Graph-based methods for analyzing orchard tree structure using noisy point cloud data

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Abstract—Digitisation of fruit trees using LiDAR enables analysis which can be used to better growing practices to improve yield. Sophisticated analysis requires geometric and semantic understanding of the data, including the ability to discern individual trees as well as identifying leafy and structural matter. Extraction of this information should be rapid, as should data capture, so that entire orchards can be processed, but existing methods for classification and segmentation rely on high-quality data or additional data sources like cameras. We present a method for analysis of LiDAR data specifically for individual tree location, segmentation and matter classification, which can operate on low-quality data captured by handheld or mobile LiDAR. Results demonstrate viability both on real data for avocado and mango trees and virtual data with independently controlled sensor noise and tree spacing.

Keywords—agriculture; lidar; pointcloud; classification; segmentation

1 INTRODUCTION

Understanding tree growth is an important consideration for commercial orchard operators. There are many ways to manually measure growth factors, including mobile Leaf Area Index (LAI) measuring devices presented by Confalonieri et al. (2013) and Francione et al. (2014) or ceptometer sensors which Ibell et al. (2015) showed could be used to study tree productivity. However, manual measurements are difficult to automate and can have prohibitive restrictions including time required to take measurements, a requirement to measure in many locations, or weather limitations (such as a need for clear sky). As an alternative, reality capture can be used to get digital models of the trees which can then be analysed. Electromagnetic digitisation methods such as those presented by Ankapudi et al. (2015) are highly accurate but difficult to implement in practice on an orchard scale. Cameras like those applied by Underwood et al. (2016) are cheap, accessible and flexible, but cannot always reconstruct geometric data. LiDAR technology is rapidly improving, and can be a quick and detailed method of reality capture which provides large masses of data and is easy to automate. Wu et al. (2020) shows excellent results for mapping structural metrics like crown volume using airborne LiDAR which scales easily. Here, we explore three separate operations which can be performed on low-quality LiDAR scans of orchard trees to enable further analyses, namely trunk location, individual segmentation and matter classification.

Previous works in trunk location in an orchard environment are typically focused on mobile platform localisation and mapping, and involve the use of multiple sensors. Bargoti et al. (2015) locate trunks primarily in the point cloud space using Hough transforms (89.7% accurate), and then reproject the detections into the camera frame to improve the results (95.8%). Shalal et al. (2015) similarly fuse laser scanner and camera data and distinguish between tree and non-tree objects, using the laser scanner to detect edge points and the camera for colour verification (96.64%). Chen et al. (2018) instead fuse camera and ultrasonic data and train an SVM classifier to localise their robot using detected trunks (98.96%). However, all of these methods are working in a limited context, with a platform travelling parallel to rows of trees and processing on a frame-by-frame basis.

Segmentation in this paper is defined as separating individual trees in the data, namely identifying which points belong to which trees. This can allow better insights for end users, since results including tree growth parameters can be mapped to specific trees (Underwood et al. 2016). McFadyen et al. (2004) showed that yield improves with light interception and tree volume, but only up to a certain point, beyond which orchard crowding reduces yield over time. If individual trees can be discerned, these effects can be better understood than if each row is just a wall of foliage.

Driven by the recent interest in autonomous driving applications, many of the current approaches to point-cloud semantic segmentation and classification operate on small pointclouds (e.g. Guo et al. 2019, up to 4096 points) as they are designed to run in real-time on single frames. Most modern methods for segmentation in larger point clouds are in specific contexts with simple structures (Poux and Billen 2019) or work on simplified data from sampled CAD models rather than LiDAR data.
Liu et al. (2019). In agriculture specifically, a variety of methods have been explored. Underwood et al. (2016) use cameras which have many advantages, but demonstrate difficulties in distinguishing overlapping branches, particularly since there is only one vantage point. Guan et al. (2015) uses euclidian distance clustering to segment trees, but the trees shown are spaced apart with minimal encroachment. Good results were achieved by Li et al. (2012) with aerial LiDAR data using convex hulls, but this was a forestry application where again trees tend to be spaced out enough to make segmentation simple. Reiser et al. (2018) presented good results on ground crops using very sparse point clouds, however their method relied on prior knowledge of crop spacing as well as a known location for each plant. We aim to implement a method which works on very large point clouds with overlapping trees and no prior.

