Review of Row Detection Algorithms for Orchard Data

Leonard Chuang
Department of Computer Science
University of Cape Town
South Africa
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Abstract

Precision Agriculture (PA) is the expanding study of applying geospatial information to site specific farming with the intention of both maximising and monitoring crop yield while minimising resource expenditure. One of the main steps in PA is field mapping and can be completed through row detection. Currently the use of Low Altitude Remote Sensing (LARS) systems, which includes Unmanned Aerial Systems (UASs), have presented a new area of study. The most popular UASs are Unmanned Aerial Vehicles (UAVs), which act as a means for inexpensive data gathering and the data gathered is generally of high spatial and temporal resolution i.e. images are of good quality and are obtained daily. Although new row detection techniques are designed for crop fields and vineyards, the lack of row detection techniques for orchards are apparent. Orchards present challenges which crops and vineyards do not. Two challenges to consider when dealing with orchard data are: (1) highly dense growth areas that lead to overlapping between trees which results in poor initial object detection, and (2) planation methods that result in heavily curved rows to suit the terrain. Recent studies show that crop rows and vine rows can be identified from images taken using UASs with reasonable accuracy. Analysis of these methods will be performed with the intention of applying them or using them as a basis for new methods suitable on orchard data.

Introduction

Tree row identification can be considered as part of precision agriculture (PA) where, currently, Unmanned Aerial Vehicles (UAVs) are deployed to take images of fields[1] so that they can be mapped out for further agricultural decisions to be made. The main steps of PA are data collection, field mapping, decision making and management practice [2]. Without completion of the first two steps, data collection and field mapping, farmers are unable to continue with making informed decisions and improving their management practices. PA techniques are meant to be cheaper, faster and automated - unlike manual methods which are slow and laborious because they require professional input to identify rows. The goal of applying PA is to achieve a series of real-time automated processes in order to measure biomass, monitor crop growth and crop yield, detect diseases, administer resources etc.

There are several row detection methods that exist for specific crops, weeds and grapevines, however, there are not many published methods for identifying tree rows within an orchard. The focus of this review is to identify methods to detect the internal row structure in an orchard. Row detection can be particularly challenging when the rows can be a combination of either straight or heavily curved to match the terrain. Other challenges include ambiguity in the directionality of the rows, poor initial object detection when the data is collected and misclassification or inclusion of unwanted objects such as weeds or houses. A comparison of row detection methods for crops and grapevines is used to determine suitable and accurate row detection ideas for trees. Once the tree rows have been identified and mapped out, farmers can easily verify gaps of missing trees so that they can replace them.

Implementations of well-known algorithms such as the Hough Transform, Least Squares Polynomial Fitting and Image Segmentation could serve as the way forward in discovering an algorithm that solves the complications when dealing with high tree density and poor row plantation.

Image processing and computer vision play very important roles in the pre-processing stage where vegetation identification is done. Row detection usually requires pre-processing of the images for vegetation segmentation so the crops can be separated from the background soil. The data is often converted from a normal image to a multispectral image such as RGB imagery[3] or HSV imagery[4] and then into a binary image. A binary image is used to distinguish the crops (usually white pixels) from the background soil (usually black pixels). These crops can be viewed as points on a plane so different techniques are used to link the points and form rows.

Straight row detection algorithms

The simplest case of row detection occurs when the initial object detections are clear, and the crops are planted in a parallel straight row method as shown in Figure 1(a). The inter-row spacing is clearly defined and can be used help to identify individual rows. The only challenge in this situation would be identifying gaps of missing crops in the rows and incorporating this information when identifying rows. This case of row detection is common and has several methods that produce accurate results. Algorithms include the Hough Transform[5], crop row orientation detection [4, 6] and Encasing rows in Quadrangles[7]. These algorithms require pre-processing for vegetation segmentation and identification before they can be applied to the data.

(a)

(b)

Fig. 1. Data Set Example: (a) shows good initial object detection with straight rows and (b) shows poor initial object detection with mostly straight rows.

The Hough Transform is a mathematical algorithm used for line detection[8] and has been applied in PA for crop row detection. Many crop row detection methods use the Hough Transform as a basis to build upon or, alternatively, as a comparison to determine how well the proposed line detection algorithm performs. The algorithm is commonly used in PA to identify crop rows and produces highly accurate results when the rows are mostly straight. It can be applied to a full image or a grid of a segmented image that can be recombined to form the original image. This is the preferred method for row detection[9] if the computational resources are not a problem.

Alternatively, the crop row orientation algorithm exploits the requirements and make the assumption of straight rows so that it can be simplified computationally. Since the rows are assumed to be straight and planted in parallel with specific inter-row spacing, there exists some angle theta (θ) that is the orientation of the entire row. This angle can be determined between 0° and 180° since any angle greater than this will be referring to the same row orientation. The angle is determined through increments of 1° or less in the orientation angle and the grouping of similar coloured pixels which signal the crop row. Although the algorithm can detect whole rows, it would struggle to determine gaps where crops struggle to grow or did not grow due to the simplifying assumption of working with an entire row.

Encasing rows in quadrangles is another algorithm that is simpler than the Hough Transform in terms of processing requirements. The algorithm creates four vertex points on the image and the points are joined to form a quadrangle. The size of the rectangle can be adjusted through adjusting the co-ordinates of the four vertices. The pixel density within each rectangle is then calculated and compared against a threshold. It was proposed that if one quarter or more of the pixels in the rectangle are soil pixels, the row detection is rejected and the size of the rectangle is adjusted for the next detection. This process is repeated until either an accepted row is detected, or all possible combinations of quadrangles have been tried.

