Ground plane removal from drone images of orchards

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ABSTRACT

Remote sensing techniques and in particular, unmanned aerial vehicles (UAVs), are increasingly used in the collection of survey data for monitoring the maintenance of agricultural land. These surveys provide information about the elevation of the top surfaces of farmland *i.e.*, elevation values for tree canopies include the altitude of the terrain on which they are planted. Theoretically tree heights can be extracted by subtracting the height of the terrain from those of the tree canopies. For this reason, various methods have been employed to extract canopy and individual tree heights from the digital elevation models (DEMs) produced by these surveys. This paper reviews literature on such methods, for ground plane removal using UAV survey data of orchards. Orchards are cultivated on sloping terrain, as well as hilly and mountainous terrain. Reviewed methods are analysed with this in mind. The methods investigated in this review are concerned with DEM extraction and synthesis—identification of the ground plane in the original image and completion of the terrain obscured by the trees. Ground filtering methods, progressive morphology and triangulated irregular network (TIN) based algorithms, are discussed for the extraction step of the solution. Progressive morphology (PM), while highly accurate for light detection and ranging (LiDAR) point cloud data, performs less so on UAV data. Improvements to PM require additional data such as RGB colour values. As such Chen *et al.*'s modified progressive TIN densification (PTD)[9] algorithm is recommended as a basis for the ground filtering solution. For the synthesis step, interpolation methods often used with the above filtering algorithms were discussed. Kriging is the one of the best performing algorithms on all terrain types that are of interest to us. However, it is also the most computationally intensive. Hybrid interpolation techniques are thus recommended to reduce the intensity of computation while maintaining accuracy.

CCS CONCEPTS

• **Computing methodologies → Image processing**; Parametric curve and surface models; Model verification and validation.

KEYWORDS

Ground plane removal; Digital terrain model (DTM); Ground filtering; Interpolation; DEM synthesis

1 INTRODUCTION

Orchard farmers—and farmers in general—have monitored tree growth for years using manual measurements of tree heights (among other parameters). The agricultural tree height metric carries information about crop production, plantation status and soil quality, that assist with the management of farmland[26, 33]. In addition, tree height information can be used to monitor farms for compliance with greening regulations, for biomass predictions and for other ecological applications[6, 11, 28]. Remote sensing techniques have been employed in the retrieval and calculation of canopy and individual tree heights because of their accuracy, and time and cost efficiency over manual data collection[7]. Increasingly, unmanned aerial vehicles (UAVs) are being used to conduct these remote sensing surveys to even further reduce survey costs. Our input data is a digital elevation model (DEM) generated from such a UAV *i.e.*, drone images of orchards. Each DEM will be used to estimate canopy and individual tree heights for rows of trees in an orchard.

Tree height estimation will require digital terrain model (DTM) extraction from each DEM. This paper reviews DTM/ DEM extraction and synthesis methods that are effective on the types of terrain on which orchards can be found *i.e.*, flat and gentle slopes[16, 23] as well as hilly and mountainous terrain[18]. DEM synthesis, in this paper, refers to the generation of new terrain where elevation values are missing. The synthesised terrain should match the actual terrain as closely as possible to ensure the accuracy of the estimated tree heights.

2 BACKGROUND

A digital elevation model (DEM) is a 2D pixel height map: a 2-dimensional array of equally spaced pixels/squared cells each with an elevation value[19]. DEMs representing the bare-earth terrain are often termed a digital terrain model (DTM); and a DEM containing height information for the top surfaces of the terrain—including off-terrain objects—is what is known as a digital surface model (DSM).

Theoretically, we can calculate canopy heights by subtracting the DTM from the DSM generated with UAV survey data[7, 27]. The resulting DEM is a normalised DSM (nDSM) from which individual tree heights can be determined. In order to calculate canopy and tree heights, we therefore need to extract the DTM from our input DEM/ DSM. A result of survey data being collected from orchards is that tree canopies occlude the terrain. Therefore the extracted DTM will contain voids where elevation values are missing for the terrain. Hence, the DTM extraction process is divided into 2 subprocesses: ground filtering for identifying terrain points from the DEM; and interpolation for DEM synthesis of the filtered terrain.

