Review of methods for tree row detection

Literature Review

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ABSTRACT

The ever-growing human population is rapidly increasing the demand for food, placing the agricultural industry under immense pressure. In order to meet the projected demands of 2050, agricultural production will need to rise by 70%. This can be obtained through better crop management and increased production yields which may be provided by precision agriculture. The important role of precision agriculture in modern-day farming is explored further in the introduction. Automatically detecting rows of trees or crops allows the farmer to quickly establish where there are issues with the yield and fertility. The problem is to associate detected trees to individual rows in an orchard which contains an internal structure of trees planted in coherent rows. Secondly, the problem is to identify patches in the orchard that may contain missing trees. This will be aided by the assumption that the spacing between trees is smaller than the spacing between rows. The problem is remarkably similar to crop row detection with no a *priori* assumptions, but without using the source image as an input to the solution mechanism. This can be simplified to a graph problem where the nodes are tree objects, and the edges are the distances between them. Thereafter, optimization techniques are used to identify disjoint graphs that represent tree rows. We start by researching the fields which could provide a conceptual framework to this optimization problem. The industry standard pathfinding algorithms, for two and three dimensions, were analysed to try to identify any candidate solutions to the tree row detection problem. Next, the state-of-the-art multi-objective genetic algorithms were studied, in order to constrain the meta-heuristic search to this problem domain. Lastly, we examine swarm algorithms with good convergent capabilities to the global optimum for multi-objective problems. The two competing algorithms for the initial straight row detections are the geometric model-fitting algorithm and the particle swarm optimization algorithm as they both have extremely fast execution times with great accuracy. Because of the flexibility of objective functions and the speed of execution, the best performing algorithms for straight and curved crop row detection are the multi-objective genetic algorithms.

CCS CONCEPTS

• Precision Agriculture • Optimization • Row Detection

KEYWORDS

Line Detection, Path Planning, Evolutionary Algorithm

1 Introduction

The demand for the agricultural industry to provide crops is exponentially increasing due to the rapid increase in the human population. The agricultural production will need to grow by 70% to meet the projected demands in 2050. Unfortunately, there is limited space for agriculture expansion as the majority of land available is currently occupied or unavailable. Consequently, the increase in production needed to fulfil the demand must come from a higher crop yield on the currently occupied land.[1] Annually, the loss of crops due to diseases and pests can reach 40% of the global crop yields and this is expected to increase in the years ahead.[2] The agricultural industry must deploy methods that maximize farm profitability, minimize crop loss and reduce their environmental impact in order to meet demands[3]. A solution to these challenges is precision agriculture. Precision agriculture (PA) is a modern-day concept that has recently surged in the farming industry due to the labour shortage coupled with the economic pressures on farmers. Precision agriculture describes an agricultural system that benefits from a low input and high-efficiency sustainable system. It is an accumulation of the best practices for cost reduction, increasing crop yield, and the optimization of system input through information technology. The system uses cheaper emerging technologies, including geographic information system(GIS), Global Positioning System(GPS), cheap and high-resolution optical equipment, automated remote sensing equipment, and advanced data processing algorithms.[4] Precision agriculture has a general practice method deployed to guarantee better crop yield results. Unmanned Aerial Vehicles (UAV) are low altitude remote sensing systems that provide high-resolution multidimensional images with GPS coordinates for ground analysis. Unmanned Aerial Vehicles are the new standard for surveying a large landmass and are essential in the precision agriculture workspace. With the mass scale of modern farming, it is not uncommon to have many patches where trees are unable to grow or have died out. To ensure the farmers have the best possible understanding of their orchards, this project provides a new cost-effective method to fix these agricultural issues promptly. Through the mass surveillance of orchards, the identification of areas where trees need to be replaced becomes easier. Automatically detecting rows of trees or crops allow the farmer to quickly establish where there are issues with the yield and fertility.

