Determining Tree Boundaries and Tree Height from Digital Elevation Models

Literature Review

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ABSTRACT

The calculation of tree height from data gathered by aerial surveillance is a popular topic. Many use Light Detection and Ranging systems, mounted onto drones, which measure the distance between itself and whatever is underneath it. This means that the measurement of the height of a tree will include the height of the land underneath the tree. As a result, many of these studies use supplemental data in the form of ground height measurements to aid their calculations. This ground height data is subtracted from the total height data to calculate the actual height of the trees. This project will explore ways to calculate the height of trees from Digital Elevation Maps (DEMs), which are height maps of an area, without the use of additional ground height data. Before tree heights can be calculated, trees must be isolated in the DEM to obtain the total height of each tree, rather than having the total height of every pixel in the map. Tree height calculation algorithms can then be applied to the trees identified. Therefore, this review will evaluate research on tree segmentation and tree height calculation. To solve the problem of determining tree boundaries, watershed processing, and its variations, were discussed. Convolutional neural networks are also discussed, but they may require too much time to implement. Watershed processing will be investigated further. To solve the problem of determining tree heights, extrapolation was looked at as a way of estimating the height of ground beneath trees. An analysis of tree characteristics is also discussed with the aim of determining the relationship between a tree's height and crown projection. This accuracy of this method varies depending on many factors. Therefore, extrapolation of the ground surface will be considered as the method to calculate tree height.

CCS CONCEPTS

• Computing methodologies → Computer graphics → Image manipulation → Image processing

KEYWORDS

Tree Segmentation, Watershed, Convolutional Neural Networks, Tree Height, Extrapolation, Infilling, Digital Elevation Models

1 Introduction

The agricultural industry is vital for the survival of humanity. Farms need to improve efficiency to ensure that they can keep up with the increased demand for nourishment. This project will focus on orchards, where trees are planted in rows and often occlude each other. To monitor tree health, farmers would need to determine the heights of their trees. A way to improve orchard farming would be to calculate tree heights more efficiently. The current way of doing this is by manually measuring tree heights using direct measurement or trigonometric based methods, which can produce accurate results. However, these methods are slow. Another way of doing this would be to use LiDAR (Light Detection and Ranging). A LiDAR sensor can measure the distance between an object and itself. By placing a LiDAR sensor on a drone, and capturing a series of images of the ground during flight, a DEM (Digital Elevation Model) of the landscape below can be produced. However, a tree point on a DEM will include the height of the tree as well as the height of the land immediately below the tree. A method of determining the actual height of trees from DEMs is required. This is the focus of this project and will require many steps. This paper will review methods of solving two problems: segmenting trees in a DEM and ways of determining the height of trees in a DEM. For the tree segmentation problem, the paper will discuss watershed processing and its variations [7] as well as Convolutional Neural Networks [29]. For the problem of determining tree height, this paper will review methods of extrapolation [8] and tree character analysis [24].

2 Background

DEMs are images where pixels values represent elevation on the ground. This project will work with greyscale DEMs where darker pixels represent a region with a lower altitude and lighter pixels represent a region with a higher altitude. There are many ways to extract information from a DEM. As this project aims to calculate the actual height of trees from a DEM, some background information will be provided about some of the methods required.

2.1 Segmentation Methods

Segmenting in image processing refers to the ability of an algorithm to partition images based on some heuristic. In this project, the focus will be on segmenting trees in orchards. This can be done through surface modelling [41]. There are many steps involved in this method. DEMs are first cleaned to remove noise using low-pass filters [32]. Points are interpolated into a grid [40], which is then processed by a Gaussian filter to smoothen it [28]. Local maxima can then be identified in the DEM, representing the middle of each tree. An algorithm can then be used to expand from each local maximum in a star shape to identify the rest of the tree [39].

Watershed segmentation is another way to segment trees [7]. It works specifically on DEMs as it uses the height information provided by the pixels of the DEM. In the DEM, the watershed algorithm identifies *catchment basins*, which are areas where a local minimum is present [33]. The catchment basin also includes points around the local minimum which have their steepest gradient ending at the minimum. Pixels are either assigned to a basin or a watershed. DEMs can be divided into regions through *merging basins.* Basins are flooded until they merge with neighbouring basins. This separates the watersheds, which now form their own regions [3].

