

Automatic Tree Annotation in LiDAR Data

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Abstract: LiDAR provides highly accurate 3D point cloud data for a number of tasks such as forest surveying and urban planning. Automatic classification of this data, however, is challenging since the dataset can be extremely large and manual annotation is labour intensive if not impossible. We provide a method of automatically annotating airborne LiDAR data for individual trees or tree regions by filtering out the ground measurements and then using the number of returns embedded in the dataset. The method is validated on a manually annotated dataset for Dublin city with promising results.

1 INTRODUCTION

Trees are critical to the healthy functioning of the ecosystem and provide a number of benefits to the environment such as regulation of water systems, maintaining air quality, carbon sequestration and promoting biodiversity. Hence, up-to-date tree inventories are extremely important for monitoring and preservation of ecological environments so much so, that, one of the key items on the top ten initiatives of the World Economic Forum on the Future of Cities in 2015 was to increase green canopy (Treepedia, 2015).

LiDAR sensors are a good tool for acquiring dense point cloud data for the purpose of surveying in short ranges. These sensors measure the distance by timing a laser pulse reflected from a target and have been applied in a number of remote sensing applications ranging from mapping (Schwarz, 2010), landslide investigations (Jaboyedoff et al., 2012) to tree inventories (Shendryk et al., 2016b). LiDAR systems are particularly suited to surveying forest canopies due to their active sensors and their ability to penetrate canopies.

Currently, most of the research on isolating trees focuses on forested areas, with little emphasis given to urban areas where there are more complex environments due to the presence of multiple types of natural and artificial objects. However, surveying trees in urban areas is of paramount importance for applications such as city planning, estimating green canopy of areas and monitoring solar radiations (Jochem et al., 2009).

In this work, we provide an algorithm to identify trees in urban areas using information embedded in the LiDAR data without requiring human intervention. Contrary to the common use of the Canopy Height Model (CHM) for this task, our method works directly with the LiDAR data and uses the number of returns information from the LiDAR data to isolate trees.

2 RELATED WORK

A number of methods have been developed to segment trees in LiDAR data with the most common being based on CHM (Lu et al., 2014; Ferraz et al., 2016; Reitberger et al., 2009; Smits et al., 2012; Mongus and Zalik, 2015).

Hyypa et al. (2001) pioneered work in this area; they used the information from the highest laser returns to build a tree height model and then used region growing techniques to for tree segmentation. Koch et al. (2006) used local maximum filters to identify potential tree regions followed by the use of a pouring algorithm and knowledge-based assumptions to identify tree crowns. Li et al. (2012) took advantage of the spacing between treetops at their highest points to identify trees and used a region growing algorithm to segment them. More recently, Shendryk et al. (2016a) used Euclidean distance clustering to delineate trunks in eucalypt forests. These methods proved highly effective in identifying trees in forested areas but are unsuitable for use in urban environments

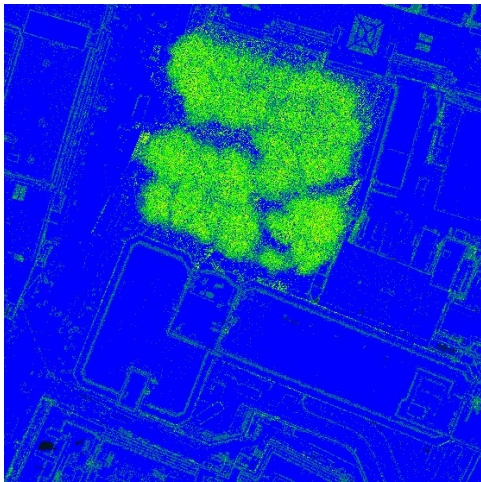


Figure 1: LiDAR point cloud showing decreasing number of returns where Red>Yellow>Green>Blue.

since the assumption of highly dense collections of trees does not apply to isolated individual trees.

