Project Proposal: Tree Height Extraction on Orchards

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CCS CONCEPTS

• **Computing methodologies → Image processing**; **Image segmentation**; *Model verification and validation.*

KEYWORDS

Tree height quantification, Ground plane removal, Ground filtering, Tree segmentation, Watershed, Digital Elevation Models, Kriging

1 PROJECT DESCRIPTION

Determining the heights of trees is useful for agricultural farmers. Farmers can use this information to track the growth of plantations, find areas in danger of soil erosion and keep farms within possible greening regulations [34]. Manual collection of height data however is time consuming and cost ineffective. New methods in farming are incorporating the use of drones commonly referred to as Unmanned Aerial Vehicles (UAVs) to quickly collect large amounts of GIS (Geographic Information System) data about farmland through photo imagery and LiDAR (light detection and Ranging) [27].

A heightmap or Digital Elevation Model (DEM) is a discrete 2-dimensional grid of elevation values that can be viewed as a raster image (see Fig. 1). If farmland is represented by such a heightmap then determining individual heights of trees can be done by subtracting the height of the ground from a tree in the map, leaving just the tree height. Distinct problems arise such as determining where each tree is on the heightmap and accurately determining the height of the ground terrain below each tree.

Another difficulty is that where tree canopies are thick most of the ground will be occluded. To determine the height of the ground below the trees will require interpolation and thus some estimation of the height of the ground at each point. Note that in the remainder of this document the term ground plane refers to the underlying terrain ground surface, whether it is planar or not. Another issue that we face is that our input data lacks the correct ground and tree height measurements to compare our results against. We will be generating our own synthetic DEMs so that we can specify known height values and use our image processing methods on these 'test' DEMs to evaluate our algorithms.

2 PROBLEM STATEMENT

Design methods to determine the heights of trees given an input heightmap in the form of a DEM recorded from tree grove farmland. The input DEM must be processed to determine which values on the heightmap represent trees and the correct height of the ground below each tree so that the true height of the tree can be determined.

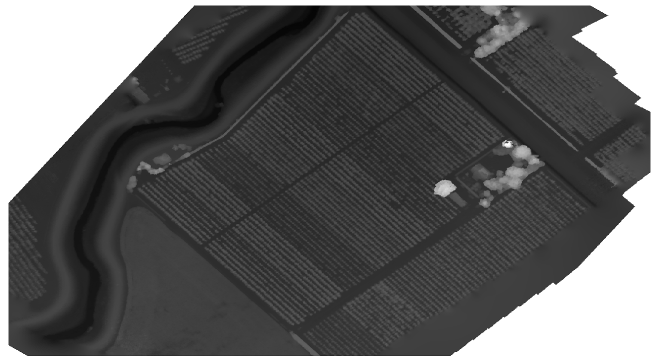

Figure 1: Sample heightmap of an orchard—part of our input data

2.1 Aims

This project has three aims. Firstly, to produce DEMs of increasing complexity that closely resemble orchards. Secondly, to segment trees in DEMs. Thirdly, to remove the ground plane from DEMs.

2.2 Research Questions

Below are the research questions for this project:

(1) Can data in a DEM of recorded trees be correctly classified and differentiated from ground data?
(2) With what accuracy can we calculate the height of the ground plane given a heightmap when occluded by tree cover?
(3) Is it possible to create synthetic DEMs of sufficient complexity to test the developed interpolation and tree segmentation algorithms for real data?
(4) Can the tree segmentation algorithm developed consistently produce more accurate results (measured using the Sϕrensen-Dice coefficient) than competing methods [6, 18, 35]?

3 RELATED WORK

3.1 Digital Elevation Models

DEMs are the most common form used in representing height data for landscapes in GIS (Geographic Information Systems). The alternative being TIN (Triangular Irregular Network) surfaces which we will not be using due to them being more computationally expensive and better suited to smaller areas with higher precision measurements [11]. One method which can be used to record data for DEMs is Light Detection and Ranging (LiDAR). LiDAR is a method for measuring distances and geographical data using a laser light being aimed at a point on the ground and the reflection of this light being measured by a sensor and typically yields high resolution maps compared to other methods [28].