2.2 Convolutional Neural Networks

A Convolutional Neural Network (CNN) is a subset of Artificial Neural Networks (ANNs). These networks, CNNs in particular, are useful for classifying images [38]. ANNs have nodes, called neurons, in layers. Each neuron in a layer is connected to every neuron in the next layer. Each neuron has a value, called a weight, that when changed, will alter the output of that neuron. If enough weights are changed, the output of the network will change as well. The network works by accepting an input, feeding it into the input neuron layer for processing, which then pass their outputs into the next neuron layer. The last layer will produce an output. The network can learn to identify objects by changing its weights. However, a drawback of using ANNs is that they can overfit data, due to having too many connections between the neuron layers [29]. CNNs overcome this issue by reducing the number of connections between layers – some neurons will not be connected to all neurons in the next layer.

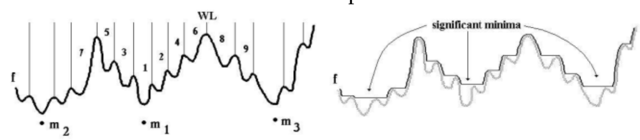
2.3 Tree Character Analysis

Many studies on relationships between tree variables, such as height, crown projection and stem thickness, were performed. As DEMs will be used in this project, tree boundaries could be determined, from the maps, using one of the segmentation methods discussed in this paper. This would provide crown projection data. Many studies use regression analysis, which is a way of determining the relationship between two or more variables [36], to examine tree attribute data. A figure, known as *p-value*, determines if a relationship described by a statistical model is significant: a lower p-value indicates a higher significance. Another figure, the *R-squared* value, determines how well data is explained by a statistical model: a higher R-squared value indicates that the model better explains the data. These values are provided by studies to indicate the accuracy of the models they develop. It will be discussed further how the models developed by these studies can be used to determine tree height.

3 Watershed Segmentation

Watershed algorithms have been used many times in peak-valley segmentation problems. They can be made more efficient through the use of parallelisation [27]. It would be suitable in this project as in the DEM, treetops would represent peaks, while the space between trees would represent valleys. There are many heuristics that can be used in the watershed algorithm, such as spanning trees, shortest path and topological distance [26]. The best one can be selected depending on the characters of the DEM. A common drawback with this algorithm is that is can oversegment data, which happens when variations in the DEM cause the algorithm to form many little catchment basins, where only one large basin should exist.

A way to overcome oversegmentation of data is to indicate where the significant catchment basins should form [7]. These are known as markers and can been seen in Fig. 1(b), whereas Fig. 1(a) displays the unprocessed function. Little basins around the marker will form part of the significant basin. Markers can be found manually, or by calculating them using geodesic reconstruction [42], which is an operation which dilates a function to get spread out markers. Another method to identify these markers is known as the waterfall algorithm [6]. A local minimum is flooded. When this occurs, it will overflow into a neighbouring local minimum. When the second minimum is filled, it will either overflow back to the first minimum (in which case the first minimum is significant) or onto the adjacent local minimum (in which case the minimum that was first is not significant). This process is repeated until all local minimums have been processed.

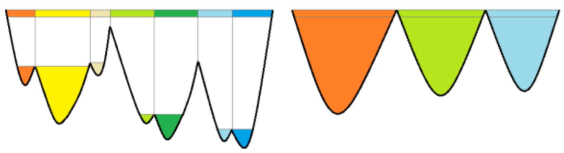


a) **b)**

Figure 1: A function showing watershed lines in an unprocessed function (a) and significant minima (markers) identified in the function (b) [6].

Inverse watershed is a method of watershed processing where DEMs are inverted [15]. This is a useful approach as is it effective in cases where trees grow close to one another – the ground may not be visible between trees. In the case of an orchard map, when inverted, treetops would become catchment basins and the ground around trees would become watersheds. A direction layer, which looks for drops in the DEM, can be created to identify the basins [43]. This alone may not identify all tree crowns, which leaves gaps in the output where a tree should be but was not detected. A solution would be to use a threshold value, pre-determined through trial and error, to determine if the gaps in the output, should be classified as ground or a tree [31].

Deep watershed was developed as another way to overcome the issue of over segmentation of data [3]. An ANN is used to learn the characteristics of the DEM. The network is then used to predict an area where each catchment basin would correspond to an entity. This effect can be seen in Fig. 2. The traditional method (Fig. 2(a)) produces many catchment basins for a single entity, whereas the deep watershed method (Fig. 2(b)) combines the related catchment basins.



a) **b)**

Figure 2: A comparison of the segmentation done by traditional watershed (a) and deep watershed (b) [3].