Classification in this paper is defined as assigning pointwise semantic meaning, specifically identifying which points represent leafy versus woody matter. The key insight here is that woody matter (i.e. trunks and branches) are non photosynthetically active, and as explained by Ma et al. (2016b) there is benefit in measuring the amount of photosynthetically active material in a tree for growing purposes. One application of this was presented by Westling et al. (2018), who simulate the amount of light absorbed by trees digitized using LiDAR. Identifying woody matter improves the quality of simulation with more accurate light transmission characteristics as well as better estimates of light absorption.

Trunk classification on pure point cloud data can be done in a wide variety of ways. Fritz et al. (2013) and others focused on tall trees with a single primary trunk apply cylinder fitting to detect that trunk, and classify surrounding points as leaves. Su et al. (2019) uses a similar cylinder fitting method without the tall-tree assumption, but relies on high density scans containing minimal clutter points in order to identify cylindrical sections of point cloud. A common approach to point cloud classification presented by several authors (e.g. Lalonde et al. (2006); Ma et al. (2016a); Brodu and Lague (2012)) involves using eigenvalue decomposition to describe patches of points into broadly three categories: planar, linear and random. The patches can then be reliably classified as ground, trunk and leaf respectively, though this method is very sensitive to noise and can cause disconnected results due to its patch-based nature. Vicari et al. (2019) presented an eigenvalue method which gets around this limitation by combining graph-based methods to integrate tree structure in the calculation. Livny et al. (2010) similarly use a graph-based approach with optimised model fitting and generalised cylinders to reconstruct the skeletal structure of laser-scanned trees, while Digumarti et al. (2018) achieves good results in extracting the tree skeleton using local feature vectors. Many of these methods rely on high quality data such as that captured by slow tripod-mounted scanners and are less effective on faster mobile data.

Static (tripod) LiDAR such as that used by Vicari et al. (2019), Ma et al. (2016a) and others produce excellent results as shown in Figure 1a. However, use of static LiDAR requires time to set up and calibrate the position at each scan, and requires scanning from multiple positions for good coverage of each object, and the scans must then be combined to form a cohesive point cloud. Due to these factors, they are not practical for scanning large areas like a commercial orchard setting. At the other extreme, aerial LiDAR as used by Windrim and Bryson (2018) can cover acres of land very rapidly, but the resultant data is much less accurate and much of it is occluded. In particular, doing analyses below the top of the canopy becomes difficult. Mobile LiDAR is a good compromise, allowing scanning of multiple acres per day with less occlusion. However, the accuracy can suffer due
to the limitations of necessary automated registration. Makkonen et al. (2015) found an RMSE of approximately 15-30mm using a handheld LiDAR, which is due to a combination of scanner accuracy, training and scanning procedure. As shown in Figure 1, the handheld and mobile options show features like leaves much less distinctly because of this. Despite that, Bauwens et al. (2016) showed that handheld LiDAR produces better coverage doing forest inventory than static LiDAR and Ryding et al. (2015) concluded that handheld sensors are efficient, cost effective and versatile for forest surveying. Furthermore, LiDAR mounted on mobile platforms like that presented by Underwood et al. (2016) enables fully automated capture. When the data can be captured and processed quickly, it can be applied to orchard-scale analysis, or analysis of individual trees over the entire orchard. For these reasons, we are interested in developing methods which are applicable to low-quality point cloud data, and which ideally can be applied to data of variable quality.

Despite the lower quality, Mobile LiDAR has been used in a range of applications and industries, including building modelling in construction (Sepasgozar et al. 2014), cultural heritage surveying (Chan et al. 2016) and mining (Dewez et al. 2016). As mentioned earlier, Reiser et al. (2018) was able to achieve good results doing ground crop plant segmentation with sparse mobile LiDAR data, but relied heavily on priors. Underwood et al. (2016) used LiDAR on a mobile platform for orchard mapping and canopy volume. Westling et al. (2018) presented a light environment simulation method using low-quality point clouds from handheld LiDAR.

