ecological and environmental protection [2, 3]. In the case of urban areas, tree species classification is gaining increasing attention for noise modeling, and environmental and ecological analysis because trees play a critical role in urban ecosystems for the maintenance of environmental quality, aesthetic beauty of urban landscape [4].

The number of studies focusing on tree species classification has constantly increased over the last 35 years which is well-supported by the general trend of increased publication activity [5]. An almost exponential increase can be seen between the periods 2005–2010 and 2010–2015, driven by the increased availability of hyperspectral and airborne LiDAR data. Both data sources have been frequently applied in a forest inventory context with tree species being one of the most popular target variables besides total growing stock volume and biomass [5]. Forest plantations in the Russian Federation has their features and requires research for species of this area [6].

LiDAR (Light Detection and Ranging) is a remote sensing technology that uses light in the form of a pulsed laser to measure variable distances to an object. By emitting infrared laser pulses, as well as recording the location and orientation of the device in space, a dense three-dimensional point cloud is formed reflecting the surrounding space. The growing availability of LiDAR has generated great interest among natural resource managers, as LiDAR can be used to measure tree characteristics [7]. At the same time the accuracy of individual tree classification remains low [2].

Various types of LiDARs are already being used to classify tree species. For the past decade, researchers have examined the potential to use data from airborne LiDAR to classify forest stand types or individual species [2]. Later mobile LiDAR has attracted much attention for urban vegetation detection and modelling because it acquires data at a much higher point density and more complete data coverage than an airborne LiDAR system and at a higher efficiency than a terrestrial LiDAR system [4].

Different algorithms are applied for classifying trees. At first, the most widely used classification techniques included supervised maximum likelihood classifiers and unsupervised clustering (K-means, ISODATA). Later, non-parametric decision tree-based classifiers and neural networks emerged as an alternative to the other classifiers. Some recent studies using mixed sets of input variables have preferred the use of non-parametric machine learning methods like RF or SVM [5].

There are various models for recognizing LiDAR point clouds but the most effective are deep learning models. SEGCloud combines the methods of classical machine learning and deep architectures, that is, this model uses voxel grids and raw 3D points obtained using trilinear interpolation [8]. PointNet works directly with the point cloud [9]. This network has shown impressive results in indoor 3D object recognition and semantic segmentation [10]. PointNet++ [11] that is a variant of PointNet has been successfully applied for tree identification on point clouds [12]. Therefore, it was decided to use PointNet to classify tree species by point cloud.

2 PointNet classification of LiDAR data

A point cloud is the simplest way to represent an object as a set of single points in a X, Y and Z geometric coordinate system. Points clouds are created by scanning objects or their structure with 3D sensors such as a LiDAR. There are usually two problems to be solved in deep learning for 3D point cloud: classification and segmentation.

PointNet is a model processing unstructured point cloud data using convolutional neural network. The architecture of the PointNet [9] is shown in Fig. 1. The classification network consists of two transformation networks, each of which has a shared multilayer perceptron (MLP) with layer output sizes (64, 64) and (64, 128, 1024) and a max pooling.

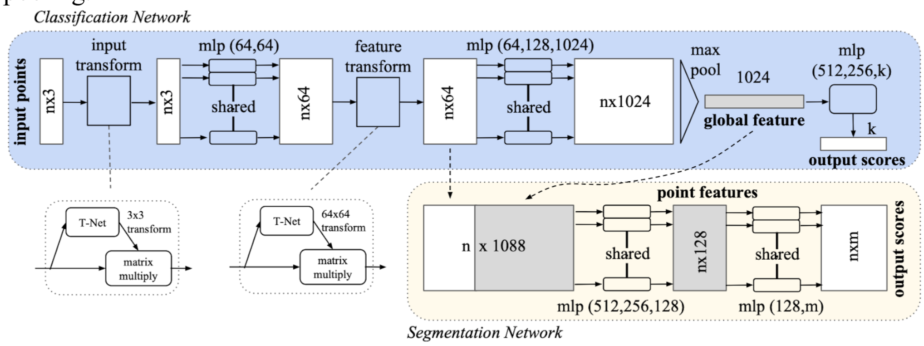

Fig. 1. PointNet architecture

This method takes scattered and unordered point cloud data consisting of N points and processes it separately by N! permutations provided that the model is invariant to these changes. A single point is not considered in isolation. On the contrary, the point interacts with its nearest neighbours and they often carry information useful for classification. Therefore, PointNet uses two symmetric functions (1) that make the model robust to transformations, the output of these functions still the same as an input:

$$f(\{x_1, \ldots, x_n\}) = g(h(x_1), \ldots, h(x_n)) \tag{1}$$

where g(x) is a max pooling layer and h(x) is a multilayer perceptron.

The MLPs are feature transformations that map independently each of the N points from one dimension to another. The last one transformation network also has two fully connected layers with output sizes (512, 256, k), where k is a number of classes. To predict the class of a given point cloud the model in its final layer has a softmax activation function, which is often used for multi-class classification problems. To minimize the model's error rate the Adam optimizer is used, which combines the advantages of RMSProp and AdaGrad optimizers.