Various online resources offer rich sources of data for DEMs and GIS data that we could use to test our algorithms. USGS (United States Geological Survey) provides scientific data related to geological mapping [16] and the ALOS Global Digital Surface Model provides similar mapping data capture by the ALOS satellite. The ALOS data set has been previously used for tree canopy height estimation of mangrove trees to track their decline [2].

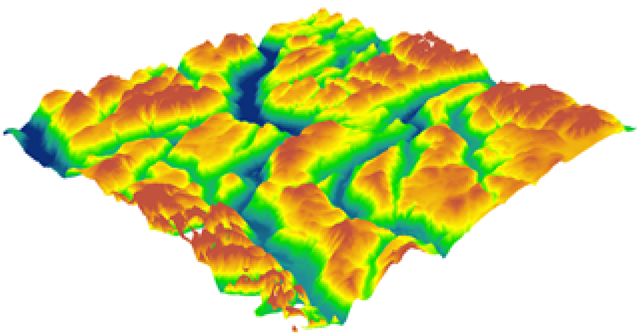

Figure 2: An example of a DEM (Digital Elevation Model)

3.2 Segmentation Methods

Image segmentation is a process of partitioning an image based on a heuristic. This is required for tree identification in the DEMs. Watershed segmentation is a method that seems well suited to the tree segmentation problem [8]. It works by identifying local minima [26] and ridges, called *watersheds*, in a DEM. Regions enclosed in a ridge are regarded as a segment, called a *catchment basin* [4]. It is faster and easier to implement than other segmentation methods, like the convolutional neural network. With parallelisation, watershed can be made more efficient [22]. It can be specialised for certain types of terrain through the use of different heuristics [21]. However, it does have a drawback of over-segmentation, which occurs when it identifies many catchment basins where only a single entity is present. This issue is very apparent with orchard DEMs, as trees often occlude each other which can lead to a very bumpy height model. There are some methods of mitigating this issue. Markers can help the algorithm determine where catchment basins should be [8] and these can be calculated using geodesic reconstruction [30].

Another method, the waterfall algorithm, uses the concept of flooding catchment basins to identify the significant local minima in the DEM [7]. In cases where entities are very close together in the DEM, inverse watershed is an effective approach to segmenting objects. DEMs are inverted and gradients from the inverted DEM are used to identify local maxima (tree tops) [32]. A threshold value is used to determine if errors in the output should be regarded as a tree or ground entity [23]. Deep watershed is another method to overcome over-segmentation [4]. The characteristics of a DEM is learnt by a neural network. Predictions can then be made about the location of significant catchment basins. This process involves many steps and it uses a separate network to learn the gradients in a DEM before passing this output on the final network, which identifies the significant catchment basins.

3.3 Ground Plane Removal

Ground plane removal, referring to normalising DEMs by correcting for (or subtracting) the terrain elevation, is not a new problem. Typically, however, research in this area is focused on ground plane removal in urban areas with the application of determining the heights of buildings[33]. There are some key differences between the aforementioned and our survey areas and research application (cultivated land—orchards—and vegetation heights, respectively) which render such research less effective for our purposes. Urban areas, in contrast to orchards, have more consistent slopes and are more planar. There is also more occlusion of the ground plane by tree canopies, which have less distinct boundaries than buildings, thereby increasing the problem complexity.

From the existing literature on ground plane removal, with the particular application of tree height quantification, a two step approach was determined[9, 25]. Step 1: ground filtering, which is the process of extracting the captured ground plane values by removing off-terrain points from the data[29]; and step 2: interpolation of the missing terrain elevation values, a result of tree canopies occluding the ground plane. One of the most robust filtering algorithms, especially on terrain with vegetation, is Axelsson's[3] triangulated irregular network (TIN) based algorithm, progressive TIN densification (PTD). However, the classic PTD algorithm falls short where terrain is discontinuous. A modification by Chen et al.[10] yields higher accuracy in these regions by introducing rule-based ridge point detection during seed point collection. Interpolating terrain models has more research available than ground filtering. PTD is often paired with kriging and inverse distance weighting (IDW) interpolation algorithms[1]. IDW uses a weighted sum of the nearest points with weights corresponding to the inverse distance from the missing point. It is typically used on irregularly spaced data and, on the whole, is less effective than kriging. Kriging is a geostatistical method of estimation that has been identified as one of the most effective interpolation methods for several terrain types[31]. However, it is considerably slower and more computationally intensive than other interpolation algorithms[17].