Deep learning is an option for processing point clouds, though this presents its own challenges. A review of the state of the art conducted by Guo et al. (2019) found that most current approaches to point cloud object classification operate on point clouds up to 4096 points, which is insufficient for our analyses. Methods using multi-view convolutional neural networks (e.g. Su et al. 2015) are unlikely to work in our context due to complex occlusions and varied environments. Similarly, volumetric methods like that of Wu et al. (2015) or Maturana and Scherer (2015) are similarly unsuited, since trees are large, varied in size, and highly complex. These methods tend to be limited to voxels of size 32x32x32, which would lose a lot of detail in complex tree crops. Direct point learning methods like PointNet (Qi et al. 2017) and its derivatives have mostly been used on standard datasets with perfect data sampled from 3D models, which produce far cleaner inputs than data from LiDAR. Guan et al. (2015) was able to use deep learning techniques to identify tree species by LiDAR, but not on the raw pointcloud, instead computing the waveform of the data and passing that into a neural net. Windrim and Bryson (2018) and Xi et al. (2018) use fully connected 3D CNNs to perform tree classification to good effect, though were applied to trees which are similar in size and shape and have little overlap. Kumar et al. (2019) was able to identify that objects as trees or non-trees with 90% accuracy, which is an operation on the macro scale and may not be applicable to small-scale features like branches and leaves. Modern machine learning methods rely on extensive labelled datasets that are not readily available in orchard applications. We instead focus on analytical methods rather than deep learning in order to avoid the need for labelled data in new contexts.

We present a system which, like Vicari et al. (2019), uses graph-based methods to perform a range of tasks on point clouds in tree crops, with specific emphasis on handling low-quality and often overlapping data. The method we present relies on the basic geometry of tree-like structures, namely that trees are connected by a network of woody matter, which is invariant to noise, fidelity and occlusion.

## 2 Method

In this section, we first describe the methods used to collect or generate data for all experiments. Then, the basic operation implemented is described, namely graph creation and search with an optional feature enrichment edge weighting scheme. Finally, we describe the three operations to which the graph operation was applied.

### 2.1 Data capture

The data used in this study can be divided into real-world data captured using a LiDAR sensor from two orchards in Queensland, Australia and simulated (virtual) data designed to emulate the properties of LiDAR scans with generated tree object models.

#### 2.1.1 Scanning method

![Fig. 2: GeoSLAM Zeb1 sensor scanning a young mango tree](image-url)
The primary data used was captured at the Simpsons Farms commercial avocado orchard, with mature trees of varied shape and considerable overlap. The trees are scanned using a handheld LiDAR, specifically the GeoSLAM Zebedee 1 shown in Figure 2. 8 datum trees were selected to represent a variety of tree shapes, and each tree was scanned five times at different occasions over a period of two years during which they underwent fruit growth, harvest, and pruning. The trajectory of the scan was kept reasonably consistent for each (accounting for operator error) and the path taken was designed to maximise coverage and minimise occlusion. To fix the quality at a consistent level, we cropped the point clouds for each datum tree down to just the tree and its two closest neighbours.

To provide a ground truth, we manually assigned labels to each point cloud in two steps. First, we labelled the points as to which tree they belonged out of the three visible trees or the ground. Second, we added a label to classify matter as leafy or woody matter. An example of one stand of avocado trees with both labels is presented in Figure 3. For the avocado dataset, we generated 40 point clouds in this format.

A second set of real data was also collected, to allow for better testing of the trunk location operation. This data was captured at a Queensland Government orchard intensification trial using young mango trees where various planting densities are replicated and studied. For these experiments, entire orchard blocks were scanned at a time to simulate the trajectory of a mobile sensor platform, so the data is less distinct for any individual tree but far more trees are included in each set.

2.1.2 Virtual Dataset

In the interest of more data for testing, as well as experimenting with different parameters, we produced a dataset of virtual tree scans. With a non-deterministic and fully automated process, this dataset can be arbitrarily large and is perfectly labelled. However, since simulated data is never a perfect substitute for real data, we use this as a supplemental set with which we can alter independent variables to better understand algorithmic robustness rather than as a primary indicator of quality. An example of virtual generated data with no noise is shown in Figure 4, though the sets used in our experiments contain a small amount of gaussian noise, and is sampled according to the known LiDAR trajectories of the real data in order to provide a dataset with similar characteristics to the real data.