Learning the characteristics of the DEM is difficult but is made easier by breaking down the learning into tasks. The direction of gradients is learned and the output of this is fed into another network that learns the final landscape [3].

4 Convolutional Neural Networks

Neural networks are useful for identifying patterns in images. A CNN could be used to identify tree crowns in the DEM. However, a drawback is that they require many training data sets. Networks can also get very large, which increases processing time [22]. Ronneberger et al. [34] developed a network, a *U-Net*, based on the work by Darrel et al. [38] that requires fewer training data sets. Ronneberger et al. added additional layers to their network. Pooling operators, which combine the output of neurons in a layer, were removed and upsampling operators, which pad data segments with zeros, were used in their place instead. Images were then combined with the output produced by the upsampling operators. As they had limited training data sets, they altered their existing data using deformations to prevent the network from overfitting data [14]. These changes resulted in a segmentation solution with a higher accuracy, which can be seen in Fig. 3. The output area, enclosed by the yellow square, requires the area enclosed by the blue square as input. Missing data, at the upper and left edges, was extrapolated.

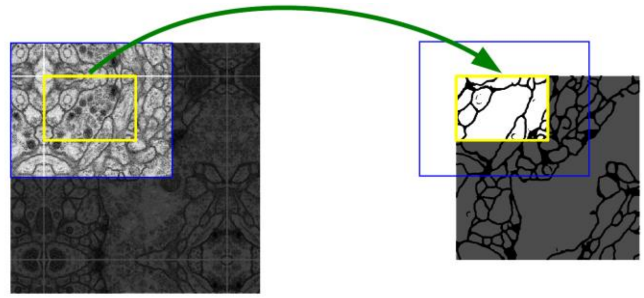


Figure 3: Segmentation result produced by Ronneberger et al. [34].

Atrous convolution was used to segment images at different scales [10]. In atrous CNNs, the field-of-view is dilated, while using fewer pixels, by only considering every other pixel. It is effective at separating objects from noisy backgrounds.

5 Extrapolation

Extrapolation is the process of extending a graph, or other series of values, based on the trends of the known values [8]. This would be useful for determining the actual height of the ground beneath the trees in cases where the ground is occluded due to a dense tree canopy. Trends about the height of the land could be formed from the areas of land that can be seen in the DEM. This information is then used to estimate the height of the land in the areas where land cannot be seen. Once this has been achieved, the height of trees can be determined by simple subtraction of the ground height DEM, which is calculated, from the total height DEM provided.

Context-based filling aims to extrapolate missing object points based on patches of similar, known object points [37]. In their study, Sharf et al. focused on reconstructing surfaces. The area of missing data, the hole, is filled with patches of similar points. These patches must be carefully selected based on some criteria [1]. The patches must also be correctly aligned to best match the surroundings, using rigid transforms and closest point procedures [5]. This process is repeated, which results in the boundaries between patches being refined and smoothed, until a satisfactory extrapolation is achieved. A similar approach was used by Adan et al. [35]. However, they had projected their 3D objects onto a 2D surface before performing context-based filling.

A method of depth gradient infilling was developed by Doria et al. [13], based on the work by Sharf et al. [37]. They removed objects from LiDAR scans and replaced the missing textural and structural data using patch-based inpainting algorithms. An algorithm by Criminisi et al. was used to copy patches of similar pixels from elsewhere in the image onto the area with missing pixels [11]. Data from the height map was also used to construct missing data. They found that although colour pixel patches may look similar (they have a similar colour pattern), the magnitudes of their depths in the height map often differed. Gradient, instead of absolute depth from the height map, was used. The results of their algorithm can be seen in Fig. 4.