3 GROUND FILTERING

Ground filtering refers to the extraction of terrain by removing off terrain points from (usually point cloud) data[9]. Sithole and Vosselman[24] categorised filters according to their assumptions about terrain structure within a local neighbourhood: slope-based, morphology-based, surface-based and clustering/ segmentation-based. In slope-based filters, algorithms use the assumption that the higher of two points between which the slope exceeds a determined slope threshold is off-terrain. These algorithms differ by their threshold selection and the way data is partitioned for slope calculation. They are computationally efficient but perform worse on mountainous terrain[9]. Morphology-based algorithms operate under the assumption that local terrain can be described by a plane. Points in the local neighbourhood are selected or discarded based on a buffer zone around this plane. Morphological filters have high accuracy in relatively flat terrain.

Surface-based filters classify terrain points using the assumption that they fall within a buffer zone around a parametric surface. Finally, clustering filters assume that clustered points are off-terrain if their cluster lies above its neighbourhood. This class of filters preserve terrain discontinuities but are dependent on the quality of segmentation. Sithole and Vosselman[24] determined that surface-based filters produce better results in general for all fifteen tested terrain types, however the suggestion remains that filter selection depend on the type of terrain.

Our concerns with filtering results include necessarily the removal of vegetation, where low vegetation and heterogeneous and steep terrain may pose difficulties[9, 24]. The following are filtering approaches that have been applied to the problem of tree height detection.

3.1 Progressive morphology

Progressive morphology (PM) is a morphology-based ground filtering algorithm[9]. It works by using gradually increasing window sizes and elevation difference thresholds to classify points as terrain/ off-terrain[34]. The different window sizes allows the algorithm to pick up off-terrain objects of different sizes. PM is used often and performs well when used on point cloud data obtained via light detection and ranging (LiDAR)[1, 25]. When used on data obtained via UAVs however, PM can misclassify vegetation as terrain. This has led to the development of adaptations[21, 25] of PM which aim to improve the filtering accuracy on terrain with vegetation, for UAV point cloud data. Many improvements use data additional to elevation value and as such cannot be applied to this project. The "improved Progressive Morphological filter (IPM)"[25] is one such adaptation, applicable if additional—specifically colour—data is made available.

PM (and IPM) operate on a DEM. An initial surface is generated from the LiDAR/ UAV point cloud—usually a minimum surface created by assigning to each cell in the DEM grid, the minimum elevation value within the cell. The window size increases iteratively, and during each iteration the mathematical morphology sourced dilation and erosion algorithms[15] are applied (in that order) and the elevation differences between the original and filtered surface are calculated. Points whose elevation difference exceed the elevation threshold are classified as off-terrain and this process continues until the window size exceeds a predetermined maximum.[25, 34]

IPM improves on this algorithm by introducing the Wang *et al.* [32] visible-band difference vegetation index (VDVI). It post-processes the filtered surface using the VDVI values calculated for each identified terrain point, to identify misclassified off-terrain vegetation according to a threshold. Following this, PM is performed again to eliminate any remaining off-terrain vegetation points. Quantitatively, IPM resulted in higher accuracy than PM for all 4 sites tested.

3.2 Triangulated irregular network

The classic triangulated irregular network (TIN) based algorithm by Axelsson[3], progressive TIN densification (PTD), is one of the most robust filtering algorithms[20, 21]. Using Sithole and Vosselman's classification, it is a surface-based algorithm[24]. PTD begins the creation of the TIN surface with seed points (local minima) from the data and iteratively adds points based on height differences and direction to the plane of the nearest triangle—a process referred to as densification. A shortcoming of PTD, however, is detection of discontinuous terrain. Chen *et al.* proposed a modification to PTD which yields higher accuracy for mountainous regions[9]. These modifications are as follows:

i. Collecting additional seed points from mountain ridges using a rule-based ridge point detection method.
ii. Systematically discarding erroneous seed points by comparison with a confidence interval.

The goal with this new algorithm was to improve filtering results for mountainous terrain by including ridge points and to optimise seed point selection, while increasing memory efficiency for its application on dense point clouds. In their paper, its performance was compared against the classic PTD algorithm as well as 3 other filtering algorithms, both visually and statistically. For homogenous terrain, the proposed algorithm is comparable to PTD (an interpretation confirmed in the literature[21]). In mountainous terrain, overall it exceeds the performance of all 4 algorithms. Additionally, the authors note the algorithm's robustness against vegetation on steep terrain, ensured by the optimisation of seed points, as well as point selection in cells during densification.