2.2 Graph operation

The core method in our implementation involves a graph search over the point cloud, finding all paths through the cloud to any identified trunk points, and is illustrated in Figure 5. Trunk points are defined as a single point per tree at the interface between the tree and the ground plane. The ground is first removed by finding the local minima for each point in the Z axis within a lateral search radius \( R_{g} \). Assuming sufficient LiDAR coverage such
that any gaps in the scanned ground are smaller than \( R_g \), this method can quickly identify the ground points and they can be excluded from graph construction since we know that no part of the ground can represent woody or leafy tree matter. To normalize matter density and reduce search time, we first voxelise the point cloud at a given voxel size \( v_s \), defined as the side length of a cubic voxel element. The nodes of the graph are then defined as the average position of all the points in each voxel. The edges for the graph are then defined. In its simplest form, each node is connected to all neighbouring nodes with a fixed radius \( R_e \). When a query is performed, the shortest path is found using A* (Hart et al. (1968)) from the trunk node of each tree represented in the point cloud to each node in the graph. By aggregating all these paths, we can score each node according to the number of times the node appeared in paths, which is proportional to the node’s participation in the trunk network of the tree, and the length of the shortest path to that node. We use these scores to achieve the various desired results.

The reason this method is applicable is due to the basic geometry of trees. The trunk and branches produce a network of connected matter to which all leaves are connected, and the paths through the canopy also form such a network, which overlaps in most cases. Where paths exist through leaf matter, the point density tends to be very different, so edge weighting can be applied to encourage paths to traverse more trunk-like areas. Figure 6 shows an example of how the graph score tends to follow woody matter.

Fig. 5: Illustration of the graph operation. The point cloud is voxelised and each node is connected to its neighbours. The shortest path is found from each node to the trunk node, and these paths are aggregated to produce a nodewise score.

(a) Graph with single path highlighted

(b) Graph with all paths aggregated

The multiple existing methods of point cloud classification utilise handcrafted features relying on local spatial features of the point cloud (Lalonde et al. (2006); Ma et al. (2016a)). However, the quality of the point clouds produced by handheld or otherwise mobile LiDAR is too low for methods relying solely on eigenvalue decomposition or local normals, since planar or cylindrical surfaces may present incorrectly due to occlusion, sensor noise, varying distance to the sensor, or movement due to wind. That being said, computing these spatial features may enable better graph computation, so we implemented an enrichment approach which converts raw XYZ points into a set of additional features presented by Poux and Billen (2019), which are summarised in Table 1. During graph construction, we can use these features to introduce weights to the edges based on the relation between features of connected nodes. Figure 7 visualises two such weighting schemes, namely difference in density and cosine similarity between all enriched features.

Multiple methods of computing edge weights from descriptors were investigated. Ideally, the edge weighting scheme should present with a low weight for trunk to trunk edges, and a high weight for edges to or from leaf nodes. The method chosen as that which best exhibited this behaviour was the cosine similarity of normalised values,

\[
S_C = \frac{\vec{f}_A \cdot \vec{f}_B}{\| \vec{f}_A \| \| \vec{f}_B \|}
\]
Feature Description

Eigen-based features

| Feature   | Description                                                                 |
|-----------|-----------------------------------------------------------------------------|
| $\lambda_1, \lambda_2, \lambda_3$ | Eigen values of $V_{i,j,k}$                                                  |
| $\bar{v}_1, \bar{v}_2, \bar{v}_3$ | Respective eigenvectors of $V_{i,j,k}$                                       |
| $\bar{e}_i$ | Normal vector of $V_{i,j,k}$                                                 |
| $\lambda_a$ | Anisotropy of $V_{i,j,k}$                                                   |
| $\lambda_e$ | Eigen entropy of $V_{i,j,k}$                                                 |
| $\lambda_l$ | Linearity of $V_{i,j,k}$                                                     |
| $\lambda_o$ | Omnivariance of $V_{i,j,k}$                                                  |
| $\lambda_p$ | Planarity of $V_{i,j,k}$                                                     |
| $\lambda_s$ | Sphericity of $V_{i,j,k}$                                                    |
| $\lambda_v$ | Surface variation of $V_{i,j,k}$                                             |

Geometric features

| Feature   | Description                                                                 |
|-----------|-----------------------------------------------------------------------------|
| $V_{ix}$, $V_{iy}$, $V_{iz}$ | Mean value of points in $V_{i,j,k}$ respectively along $\bar{e}_x, \bar{e}_y, \bar{e}_z$ |
| $\sigma^2_{ix}, \sigma^2_{iy}, \sigma^2_{iz}$ | Variance of points in $V_{i,j,k}$                                             |
| $A_{Vp}$ | Area of points in $V_{i,j,k}$ along $\bar{e}_3$                             |
| $A_V$ | Area of points in $V_{i,j,k}$ along $\bar{e}_z$                            |
| $m$ | Number of points in $V_{i,j,k}$                                              |
| $V_V$ | Volume occupied by points in $V_{i,j,k}$                                    |
| $D_V$ | Point density within $V_{i,j,k}$                                            |