Pioneering work in urban tree detection was based on machine learning techniques. Secord and Zakhor (2007) used a combination of aerial images and LiDAR data for segmentation and classification with Support Vector Machines (SVM). They extended this work to using features derived from depth images of LiDAR data with an SVM classifier (Chen and Zakhor, 2009). Carlberg et al. (2009) used a cascade of binary classifiers to progressively identify water, ground, roofs and trees by conducting 3D shape analysis. Segmenting foreground and background and classifying object-like clusters was used to locate different 3D objects in an urban environment (Golovinskiy et al., 2009). Decision trees and Artificial Neural Networks have also been used for segmenting features from Digital Surface Models for classification (Höfle et al., 2012). The main drawback with these methods is that they need pre-labelled data in order to train their models and cannot work in an unsupervised manner.

There has been some work done on identifying trees in urban environments without the need for labelled data. Liu et al. (2013) proposed a method for extracting tree crowns by filtering out ground points and using a spoke wheel method to get tree edges. Wu et al. (2013) proposed a voxel-based method to extract individual trees from mobile laser scanning data but their method is not suitable for use with airborne LiDAR scans. Zhang et al. (2015) developed a method to estimate tree metrics for urban forest inventory purposes by detecting treetops and using a region growing algorithm for segmentation.

We propose a new technique for automatically de-

tecting trees in urban environments by using the number of returns information embedded in LiDAR data. Similar to previous approaches, our method starts with ground removal; however, following that step we voxelise the point cloud data and show that trees can easily be extracted from this subsampled data by using certain heuristics and data analysis.

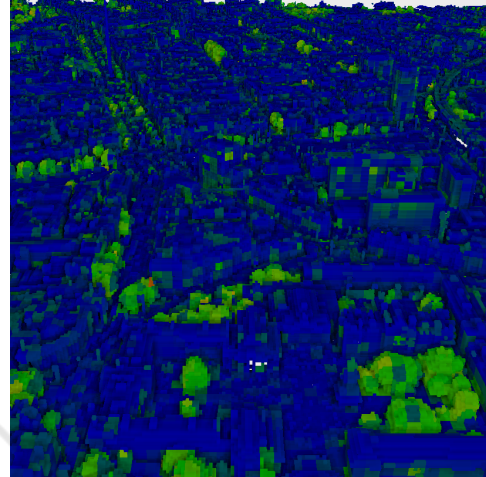


Figure 2: Voxelized point cloud showing number of returns.

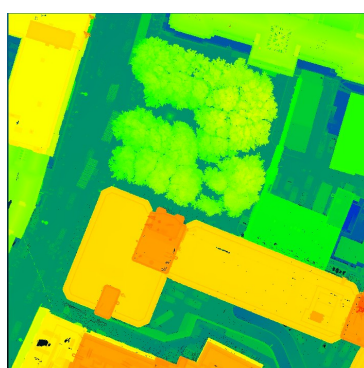
3 METHODOLOGY

Our method for labelling trees is based on four distinct steps: ground filtering, voxelizing non-ground point cloud data, isolating tree-like regions using the information gained from the number of returns, and post-processing to remove false positives.

3.1 Ground Filtering

A Digital Terrain Model (DTM) is used to represent the surface of the Earth and there is a vast body of research in extracting ground points from LiDAR scans in order to produce a DTM. There are number of different algorithms for ground filtering such as morphological filtering, surface based adjustment and statistical analysis (Chen et al., 2017).

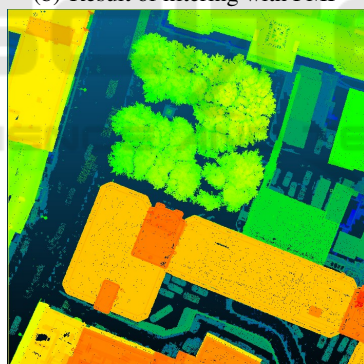
We use a Progressive Morphological Filter (PMF) (Zhang et al., 2003) to identify ground points. PMF uses the morphological operations of dilation and erosion, where it uses progressively increasing window sizes to identify non-ground points. We filter out the ground points identified using this technique and the results are shown in Figure 3(b). However, it is not successful in removing all the ground points, hence we do statistical outlier removal on the filtered point cloud and get a much cleaner result can be seen in Figure 3(c).



(a) Original Point Cloud



(b) Result of filtering with PMF



(c) Result after cleaning for noise

Figure 3: Ground Filtering.