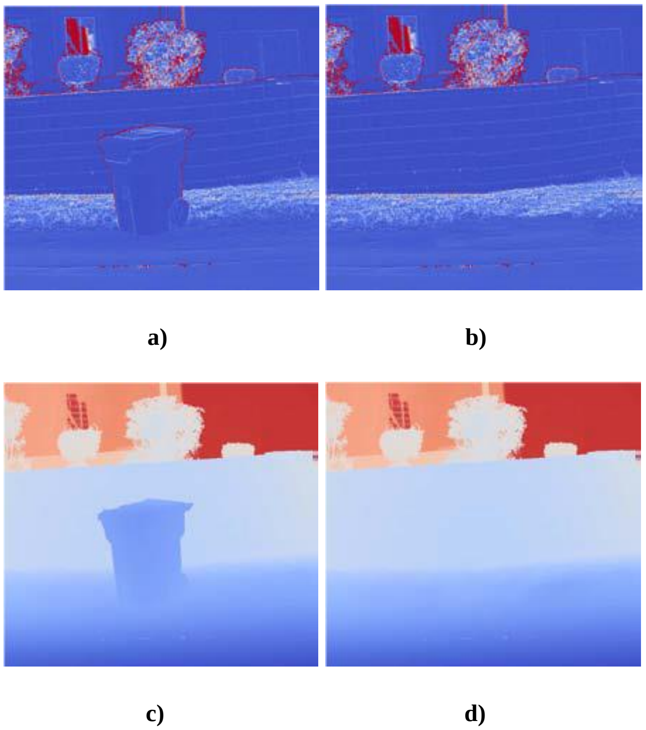


Figure 4: The result of the depth gradient infilling technique. (a) and (b) show the gradient image before and after reconstruction, where blue shows areas of low gradient and red shows areas of high gradient. (c) and (d) show the depth image before and after reconstruction, where blue shows areas nearer to the scanner and red shows areas further away from the scanner [13].

6 Tree Character Analysis

There is a greater need to update forest models as newer technology to gather data about them arrives [24]. As the DEM provides elevation data about the landscape, the diameter of the tree crown can be determined at different heights. This provides more data than in the case of a regular aerial photograph, where only the total crown projection can be determined. Models were developed to determine the relationship between these tree attributes. It is important to note, however, that tree growth depends on many conditions. Trees growth in orchards differ from trees that grow in the open, as neighbouring trees in orchards restrict the amount of light that reaches them [18].

McDowell et al. studied the relationship between the leaf area of a Douglas-fir tree and its height [25]. They found that the ratio between leaf and sapwood area decreased as trees aged. Regression analysis was used to examine the data collected from different trees [36]. Linear regression was found to be the best fit. Avsar et al. also made use of regression analysis to determine the relationships between Calabrian Pine tree attributes and found that there was a significant relationship between tree height, diameter at breast height and crown diameter [2]. The p-value for this model was $P<0.0001$. A strong R-squared value was found for the relationship between tree height and diameter at breast height: $R^2=0.82$. Functions for estimating tree characteristics were developed by Kalliovirta et al. and these, depending on the variables used, had a root mean square error between 7.3% and 14.9% [21]. LeBlanc found that relationships between tree breast height and tree stem variables varied between trees with similar ages [23].

Özçelik et al. also created a model to determine the height-depth relationship of trees [30]. They recognised that these models may not be accurate as the height-diameter relationship of trees, growing in the same area, may not be constant as they age [12]. To solve this problem they used an ANN with backpropagation to identify patterns in the height-diameter relationship [17], using a MATLAB tool [4]. In this case an error is produced when the output of the network is not the expected output. This error is passed back though the network and is used to change the weight values of the neurons, to improve the recognition ability of the network. As a new calculation is done on every plot, the patterns of different plots will not affect each other when they are processed. A similar approached was used in a study of beech trees in Spain [16]. Jutras et al. used ANNs as well to estimate the height of trees in urban environments [20].

7 Discussion

With the advancement of technology, autonomous surveillance has become much more commonplace, such as with satellite or remote drone photography. This means that there are many images available for analysis, but not all would have been captured during ideal conditions. For example, aerial images of orchards may contain cars and people. Therefore, the solution developed in this project should be robust to cater for outliers and noise in data.

To determine tree boundaries, individual trees would need to be isolated in the DEMs provided. An advantage of using orchard images is that trees are usually planted in rows. Watershed processing, when determining tree boundaries, can be simplified through the use of markers [7], as these tell the algorithm where to focus its flooding attempts, which reduces oversegmentation. Therefore, grid-like markers could be developed to aid the segmentation process. If the output of segmentation produces gaps in an area filled with trees, it may be assumed that there should be a tree present there, due to the grid-like nature of orchards.

When segmenting trees, noise in the data would pose a challenge to the effectiveness of the algorithm developed and could lead to issues such as oversegmentation. Considering that the DEM will contain information about tree heights, noise is very likely – the uneven surface of trees due to leaves will produce tiny bumps in the map. Modifications to the watershed algorithm were proposed as ways to deal with this. The waterfall technique [6] uses standard algorithms, thus, it is computationally cheap. The deep watershed method [3] makes use of CNNs and requires a greater number of steps. This would add complexity to the algorithm and may make it difficult to locate errors. Training the neural network used by deep watershed would also pose an issue: overfitting of data and obtaining suitable training data would be difficult. There are also cases where the ground in the orchard is occluded by the canopies of trees. The inverse watershed method [15] is effective in these cases. This method also makes use of simple transforms to process the image. The combination of inverse watershed and the waterfall technique could be investigated further to gain the benefits of both. Their simple nature should limit the computational power required to process them, thus, saving time.