4 METHODS AND PROCEDURES

This project will follow a modular approach. Our subprojects will be able to work independently from each other. A pipeline will be arranged for the final system, where the output of a subproject will be fed as input into another subproject. This will be done by implementing a main program, in C++, to run the subprojects and to control their inputs and outputs. A system architecture diagram of the project can be seen in Fig. 3. There are three subprojects: DEM Generation, tree segmentation and ground plane removal. These are discussed further below.

4.1 DEM Generation

One of the problems we face is that we lack the ground truth measurements for the heights in our input data, meaning it will be difficult to correctly assess whether our image processing methods were successful in predicting the height of the trees. We will be synthetically producing 'fake' DEMs in order to test our segmentation and classification algorithms.

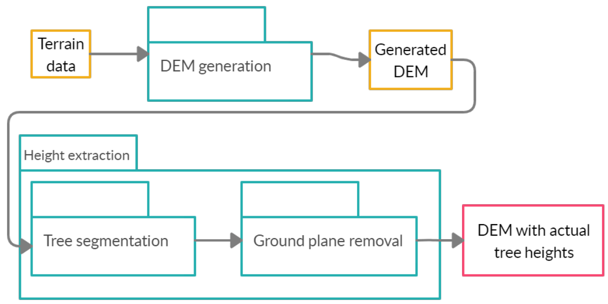

Figure 3: A system architecture diagram of the project

4.1.1 Method.

For landscape DEM data we will source existing landscape heightmaps from online resources such as USGS. Additionally, we will be exploring the automatic generation of landscapes to create DEMs. Successful methods for generating artificial landscapes include fractal generation, physical simulation and example-based methods [13]. These three methods are complex, but there is software available such as Bryce 7 which specialize in these methods that we can make use of.

To impose tree data on our landscapes we will develop an automated tree placement algorithm which we can implement using a Poisson-disk sampling method to place trees at random, but in an irregular more natural way. Poisson-disk sampling involves the random generation of points around points limited to some minimum distance threshold, which can produce closely packed tree positions [15]. We can add heuristics to improve tree placement limiting it to areas where ground space is available and where the landscape is not too steep for a tree to be planted and grow. The actual tree model to be added will be variations of manually created DEM data that can resemble a tree. Tree objects will increase in complexity starting with simple geometric shapes. To test the robustness of our classification algorithms, noise will be added manually to our DEMs that should not be classified as trees or ground.

4.1.2 Evaluation.

Table 1: Feature requirements for our test DEMs

Feature	*Requirement*
Surface texture	Must be smooth where trees grow
Tree density	Ranging from thick to sparse
Slope angle	Gentle
Ground visibility	Ranging from low to High
Natural realism	Ranging from simple geometric shapes to realistic tree canopy shapes
Noise objects	A few manually placed objects to act as noise

Our focus is on tree farmland which results in neat and uniform groves of trees on hilly areas. In evaluating our test DEMs we must consider all these requirements and judge the visual representation of the models compared to our input data as well as evaluating whether our test DEMs are effective in simulating the problems that must be overcome. In evaluation a similar table will be drawn up as Table 1 for each test DEM with a rating of 1-10 for how effective the DEM represents each requirement and a rating for the importance of each requirement. Our landscape data will be judged on how effectively it resembles a tree grove in surface texture and slope angle. Surface texture refers to the frequency of ditches and mounds. Slope angle refers to average steepness of a segmented area on the heightmap of 50 square meters. Our automated tree placement will be judged by tree density, ground visibility and natural realism. Tree density refers to correct placement of trees. Examples of where a tree should not grow are steep slopes and too close to other trees. Ground visibility refers to how much ground there is available to test interpolation of ground heights. Natural realism refers to how well the model of the imposed tree data resembles an actual tree. The requirement of noise objects will judge the effectiveness of manually added objects to act as 'non-trees'.