3.2 Voxelization

An aerial LiDAR survey returns an extremely large volume of data, with an hour-long survey generating over a billion unique points (Geosystems, 2015). Even after filtering the ground points, the dataset can retain more than half of the original points if the survey was in an occupied region, such as forests or urban areas. Hence, LiDAR point cloud data is often converted to a mesh in order to reduce its dimensionality. However, meshing algorithms can be error prone when there are voids in the data since they make assumptions about the shape in order to make water-

tight meshes. Meshing algorithms such as Poisson reconstruction require normals for the points which are not directly available from the LiDAR output. They also remove tall thin objects such as lampposts, tree trunks and chimneys during the fitting process.

We convert the data into a volumetric occupancy grid in order to overcome the limitations of meshing algorithms while reducing its dimensionality. A fixed size 3 dimensional grid is overlaid on the point cloud and the occupancy of each cell depends on the presence of points within the cell, i.e. the cell is unoccupied if there are no points in the cell's volume and vice versa. In this case, each volumetric element, Voxel, represents a region in the subsampled point cloud. Following the original tile dimensions of $100m \times 100m$, we convert each tile into a voxel grid of dimensionality $256 \times 256 \times 256$ hence limiting the resolution of the voxel grid to be $\approx 0.39m \times 0.39m \times 0.39m$ per voxel. Any further increase in resolution does not noticeably increase accuracy and causes an exponential increase in the processing time due to the increased dimensionality of the data.

Furthermore, we use VOLA (Byrne et al., 2017) to sparsely encode the voxel representation. VOLA is a hierarchical 3D data structure which only encodes for occupied voxels with a one bit per voxel using a standard unsigned 64 bit integer. Unlike standard octrees, which does not explicitly encode empty voxels, we use a 2 bits per voxel approach to encode the additional information per voxel such as colour, number of returns and intensity value.

3.3 Isolating Tree Regions

LiDAR pulses reflect from surfaces they encounter such as buildings, vegetation and ground. Each pulse can return to the LiDAR sensor once or multiple times, depending on the number of surfaces it encounters. Trees typically have a high number of returns since the laser pulses can reflect from multiple edges of leaves and branches. Other features that can have a high number of returns are the edges of building and window ledges. However, these latter values are more scattered than in the case of trees which have a large number of high returns closely packed as can be seen in Figure 1.

We use this insight to isolate tree regions by identifying voxels with multiple returns (greater than 3 per voxel) and then doing a connected component analysis on these voxels. Regions with a minimum number of connected components are then identified as tree regions, while any regions with smaller than the threshold value are discarded as noise from buildings, corners, etc.

3.4 Identifying Individual Trees

The tree regions isolated by using connected components typically only return tree canopy as trunks might have only a few disconnected voxels. Hence, in order to find tree trunks, the maximum and minimum x and y coordinates of each region are identified, along with the maximum z coordinate. These coordinates are then used to place a three dimensional bounding box in the original data which is extended to ground level in order to capture the trunk information.

The width to length ratio of the bounding box is constrained so that one dimension is never more than twice the other. Any regions not matching these constraints are discarded as a false positive. This allows to discard walls covered with ivy since walls are typically long but not very thick, whereas trees have similar widths and lengths and hence the width to length ratio ≈ 1 .



(a) Experiment 1



(b) Experiment 2

Figure 4: Map of survey area with tree locations shown in yellow and the outputs of our labelling algorithm shown in red.

4 EXPERIMENTS AND RESULTS

4.1 Data

This method was tested on a dense LiDAR dataset of Dublin city (Laefer et al., 2015). This dataset was captured at an altitude of 300m using a TopEye system S/N 443. It consists over 600 million points with an average point density of $348.43 \text{ points/m}^2$. It covered an area of 2 km^2 in Dublin city centre.

We tested our results with the labels from Ningal (2012) containing tree annotations around some of the major streets in Dublin from 2008. In order to get more up to date results, we manually annotated the region north of the Liffey river for trees.