4 INTERPOLATION

Following the ground filtering process, interpolation algorithms are applied to the incomplete resultant DTMs in the attempt to model the previously obstructed terrain. Interpolation refers to the process of estimating missing data. These algorithms use data surrounding missing values to generate/ determine appropriate values for the missing data. Deng *et al.* claimed that interpolation algorithms can be roughly divided into 3 categories: regression-based, inverse distance weighting (IDW) and kriging[12]. The classes of methods that this paper will review are commonly used in conjunction with the ground filtering methods reviewed. Image inpainting, a widespread method borrowed from art restoration[17], is also reviewed.

4.1 Inpainting

Texture or image inpainting refers to the process of correcting/ completing patches in images[31]. Inpainting learns from the areas surrounding missing patches to synthesise a suitable fill[17]. The novel inpainting technique, Contextual Void Patching (CVP)[31], was developed as an application of inpainting for DEM synthesis which exploits the DEM structure, as opposed to treating them as textures. This interpolation method is often applied after morphology-based filters[9], on DEMs with missing data points, such as when foreground objects (*e.g.* trees) have been removed.

CVP is a 3-step process: (1) identify the voids in the DEM, (2) synthesise a smooth patch using overall directions of the surrounding area for each void; (3) extract surrounding area characteristics and apply to the smooth patch. Qualitative analysis shows that patches produced by CVP seamlessly match the surrounding terrain with above satisfactory results[21, 31]. A patch generated by the algorithm for an artificial void was tested against the original terrain and visually, the results were near identical. However, quantitative analysis for terraced and steep regions revealed inpainting to over-smooth discontinuities, thereby increasing total error[21].

4.2 Kriging

A number of authors have identified kriging (a method of geostatistical estimation)[29] as one of the most effective interpolation methods for smooth plane, sloping and heterogeneous terrain[2, 12, 14]. Studies comparing Kriging to other interpolation algorithms have found it to produce the most accurate terrain estimations. Kriging produces highly accurate and unbiased estimates with minimal variance[2, 12] *i.e.*, estimates obtained have a mean residual error of zero.

Kriging algorithms use a system of linear equations to provide their estimations. The missing values as well as the values in their neighbourhoods, are interpreted as random variables. Linear combinations of these, which are themselves random variables, are then used as estimators for the missing values[5, 12].

4.3 Hybrid interpolation techniques

Kriging is a high accuracy interpolation method but complex and computationally intensive[14]. Simpler methods, while fast, have higher error rates. Combinations of multiple interpolation methods (hybrid techniques) have been proposed as a solution to retain accuracy of kriging while reducing the computational intensity.

5 VALIDATION

Theoretically, canopy and tree height details will be determined from the nDSM. Therefore the accuracy of the extracted DTMs will affect the accuracy of the retrieved tree heights. Thus this paper reviews methods of error evaluation/ validation.

5.1 Error statistics

Bater and Coops[4], in their paper analysing algorithm performance through interpolated DTMs, use the statistics: residual mean squared error (RMSE) and mean absolute error (unsigned error) to assess performance. These are calculated using the estimation error from each cell in the DTM *i.e.*, predicted elevation value *minus* actual elevation value. These statistics provide a measurement of the overall accuracy of the interpolated terrain.

For a more fine-grained error analysis, several authors have used the following metrics: Type I, Type II and total error rates[9, 21, 24, 27]. The 2 error types represent different types of misclassification. Type I errors occur when terrain points are misclassified as off-terrain and Type II errors when off-terrain points are misclassified as terrain. To calculate the error rates, the total number of Type I and Type II errors is divided by the total number of true terrain and off-terrain points, respectively. These calculations occur directly after ground filtering and provide insight—Type II errors will necessarily result in errors in the final extracted DTM. To get the total error rate, divide the number of misclassified points by the total number of points in the grid.