4.2 Tree Segmentation

The tree segmentation problem requires trees to be identified from DEMs. This subsystem will take in a DEM of a terrain with trees. It will output a mask DEM where the ground height pixels are set to black, but the tree height pixels are set to white. A light grey outline around trees will be used to distinguish them, for testing purposes, as they may occlude each other. After reviewing different methods of solving this problem, watershed processing was chosen due to it being cheaper to compute and faster to implement than other methods. There are many variants of watershed segmentation that were developed to specialise the algorithm to allow it to produce more accurate results for data with different characteristics. This subproject will have three phases: the investigation of watershed variants, the comparison of watershed variants to one another, and then the selection and refinement of the variant(s) that will be most suitable for the type of data used in this project. This chosen algorithm will then be used in the final system.

4.2.1 Method.

The first phase of this subproject is the investigative phase. During this phase, different variants of watershed will be developed and tested using C++ and the OpenCV and Rasterio libraries. Marker-aided watershed segmentation uses markers to identify significant catchment basins [8]. This variant will be developed using both hand-drawn markers and geodesic reconstruction [30]. The waterfall variant [7], which also identifies significant catchment basins, will also be developed. Inverse watershed, which was developed to work in dense DEMs where trees often occlude each other, will also be developed [14].

The second phase of this subproject is the comparison phase. The watershed variants will be compared with each other. Metrics, such as the computational resources required and accuracy of each variant, will be recorded.

The third phase of this subproject is the selection and refinement phase. During this phase, the best variant(s), identified in the previous phase, will be selected to be a part of the final system. The variant(s) chosen will have the best compromise between accuracy and computational efficiency. If more than one variant is chosen, they will be combined. The algorithm will be further refined to improve efficiency through the use of parallelisation [22]. This is also where a neural network add-on will be implemented and tested [4]. The aim of the neural network will be to improve the accuracy of tree detection, such as by identifying trees in an area where watershed segmentation has failed to properly do so.

4.2.2 Evaluation.

The efficiency and accuracy of the different watershed variants will be evaluated. Profiling tools from Visual Studio Community 2019 will be used to measure CPU and memory usage and computation time of the watershed variants.

To determine the accuracy of the segmentation of the different watershed variants, the Sϕrensen-Dice coefficient will be used [5]. A comparison is made between the ground truth, the manually segmented DEM, and the output of the segmentation algorithm. The coefficient represents the ratio between true positive (correct) segments and false positive and negative segments.

The Hausdorff Distance algorithm [20] is another way of determining the accuracy of image segmentation. It works by calculating the distance between boundary lines of the ground truth and corresponding boundary lines of the output DEM and then it produces the overall distance deviation between those two values.

3D Slicer is an open source tool for image segmentation. It will be used in this subproject to calculate the Sϕrensen-Dice coefficient and the Hausdorff Distance metrics. As this subproject deals with images, manual evaluation is very important. The ground truth will also be manually compared with the segmentation algorithm outputs. This is to determine the distribution of errors, which the quantitative analysis methods mentioned above cannot cater for. For example, if 10 pixels of the output DEM are incorrect, the error would be less noticeable if those 10 pixels are distributed evenly throughout the image than if they were all clumped together.

4.3 Ground Plane Removal

This subproject is concerned with the removal of heights of the terrain to obtain a normalised DEM of only canopy heights. It entails the filtering of vegetation from the input DEM and interpolating over missing values. As part of this subproject, a modified PTD algorithm will be implemented and its results tested against the more oft investigated segmentation. This subproject aims (in addition to ground plane removal) to provide a quantitative comparison of CVP against commonly used interpolation algorithms: kriging and IDW.

4.3.1 Method.

In the system pipeline, this module requires as input, the original DEM. The mask DEMs produced in the segmentation module may also be used. Local minima from the original DEM will be used to create the surface that will be densified using an algorithm based on Chen et al. 's[10] PTD algorithm. This will result in a filtered surface with only terrain points. Thereafter, mask/filtered DEMs will be interpolated over, to obtain the complete ground plane. Three interpolation algorithms: kriging, IDW and CVP; will be applied and their results compared.