Curved row detection algorithms

A more difficult case of row detection arises when the initial object detections are poor due to an overlap in objects, and the trees are planted with a mixture of straight rows and heavily curved rows to match the terrain as shown in figure 2. Very few methods have been proposed to solve this problem since the straight row plantation is preferred. Nonetheless, the problem can be simplified to points on plane and fitting a curve through the points. Algorithms that implement different forms of the least squares regression and polynomial fitting are proposed as solutions. The Levenberg Marquardt algorithm, also referred to as the damped least squares algorithm, is used to map low level polynomials to a set of points[10, 11]. Similarly, Shepard's method, used in surface reconstruction[12], can map a curve through a set of scattered points[13]. Shepard's method can effectively capture sharp curves and cusps which the Levenberg Marquardt algorithm cannot.

Fig. 2. Data Set Example: Poor initial object detection with a combination of straight and heavily curved rows.

Although the Hough Transformation has been implemented to detect curved rows through image segmentation and tiling[14, 15], the method is inefficient because it requires a post processing stage to remove noise and errors from the implementation. This method breaks down an image into a grid and then applies the Hough Transform to each tile within the grid. The tiles are then recombined and the Hough Transform is applied yet again to connect the line segments produced in each block. Combining the line segments from each tile introduces error and the need for a post processing stage to clean up the error.

Unlike the previous method, least squares methods and polynomial fitting are tailored to detect curves. The Levenberg Marquardt algorithm has been used in Precision Viticulture (PV) for vine detection. The algorithm uses a non-linear least squares approach to fit low-level polynomials of degree one (straight line) or degree two (quadratic curve) to a set of points. It was assumed that the vine rows did not contain sharp curvature or cusps when the algorithm was applied.

Alternatively, Shepard's method, an algorithm used for surface reconstruction, can be applied to detect heavily curved rows. Although the method is not used in PA, it can be potentially applied for its ability to map sharp curvature and cusps amongst scattered point. Smoother areas with the least noise are mapped out first and used to guide the mapping of denser areas with more noise.

In conclusion, the combination of both straight and curved tree rows could potentially require a combined approach of some of the above-mentioned algorithms. A combination of the Hough Transformation in order to detect straight lines and a Moving Least Squares method in order to detect curves may be the solution.

Discussions and Results

Criteria used to measure the methods include precision, complexity and flexibility with three levels each: high, medium and low. Precision measures the reported accuracy of an algorithm based on the correct number of rows detected as well as possible under or overfitting due to environmental conditions such as missing crops. Complexity refers to the estimated computational complexity of the algorithm. Flexibility measures the capabilities of an algorithm to detect both straight and curved rows.

The Hough transformation is a reputable algorithm in the field of PA. It has high precision scores but only when the rows are mostly straight. Although there are implementations such as image segmentation and tiling which allow the algorithm to be applicable to curved rows, the ability to detect curved rows does not justify an additional post-processing stage in order to remove error. However, compared to the Hough Transform, the alternative algorithms can at most provide equal precision. Therefore, they need to present advantages in computational complexity. Unlike the Hough Transform, the crop row orientation algorithm is simpler but less precise because it seeks to detect entire rows at a time. This method can only be used when the assumption of completely straight and parallel rows is met thereby severely restricting the flexibility of the algorithm. The trade-off between complexity and precision can be attractive to farmers who are entering PA and cannot afford equipment or software.

The Quadrangle method is similar to the row orientation method since its main strength is its simplicity. Also, the method cannot be adapted to find curved rows and it does not provide high precision like the Hough Transform. In terms of complexity efficiency, the method is likely not more efficient than the row orientation method.

Table 1: Simple comparison of straight row detection methods.

Method	Precision	Complexity	Flexibility
Hough Transform	High	High	Low
Row orientation	Medium	Low	Low
Quadrangle	Medium	Low	Low

The focus of this review is finding viable algorithms for rows around high density and sharp curvature. The two algorithms that solved the problem are the Levenberg Marquardt algorithm and

Shepard's method, both are least squares algorithms. Previous work has been done with the Levenberg Marquardt algorithm in the field of PV and the results were quite accurate. Shepard's method is used in the fields of edge and surface reconstruction for 3D scans but can still be relevant for tree row detections. Although Shepard's method has the advantage when there are sharp curves and cusps in the layout, it is a plausible assumption that farmers are more likely to plant in straight rows and will only include small curvature if a straight row planation is impossible. Another advantage of Shepard's method is the ability to work through dense areas and ignore the noise. This is a huge advantage for the second case where trees could overlap causing poor initial object detection. Unfortunately, Shepard's method has not been tested with agricultural data so it is unknown how the method will perform.

Table 2: Simple comparison of curved row detection algorithms.

Method	Precision	Complexity	Flexibility
Levenberg Marquardt algorithm	High	High	High
Shepard's method	Unknown	High	High

Finally, it could be possible that the solution should be a combination of both straight row and curved row methods. The underlying plantation methods could favour straight row plantations as much as possible.

Conclusions

Existing methods for row detection can produce precise results but are limited to mostly straight rows. Although this is a good entry point into the field of PA and possible row detection algorithms, future work can be done to introduce different algorithms that are capable to deal with curved rows. Nonetheless, PA already encompasses agricultural data with crops, vineyard data for viticulture and should expand to include orchard data soon. Future work can be done with data collection through UASs to improve the initial object detection regardless environmental conditions. Also, algorithms be modified to include the ability to identify missing trees so that farmers can identify areas for optimisation.

Further research can be conducted regarding edge-detection-based techniques and graph-based techniques. There are several mathematical and statistical algorithms in the field of computer geometry and surface reconstruction that could prove to be effective with some alterations. Inclusion of height data for trees could transform the problem into point cloud problems that involve 3D or contour-based solutions. These ideas are yet to be explored since PA has only started attracting attention in the last decade.

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