4.2 Evaluation Metric

There are three different results for the purposes of detection: True Positives (TP) where the trees are correctly recognised, False Positives (FP) where regions are incorrectly identified as trees, and False Negatives (FN) where trees are not detected. Based on these results we evaluate the following metrics (Goutte and Gaussier, 2005):

$$\begin{aligned} r &= \frac{TP}{TP + FN} \times 100 \\ p &= \frac{TP}{TP + FP} \times 100 \\ F_{score} &= 2 \times \frac{r \times p}{r + p} \times 100 \end{aligned} \quad (1)$$

where r (recall) is the tree detection rate, p (precision) is the tree detection precision and F_{score} is the total accuracy.

4.3 Results

The extracted trees have been shown in Figure 4 along with the original labels. We compared our labelled outputs with two different sets of annotations, the first from 2008 and the second from 2015 and the results are summarized in Table 1.

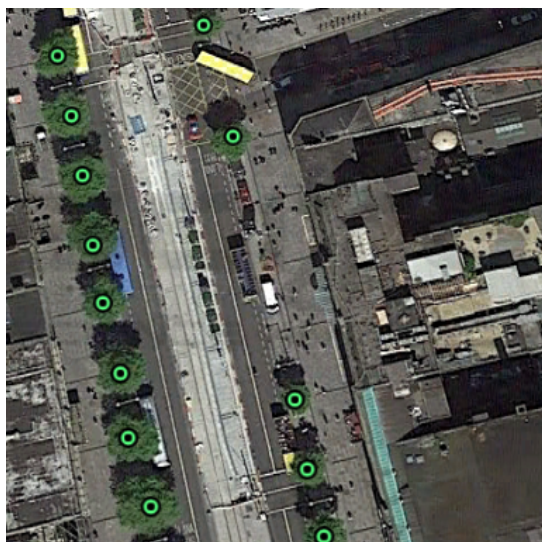
Table 1: Summary of Results.

Experiment	Trees	TP	FP	FN	p	r	F_{score}
1	313	178	45	135	0.57	0.8	0.66
2	535	469	56	66	0.88	0.89	0.88

The results of Experiment 1 (against 2008 annotations) seem to suggest that the accuracy of our labelling method is extremely low with an F_{score} of 0.66. On further analysis, we discovered that the urban landscape had changed a lot from when the tree



(a) Missed trees due to combined canopies



(b) Correctly labelled individual trees

Figure 5: Results.

labels were acquired in 2008 to when the LiDAR survey was done in 2015 due to roadworks and the construction of the city tram. Hence, we annotated a section of the city using imagery from 2015 to obtain a fair analysis of our methods.

The results from the second experiment show that our algorithm performs well by identifying almost 90% of the trees in Dublin correctly but has some weak points. It is unable to distinguish between multiple trees packed closely as shown in Figure 5(a) and assumes the entire canopy is a single tree leading to a number of missed detections. Also, it mislabels heavy ivy and bushes as trees since those produce multiple returns as well. Our method performs extremely well

in labelling isolated trees irrespective of size, one of such cases is shown in Figure 5(b), where all trees along the side of O'Connell Street have been correctly identified.

5 CONCLUSIONS

This paper addresses the challenge of automatic labelling trees in LiDAR data from urban environments. Most previous work in this area focused on extracting trees in forested regions, but the techniques cannot directly be applied to urban environments due to the complexity of the environment and the presence of multiple objects.

The proposed method uses the number of returns information present in the LiDAR data to isolate tree regions and isolates individual trees by voxelizing the data and finding clusters resembling trees using connected component analysis. It deals well with partially occluded trees and has achieved a satisfactory accuracy of almost 90% in central Dublin hence showing the effectiveness of the method. The method has some drawbacks, namely that it is unable to separate all individual trees within a large clump.

In order to deal with the current drawbacks, this work can be extended in a number of ways in the future:

- Improving individual tree detection in clumps by isolating individual trunks along with the tree canopy.
- Combining photogrammetry data with LiDAR point cloud for more robust interpretation.
- Utilising the labelled trees from this method to train a more robust machine learning based classifier which can generalise across point cloud datasets for tree detection.
- Identifying building edges and windows using the number of returns information and extrapolating from those to obtain building reconstructions.

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