Atrous CNNs [10] and U-Nets [34] are the two neural networks that are better suited to our problem. Atrous CNNs have the advantage of being able to process images even when the backgrounds are noisy. The U-Nets do not require as many training datasets, although, the researchers did have to create their own data to mimic the natural deviations in real data. These could be combined to obtain the benefits of both, although, this will require many tests to ensure that the network produced is stable and usable.

In the case of determining tree heights, the extrapolation techniques have produced accurate results. Doria et al. used depth gradient infilling to extrapolate missing depth data [13]. Colour images were used in their study as they focused on removing objects from images and replacing the resulting hole in the image with extrapolated pixels. However, this project will not use colour images, therefore, there will be no need for texture infilling. Only depth map infilling will be considered.

There are occlusion issues with the method proposed by Kalliovirta et al. [21]. It was found that branches are likely occluded by neighbouring trees when photographed using aerial photography [19]. This would mean that the maximum size of crown projections would be smaller in aerial photographs, and the DEM, than it would be in real life. This could reduce the accuracy of height estimations. The study was only performed on pine, spruce and birch trees, so the models they developed may not work for other tree types. Tree maintenance, such as the trimming of branches, is likely in an orchard. This would reduce tree crown projections which would affect height estimations.

As mentioned by LeBlanc, the relationship between tree attributes can vary depending on many external factors [23]. Although some studies have produced accurate tree characteristic models, such as the one produced by Avsar et al. [2], they have often only looked at a specific type of tree growing in a specific area. There is uncertainty regarding how these models will perform when using them on other tree types.

The method proposed by Özçelik et al., the ANN aided tree analysis [30], does fare a bit better than the one produced by Kalliovita et al. [21]. The approach used by Özçelik et al. uses similar plots in their calculations – the neural network would only be trained based on images of similar trees in similar landscapes. While this does present an issue of limiting training datasets and overfitting, it does mean that specific patterns in an orchard would be recognised, for example, if a farm regularly trims their trees. This new pattern would then be considered in the analysis. Castano-Santamaria et al., however, noted that the variability between different tree plots could lead to inaccurate height estimates [9]. This makes it difficult to acquire suitable training data for the ANN.

8 Conclusions

Image segmentation and tree height calculation have been widely researched; some of these methods have been evaluated in this paper. General solutions can be specialised to make them more suitable for certain cases.

Watershed processing is a very effective segmentation method that has even been updated to make use of machine learning techniques to improve its accuracy. The CNNs discussed, although effective, do not seem well suited to this project. They require a great deal of training datasets and processing power. This means that they would take a lot of time to learn data. This is not feasible, especially considering that it may take many attempts to develop a stable, usable CNN, and that learning data again every time would be too time consuming. Even the U-Net proposed by Ronneberger et al. [34], which was designed to use fewer training datasets, still required the researchers to create their own datasets in a way that would mimic real data. This could be another research project, to be investigated in the future, but for now, it is not within the scope of this project. Therefore, a watershed processing technique will be further investigated, using the inverse [15] and waterfall [6] approaches. This will be the method chosen to solve the tree segmentation problem. If time permits, the addition of simpler neural network based on the one used in deep watershed [3] could be explored to improve the accuracy and robustness of the algorithm.

Extrapolation has been explored in many areas to fill in missing data in 3D objects and images. The analysis of tree characters is also a vast topic. Many have found relationships between a tree's height and diameter. The drawbacks with this approach are due to the nature of orchards. Branches could be occluded, reducing the tree crown projection [19]. The maintenance of trees is likely to occur. These factors reduce the accuracy of the height estimations. Accurate tree characteristic models can be achieved [2], although these are specific to a certain type of tree growing in a specific region. Even then, trees of the same type and age, growing in the same region, can vary [23]. Although an ANN [30] can be used to determine specific patterns in orchards, training it will be difficult, for the same reasons mentioned for CNNs above. Therefore, an extrapolation technique will be further investigated, and will be the method chosen to solve the problem of determining tree heights, by removing the ground height from the DEM. Doria et al. demonstrated that depth gradient infilling can be an accurate way of extrapolating images [13]. A similar approach will be attempted.

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