3 Dataset collection

To identify trees, a survey of the area in the forest was carried out using the LiDAR GeoSLAM ZEB-HORIZON device. With a measuring range of up to 100 m, it is perfect for surveying open spaces. It scans 300,000 points per second with an accuracy of 1-3 cm. For preprocessing the LiDAR data, the GeoSLAM Hub + Draw software was used, which converts the original 3D scanning data into the pcd format.

The measurements were carried out in the central region of European Russia. This survey resulted in point cloud images of trees. Individual trees were manually selected from the full terrain images and placed in separate files using 3D Forest software. After all the transformations, 261 tree images were obtained.

After collecting the files, it was necessary to mark up the data, to determine the type of each tree. To do this, the resulting dataset was manually viewed and each tree was assigned its own label. In total, 10 species have been identified, and for all species the corresponding species names in Latin were selected. Castanea and Salix classes contained an insufficient number of examples were excluded from the dataset. The number of instances for the rest of the classes is presented in Table 1. During the marking process, for each type of tree its unique criteria were identified: the volume of the trunk, the crown of the tree, the direction of growth of branches, etc.

Table 1. Number of instances in the dataset of each class

Tree	Aspen	Poplar	Spruce	Birch	Linden	Maple	Pine	Oak
Species	Populus tremula	Populus alba	Picea abies	Betula pendula	Tilia cordata	Acer platanoides	Pinus sylvestris	Quercus robur
Quantity	17	33	48	35	8	26	66	20

The data were collected in the winter season, which made it possible to shoot trees without leaves making the crown more informative [2]. However, marking is a rather time-consuming process, since there was often not enough expert knowledge to unambiguously determine the type of the tree [2]. In the form of point clouds, it is rather difficult to determine which species a particular tree belongs to.

For a more complete picture, it is necessary to have an image of the captured tree itself. Therefore, it was decided to carry out the marking separately from each other by three participants and then form the final sample from those trees where the species is uniquely identified. Since it was not possible to accurately classify manually all the images of trees, only 253 trees were included in the final sample (Fig. 2).

Fig. 2. Examples of trees from left to right: birch, spruce, poplar

4 Experiment and results

The data was converted to mesh format and further to 2048 point format for the model. The dataset was divided into train and test samples in a ratio of 80% to 20%. To improve the quality of training, examples were shuffled and jittered by normal distribution.

The implementation of PointNet model from the keras site [13] was taken as a basis, which showed an accuracy of 73% on the ModelNet10 dataset. Training done in Google Colab using GPU. The optimizer was changed to SDG with a learning rate of 0.001 instead of Adam. During the training process, 50 epochs were performed and 32% of the classification accuracy was achieved on the test data after the 5th epoch (Fig. 3). The accuracy on the test and training samples has similar values, indicating the model is not overfitted.

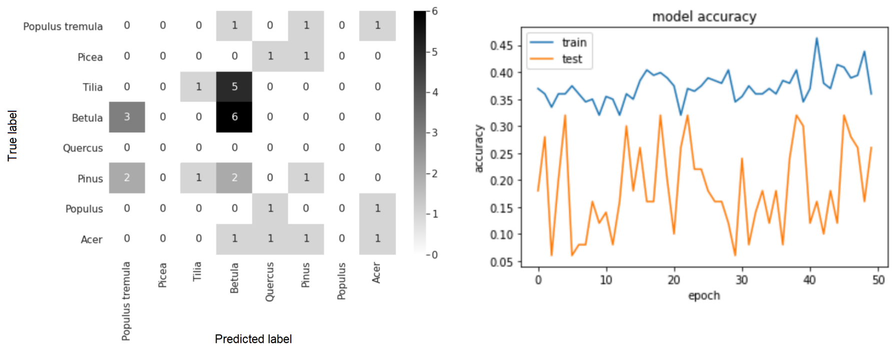

Fig. 3. Confusion matrix and model accuracy by epochs

The accuracy turned out to be below than 77.5% [2] and 86% [4]. This is due to the fact that the number of copies in the dataset is less than in these works. In work [2] there were also 10 classes, but the number of copies in each was 5000, that is, two orders of magnitude more than in our study. In a study [4], the number of examples in each class ranged from 300 to 400. This is one order of magnitude more, but the authors studied only 4 classes. The quality of the dataset markup also affects classification.

In the resulting error matrix (Fig. 3), it can be seen that the resulting model best recognizes the Betula class from the test dataset. The confusion matrix shows that most of the errors are evenly distributed in the matrix between the classes. But there is a strong correlation between the classes Betula and Picea, the model erroneously recognizes spruce as birch. However, it is difficult to draw a final conclusion due to the imbalance of classes: the Pinus has 66, while Tilia has only 6 examples.

5 Conclusion

The results obtained during investigation showed good capabilities of the PointNet model for classifying tree species even on a small amount of data. At the same time, problems were identified with manual labeling point clouds of trees. The amount of data collected for training and testing was also insufficient. In future studies, it is planned to significantly increase the number of examples for each class. To improve the quality of the markup, it is planned to use combined data from cameras and LiDAR.

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