Connectivity features

| Feature   | Description                                                                 |
|-----------|-----------------------------------------------------------------------------|
| $C_H$ | Number of horizontally adjacent voxels                                      |
| $C_V$ | Number of vertically adjacent voxels                                        |
| $C_M$ | Number of diagonally adjacent voxels                                        |

TABLE 1: Enrichment features applied to each point cloud voxel $V_{i,j,k}$, as first presented by Poux and Billen (2019). All features can be derived from just XYZ coordinates.

where $S_C$ is the cosine similarity between two graph nodes A and B while $\vec{f}_A$ and $\vec{f}_B$ are their respective feature vectors.

2.3 Trunk detection

To use our graph operation method, we must as mentioned know the location of one node per tree to serve as the start point for each path. The trunk is a good choice for this node, since it is perfectly unambiguous as to which tree it belongs to, is at a consistent height, and is easy to manually label. However, applying this method generically, autonomously or at scale requires a method for automatically locating trunk points. We applied our graph operation in a configuration to achieve this, illustrated in Figure 8. The graph construction used here is slightly different to that described. The voxelisation is performed using a larger $v_s$, then we take a spatial subsample of the non-ground nodes to generate a list of source nodes. We apply the graph search from each source node to all ground nodes, score each node by the length of the path to the target, and aggregate by taking the minimum score for each node. The resulting score map across the ground nodes is characterised by a cluster of low scores around each ground-tree interface, which can then easily be filtered to find local minima which are then classified as trunk points. Where multiple distinct trunk points exist in close proximity due to the presence of multiple targets per tree, a distance threshold is applied to cluster them as a single node.

When testing this method, we used real data with manual labelling as well as virtual data with automatically generated trunk locations using known tree spacings. We counted the true positive, false positive and false negative rate using a distance threshold to determine whether generated trunks matched the ground truth, and computed the average displacement for correctly identified trunks.

2.4 Individual segmentation

To perform tree segmentation using our graph operation, we track the paths from each trunk node to each node in the graph. In cases where trees are sufficiently spaced that there are no non-ground paths between their trunk nodes, segmentation is equivalent to simple distance-based clustering. For each tree node which was reached...
Fig. 8: Visualisation of the trunk finding operation. First the search targets are generated on all non-ground points. Then, the graph operation is used to score all ground points by path length and the result is aggregated to find ground entry points which are designated as trunks.

by a path, the node is allocated to the trunk node which originated that path. When trees are close together or have long-reaching branches, they contain overlapping geometries and each tree node has multiple candidate trunk points. In this case, we sort the candidates by the length of the shortest path from the node to the candidate trunk, assigning each node to its closest trunk. This is visualised in Figure 9. We tend towards a smaller $v_s$ and $R_e$ during segmentation, to prevent paths “jumping” between branches which are stretched into neighbouring canopies. Once each node, represented by a voxel, is assigned to a trunk, the segmentation is propagated to all points contained by the voxels. Since the path length is a good representative for “real” (that is, connected through matter) distance from the trunk to each point, this produces better results than a simple distance-based segmentation which cannot handle overlapping canopies and branches.

Fig. 9: Illustration of the graph operation applied to tree segmentation. When there is overlap, at least two paths to trunk will exist for each node, and the segmentation is determined by the shortest path.

2.5 Matter Classification

For matter classification, we aggregate the graph operation by the number of times each node appears in a path. This per-voxel score, similar to the method presented by Vicari et al. (2019), is computed as the ratio of logs over the entire graph:

$$S_x = \frac{\log(p_x)}{\log(p_M)},$$

where $S_x$ is the score for a particular node $x$, $p_x$ is the number of paths in which $x$ appears, and $p_M$ is the maximum value of $p$ over the whole graph. The logarithm of path count is used since the range escalates quickly with the number of points, and by computing the ratio we normalise the score for different point clouds. A point cloud with short trees which do not overlap will have a much lower $p_M$ than one containing tall trees with significant overlap, but $S_x$ compensates for this variability.