The interpolation algorithm that will be used to produce the ground plane DEM will be determined as the fastest algorithm which yields > 90% accuracy with a minimal 90–95% confidence interval. In the case that no algorithm achieves those accuracy stipulations, the most accurate algorithm will be chosen. The output from this module will be the normalised DEM obtained by subtracting the full ground plane elevation values from the corresponding original DEM values.

4.3.2 Evaluation.

Evaluation of the interpolation algorithms will be conducted by calculating error statistics and comparing error visualisations. These will be based on the interpolation results from their application on the test DEMs generated in the DEM generation module.

Error statistics that will be calculated are residual mean square error (RMSE), the Kappa statistic[12], as well as the global mean and variance for error with confidence intervals. The Kappa statistic will be used to measure the agreement of the actual terrain and the synthesised terrain. The statistic has range [-1, 1] $\in \mathbb{R}$. It is interpreted as a scale measuring from strong disagreement (-1) to strong agreement (1). The kappa statistic should not fall close to zero as this indicates a chance agreement—success due to randomness.

Error distribution will be determined using an error map and cross validation. The error map will be a 2D indicator of disparities between the produced DEMs and the expected DEMs. The comparison between PTD and segmentation results will have the focus of accuracy. Type I and Type II errors (false negatives and false positives respectively) will be compared in addition to metrics presented in *section 4.2.2*.

4.4 Visualisation

QGIS is an open source GIS tool which will be used to view our input data in 2D. Aerialod is a free model viewing tool which supports DEMs in our .tif format and can be used to view our final outputted DEMs in 3D. Rasterio can be used to access the height data needed to create our own visualisations.

Figure 4: A DEM of farmland from a .tif heightmap viewed in Aerialod

4.4.1 Evaluation.

DEMs will be colour encoded to allow for easy identification of errors. Average percentage error of height extraction will also be calculated for each DEM produced. An accuracy score of 1-10 will also be given based on manual evaluation.

5 ANTICIPATED OUTCOMES

5.1 System

We expect to produce a final system that is capable of accurately removing the ground plane from DEMs using subprojects that will form a pipeline. The subprojects would also be able to function independently from each other.

Challenges may be encountered when foreign objects are present in real DEMs, such as vehicles or people. We make the assumption that only tree and ground entities are present in DEMs. The occlusion of the ground in between trees also presents a challenge. This limits the height data available to the ground plane removal algorithm, which would reduce ground height extrapolation accuracy.

5.2 Expected Impact

The research being done in this project will directly benefit the forestry industry. Tree height extraction from DEMs will be made more accurate. This would allow farmers to monitor the health of their orchards more closely. The tree segmentation subproject will allow for a more accurate and efficient means of identifying trees in DEMs. Improved terrain simulation will be achieved through the DEM generation subproject.

5.3 Key Success Factors

Even if the finished integrated system does not work as expected, its subsystems should run independently. As such there are key success factors determined for each module. The main factor of success would be that the accuracy of tree height extraction should be consistently better than competing means [19, 24]. Interpolation should have consistent accuracy across terrain types. We also expect the kappa statistic (k) to indicate a strong agreement between the interpolated and actual terrain i.e. $k \geq 0.8$.

For the subproject of tree segmentation, identifying trees in the DEM should be more efficient and accurate than current means. The algorithm should consistently produce results more accurate, when accuracy is measured using the Sϕrensen-Dice coefficient, than competing methods (which, in this case, focus on marker-aided watershed) [6, 18, 35]. Additionally, the synthetic DEMs that we produce to test our algorithms need to closely represent the geographical features of realistic tree groves. Factors such as ground visibility and interpolating the height of the ground plane are important problems to overcome and these must be sufficiently modelled by our test DEMs.

6 ETHICAL, PROFESSIONAL AND LEGAL IMPLICATIONS

This project will make use of DEMs to determine the height of trees. As we will only work with height data, there is no risk that we will encounter identifiable images of people. There will be no human participants, therefore ethics clearance is not required.