A final metric that appeared in the literature[21] is Cohen's Kappa statistic[10]. Originally from the domain of psychology, the Kappa statistic is used in the paper to measure the agreement of the actual terrain and the synthesised terrain. According to Pingel *et al.* it measures model accuracy and takes into consideration the possibility of a chance agreement. The statistic has range $[-1, 1] \in \mathbb{R}$ interpreted as a scale measuring strong disagreement (-1) to chance agreement (0) to strong agreement (1).

5.2 Quantifying error distribution

In addition to global error statistics, it would be useful to analyse error patterns and areas of concentration. Local spatial autocorrelation enables such analysis by providing insight into error clustering[13]. Other statistical techniques have been employed to quantify DEM accuracy. Ordinary least squares (OLS) regression is one such method. It is normally used to estimate parameters for linear models and can be used to test DEM prediction accuracy[8, 27]. Another technique is cross validation, which is used to test interpolation algorithms[30]. It interpolates across fixed sized subsets of the DEM and compares the actual values against predicted values. Erdoğan[13] suggested graphical representations, in particular, an error map of the terrain. Another visual representations used in the literature[22] is an error frequency histogram. Error visualisations can assist with comprehension of contributing factors.

6 DISCUSSION

Much research has gone into methods of extracting information from point cloud data sourced via LiDAR and UAVs. Of these, this paper has investigated techniques with a particular relevance to the quantification of tree heights via DEM extraction and synthesis. In order to calculate tree heights from our input DEM, available terrain data must be extracted through a process called ground filtering. From the literature, it is evident that most filtering methods work well on flat and homogenous terrain with tall vegetation. However, our data will not always be found on such terrain. Orchards (our survey sites) are cultivated on sloping and heterogeneous regions, *e.g.* terraced orchards—in addition to flat and homogenous terrain. Distinguishing qualities for these algorithms are therefore, performance on (1) mountainous terrain/ terrain with large discontinuities and (2) terrain with low vegetation [1–2m] (to accommodate the younger trees on these farms). Of the methods reviewed in this paper, the modified PTD algorithm by Chen *et al.* [9] meets the performance criteria on both of those terrain categories. Classical PTD underperforms on discontinuous terrain and PM on terrain with low vegetation for UAV sourced DEMs. As mentioned in *subsection 3.1*, modifications to PM that aim to improve it's classification of low vegetation require additional data to be recorded using the UAVs.

Due to the type of survey sites (orchards) and the survey method (drones *i.e.*, UAV), extracted DTMs will have missing data where tree canopies occlude the ground. To complete the terrain, interpolation methods were investigated in this paper. Again with interpolation, as with ground filtering, synthesis over voids in flat terrain is practically a solved problem. For other terrain types (particularly those of interest to us), there is a trade-off required between accuracy of the synthesised terrain and computational intensity. Kriging is a highly effective method of interpolation but very computationally intensive. Other less intensive algorithms consistently perform worse than kriging. Hybrid interpolation techniques look to balance that trade-off and are worth consideration.

This paper also presented recurring methods of error evaluation used in literature about filters and interpolation algorithms. The literature revealed that smaller magnitudes for type II error, total error and RMSE show higher accuracy. Additionally, a smaller type I error minimises computation—removing terrain points just to recalculate them results in more computation. Standard deviation and variance are also statistics that provide information about the error dispersion around the mean. Error distribution is valuable in the assessment of algorithm performance and model accuracy. For example, spatial autocorrelation and error heat maps, provide insight on the terrain characteristics where the DEMs are most inaccurate. Some papers have used ordinary least squares (OLS) regression to test prediction accuracy. This relies on the assumption of a linear trend. Error frequency histograms can be used to present Type I and II error. However, simply presenting the values is just as effective.

7 CONCLUSIONS

Tree height quantification from DEMs requires the removal of the ground plane/ terrain elevations. To do this, this paper has reviewed ground filtering and DEM interpolation methods. PM is an efficient filtering algorithm but underperforms on terrain with low vegetation. Improvements require additional data and cannot be implemented. The otherwise robust classical PTD algorithm is inefficient on discontinuous terrain but Chen *et al.* 's[9] modifications improve its performance in that regard so it is recommended. Of the interpolation algorithms commonly used with ground filtering methods, Kriging is the best performing. It's performance is not conditional on terrain type. Because kriging is a complex and intensive algorithm, it is recommended that hybrid interpolation algorithms (as in [5, 12, 14]) are further explored.

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