Voxels are then classified by taking a percentile of the score as a threshold. Since there are typically many possible paths through each trunk or branch, we remove all nodes classified as woody matter and rerun the graph search. This process is iterated multiple times. Finally, the voxelwise classification is propagated back to the component points by computing a large-neighbourhood average to “smooth” the classification and compensate...
for paths not passing through all nodes that make up a trunk.

3 Results

In this section we present the results of experiments with our implemented method.

3.1 Trunk detection

Trunk detection was applied to real data (stands of three avocado trees as well as entire blocks of mango trees) and virtual data, of which qualitative examples are presented in Figure 10 (virtual trees) and Figure 11 (high density real trees). The mango data is a mixture of low and medium density (not much overlap) and high density trees (significant overlap). Generally trunk detection works well when trees are well defined, but not as well at the edges of scans where trees and the ground are poorly defined due to lower scanning density. In virtual data, all generated trees are included in the results including these border trees.

Table 2 display a summary of results on real and virtual data. In both datasets, the majority of trunks were correctly detected, at an average distance of 0.357 m and 0.452 m respectively from the human labelled points.

Using virtual data, we intentionally inject different levels of noise when generating the point clouds. Figure 12 shows the average F1 score across noise levels.

3.2 Individual segmentation

For tree segmentation, we compare our method to a basic distance method where each point is allocated to the nearest trunk by straight-line distance. Figure 13 shows an example of a single avocado stand with both methods applied. When scoring quantitatively, we use the v-measure cluster evaluation measure presented by Rosenberg and Hirschberg (2007). Here we score each point cloud using v-measure, with a maximum score of 1 when clusters are perfectly identified. Point clouds range in size from 3 trees to dozens.

3.2.1 Virtual data

The results of comparing our method with the direct closest-trunk approach is presented in Figure 14. Here we exclude the data where the two methods agree in order to ascertain the quality of our method on overlapping trees.

Since we have more control of the dataset in the virtual space, we also perform testing over noise levels, presented in Figure 15 and tree spacing, presented in Figure 16.

3.2.2 Real data

For comparison against real data, we focus on the avocado trees which are relatively complex in structure, closely spaced and display considerable overlap. However, an example of our segmentation applied to high density mango trees is shown in Figure 17.

Meanwhile the quantitative results on the avocado data are presented in Figure 18. We display the results for applying our method with no edge weights, as
well as applying it with the edges weighted as per the cosine similarity score between the enriched features of connected nodes.

3.3 Matter Classification

Again we present a qualitative example of the matter classification operation in Figure 19. For these experiments we used the same dataset as in the ones for segmentation, though here we score results with the F1 score derived from the binary classification of leafy versus woody matter.

3.3.1 Virtual data
- Classification accuracy
- Robustness (different types of noise)

Figure 20 presents the accuracy of 8 randomly generated stands of trees across 11 levels of introduced noise. Here we divide results between 4 tree structures: Trunk, Branch Level 1 and Branch Level 2 represent woody matter and are defined in the Arbaro tree generator. Leaf represents all leafy matter.

3.3.2 Real data

Figure 21 shows the quantitative results of applying matter classification on real avocado trees. Again, we present results using both unweighted graphs and graphs weighted by cosine similarity of enriched features.

Finally, we present results in Figure 22 of a comparison on the results on our real data of our method and the method presented by Vicari et al. (2019). For these experiments, we ran both methods with default parameters on all 40 sets of avocado data. Experimentation with different parameters using Vicari’s method was infeasible due to runtime.

4 DISCUSSION

In this section, we discuss the results of our method on the three use cases presented. In particular, we consider the main failure cases and the effect of varying physical characteristics.

4.1 Trunk detection

Table 2 shows that finding trunks works well on real data, with an F1 score of 0.78. A likely cause for false negatives is the high-density trees which are visible in Figure 11 These trees are planted close together and, in the case of trellises, feature canopy close to the ground, which makes identification of a single trunk per tree difficult. Furthermore, the mango data contains fence posts and non-tree items (e.g. vehicles) which would register false positives (for example the post on the far right of Figure 11). In the virtual data, the method performs slightly worse with a lower precision. A potential reason for this can be seen in Figure 10 where trees with branches close to the ground are counted as having multiple trunks. The method compensates for multiple trunk points detected
within a specified radius, so where the tree spacing is known this radius can be calibrated to reduce this error. The response of F1 score against introduced Gaussian noise as presented in Figure 12 shows a slight decline in F1 score as noise increases, but it is certainly not significant. Combining these observations, we can surmise that this method is potentially reliable in noisy environments, but handles poorly in sparse ones.