Third party, Aerobotics, proposed this project. We have permission to use their data in this project. Our supervisor communicates with Aerobotics on our behalf. Data, which is in the US public domain, will also be sourced from the US Geological survey for the creation of new DEMs. Open source libraries, such as OpenCV, QGIS and Rasterio, will be used. Should our work be published, we shall use the creative commons licence as per the university's publishing policy.

7 PROJECT PLAN

7.1 Risk management

The risks involved in this project are presented in a risk matrix (see Appendix B). Each risk has a probability of occurring: low, medium or high, and an impact rating on a scale of 1 (minimal impact) to 10 (catastrophic failure). Mitigation, monitoring and management measures are also provided for each risk.

7.2 Timeline

The project began on 30 March 2020, when our topics were provided. It is expected to run until 19 October 2020. The deliverables, milestones and tasks are displayed on a Gantt chart (see Appendix B).

7.2.1 *Deliverables.*

Date	*Deliverable*
12 May	Literature review submission
4 June	Project proposal submission
3 August to 11 August	Initial software feasibility demonstration
17 August	Project weighting decision
11 September	Final complete draft submission
21 September	Final project paper submission
25 September	Final project code submission
5 October to 9 October	Final project demonstration
12 October	Project poster submission
19 October	Project webpage submission
TBA	Reflection paper submission

7.2.2 *Milestones.*

Date	*Milestone*
18 June	Review of staff feedback on project proposal
29 June	Revised proposal submission
6 July	Basic draft
28 August	Finalise draft
TBA	Open evening

7.3 Resources Required

The project will make use of DEM data from Aerobotics and terrain data from the US Geological Survey for DEM generation, using Aerialod. The Rasterio and OpenCV libraries will be used for the extraction and processing of the DEM data respectively and QGIS will be used for DEM visualisation. 3D Slicer will be used for testing the tree segmentation subproject. All these libraries are open source. We will use the Visual Studio Community 2019 IDE, which is freely available, for the development of software. We will work from our personal computers.

7.4 Work Allocation

Daniel Bowden will be responsible for the generation of DEMs to be used in this project. Lynolan Moodley will investigate ways of segmenting the DEMs. Chiadika Emeruem will be responsible for investigating the ground plane removal problem. All team members will work on the main program that will run the subprojects, as well as on the visualisation of the final outputted DEM. Daniel Bowden will use terrain data collected from the US geological survey to create DEMs. These DEMs will be used by Lynolan Moodley, from where trees will be identified and a mask DEM will be outputted where all trees have white pixel values. Chiadika Emeruem will consider the original DEMs as well as the mask DEMs and will produce new DEMs, where the ground height has been removed. These final DEMs will then be visualised.

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Appendix A
Risk Table

Risk	Probability	Impact	Mitigation	Monitoring	Management
Insufficient time to complete the project	Low	8	Detailed scope and realistic schedule with deliverables and quantitative milestones approved by supervisor.	Comparing group progress against the schedule.	Adjust the schedule/scope should there be any major delays.
Team member leaves the project	Low	2	Keeping healthy and communicating with team members to provide support.	Establishing communication with all team members on a regular basis.	The project is designed such that individual components can be assessed independently.
Inadequate expertise required for the project	Medium	7	Reviewed available literature on the subject.	Regularly check if the team members are coping with the task requirements of the project.	Consult with the supervisor to decide on less complex implementation or discuss how to simplify the project components.
Issues integrating the subprojects	Low	4	Allocate enough time for integration and plan the system architecture beforehand.	Note delays during the integration portion of the project. Note changes that have to be made within subprojects and determine how those would affect the system.	Adjust success factors that depend on the integrated system. Perhaps allocate more time to the integration process if the schedule will allow it.
The solution developed does not produced the desired results	Low	9	Make informed decisions when developing the solution and implement testing at every stage for every subproject.	Compare the results of tests with the expected results at that stage.	Either adjust expectations of the final results or rethink/redesign at stages that fail.

APPENDIX B

Timeline (Gantt Chart)