4.2 Individual segmentation

Across the board, segmentation results present very well. However, the closest-trunk method also demonstrates high quality results, since the majority of points in the point clouds can easily be classified as to which trunk they belong. Where our method performs better is in the overlapping sections shown in Figure 13 which represent a small proportion of points in the entire point cloud but can be significant, for instance if interested in identifying which branch belongs to which tree. An interesting future experiment could be to remove from consideration all points on which both methods agree, and only score the remainder. This should show a more...
significant difference between the efficacy of the two methods. Experimentation on virtual data show that this method is reasonably reliable when put against varying noise as well as tree spacing. Noise in the data would not be expected to have a significant effect, since the method does not rely on geometric features but rather the relative distance between points. Similarly, the spacing of trees has some effect, but overall our method performs well even in this context. Figure 16 shows that the distance-based method performs excellently at large spacings (as can be expected), but as trees get closer together and the amount of overlap increases our graph method overtakes it. A potential reason our method does not perform as well as the distance method in some cases is that not all points in the cloud fall within the graph; any points which are not sufficiently close to the main canopy (typically those high up in the canopy) are labelled as unknown rather than allocated to a particular trunk.

4.3 Matter classification

Classification struggled to perform well across the board, with an average F1 score of 0.43 for real data.
Fig. 20: Results of matter classification on virtual data. Data were generated using consistent tree spacing of 6m across various levels of introduced Gaussian noise, and presented for 4 different levels of tree structure.

When compared with the state-of-the-art method presented by Vicari et al. (2019), our method performs quite well. Part of the reason for this could be that Vicari’s method uses the geometric features of the point cloud as well as the structural characteristics, and as we’ve shown the use of geometric features does not seem viable with this format of data. The data used here is also captured by a handheld scanner, exposing it to significant variability in point density and scan quality.

The results on virtual data were promising however, as Figure 20 show the method is almost unaffected by noise levels whose range is demonstrated in Figure 23. Also shown in this figure is that the method performs best on the most distinctive classes, namely leaf and trunk. The results are slightly worse on the smaller branches, which are more likely to “blend in” with leafy matter.

One reason the classification results are poor could be that due to sensor noise and occlusion, these labels are imperfect. Higher in the canopy, the branches tend to be thinner and the distance from the sensor is greater, leading to less distinction between leaves and branches. This problem is also exasperated by wind causing movement of elements between successive LiDAR passes.

Another issue with our method is that the graph search does not pass through every node, instead finding central “highways” to travel through. In areas where the voxel size is approximately the same as the trunk thickness, this works very well, but where the trunk is multiple nodes wide, many nodes are bypassed and therefore likely to be classified as leaves.

Fig. 21: Results of our classification on real data. Note the missing data in (b) is due to difficulties in enriching large point clouds, like those captured for 20151125.

4.4 Future work

Further study is required to understand the pros and cons of our method. More real data would be beneficial to this understanding, using a greater variety of scanners. Our study was focused on handheld LiDAR, but application to tripod, aerial and mobile LiDAR may demonstrate versatility to point cloud noise and density which we currently only theorise using our artificial noise experiments.

Also, the point enrichment scheme shows promise when examined qualitatively (as in Figure 6), but displays little or no improvements on final results. Part of this could be due to the large number of introduced features - an ablation study could clarify which ones are
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Fig. 22: Comparison between our method and that of Vicari et al. (2019) for real avocado tree scans

![Comparison between our method and that of Vicari et al. (2019) for real avocado tree scans](image)

Fig. 23: Virtual trees generated without noise and large noise.

![Virtual trees generated without noise and large noise](image)

significant and discarding the rest may improve results. The enriched features could also be used more effectively. Further study could show positive results in applying machine learning to the enriched features to improve the initial results provided by the graph operation.

Taking the method as it stands, the ability to simply understand the structure of the trees and the connectivity of the branches has further applications. In particular, we are interested in studying the effects of pruning on the canopy, which can be simulated using the knowledge of tree connectivity.

5 Conclusion

We presented a system for processing point cloud data captured using LiDAR at a fruit orchard to detect trunk location with no priors, segment individual trees even in high-density contexts, and classify trunk and leaf matter automatically. Experimental results using virtual data showed the method was fairly robust to noise and tree spacing, and results were good for a variety of real data.

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