The images provided for the problem are taken from UAV (refer to Figure 1a). This problem can be simplified to a directed graph where the nodes are tree objects, and the edges are the Euclidean distances between the nodes. The nodes cannot be put into a classic 2D grid as they are asymmetrically scattered in the domain space. There is no assumption of regular inter-row distances, a predefined number of rows or the general orientation of the trees in the orchard. There is a mix of straight and curved crop rows present that adds another layer of complexity (refer to Figure 1a). The UAV image can be used to generate a Digital Elevation Map (DEM), from which contour lines and other height information for both the ground and trees or crops can be extracted. Unfortunately, the DEM may not be present for each orchard image and height may thus not be available as an additional input channel. An object detector is provided to identify trees with confidence estimations. These trees are represented as polygon objects (refer to Figure 1b) with a confidence value, between zero and one, which may be used in the solution mechanism. The individual trees are to be linked to each other to form well-structured rows which are referred to as disjoint graphs. The disjoint graphs are created using optimization techniques, namely, pathfinding, combinatorial optimization and/or graph methods. Once the disjoint graphs have been formed, a second algorithm needs to identify potential missing trees that would fill numerous spaces to form potentially longer rows. The second algorithm is strongly related to the row finding algorithm so the literature review is centred around the row finding algorithm. The two outputs of this project are the disjoint graphs which represent the rows of trees and where the potentially missing trees are.

Figure 1a: source image from UAV

Figure 1b: classified tree objects (pink)

2 Background

In the context of this work, optimization seeks to maximize or minimize some kind of objective function which encodes information about the problem. The two optimization techniques used in the review are pathfinding and evolutionary computing. Finding the shortest path between a source and a destination node is called pathfinding. There are various algorithms to ensure that the minimal trajectory between two nodes is obtained while doing so in an efficient and fast manner.[5] The two classic pathfinding algorithms are Dijkstra[6] and A*[7]. These algorithms work with graphs that have either weighted edges or weighted nodes. After extracting the information of tree positions from the UAV images, pathfinding algorithms may be the solution for finding rows. This can be applied to the row finding problem as the shortest possible routes traversing several nodes are very likely to be tree rows and this could be a starting point for the algorithm. Evolutionary Algorithms are meta-heuristic search algorithms that search the solution domain independently of problem-specific details. The evolutionary algorithms investigated are Genetic Algorithms, Ant Colony Optimization and Particle Swarm Optimization. Genetic Algorithms (GA) are based on the principles of Darwinian evolution where possible solutions are called chromosomes. GA's work with a population of chromosomes and a fitness function. Through various iterations, the population undergoes selection, crossover, and mutation to reach optimal solutions.[8] Ant Colony Optimization (ACO) is a Meta-heuristic algorithm that is based on the swarm intelligence found in nature. ACO deploys agents (ants) to find the shortest path between two nodes on a graph using pheromone trails left by the agents. Particle swarm optimization (PSO) algorithm is a stochastic optimization method based on the simulating the movement organisms in nature such as a school of fish and flocks of birds[9]. The Hough Transform (HT) is used to compare several results from academic methods covered in the literature review section. The Hough Transform was initially proposed by Hough (1962) and is an algorithm that is based on computing accumulations of counts corresponding to crop rows.[10].

3 Literature Review

This literature review is about understanding all the prior academic work, related knowledge, and similar subfields of the project. The three fields that are review are pathfinding techniques, evolutionary algorithms, and image segmentation. Crop row detection can be linked to the section on finding tree rows section.

3.1 Pathfinding in two dimensions

The method of clustering data points based on geometric proximity to models (lines) is called Geometric model fitting. Past methods usually treat model parameter estimation and inlier classification as isolated subproblems, but a new method combines these two in the same problem space. A method proposed by Isack and Boykov (2012) performs multi-model fitting that balances geometric errors and regularity of inlier clustered data points based on global optimization. This method is called PEaRL. PEaRL finds models that explain the data points based on sparsity priors and spatial regularities. In practice, PEaRL can be shown to converge to acceptable minimum energy that allows for a small number of well-selected models to be chosen on a dataset. Using an original energy approach, it can be shown to outperform the previous state-of-the-art geometric model-fitting algorithm like RANSAC (Random Sample Consensus). This method does not need to know the number of models a *priori* to execution like Multi-RANSAC. The models were tested on randomly generated synthetic datasets, which vary in uniformity and amount of noise present and compared their estimation error concerning parameters to the ground truth.[11] Ferguson and Stentz (2006) proposed an interpolated-based path planning algorithm, called Field D*, that works with uniform and non-uniform sets of grids. This any-angle method calculates lower-cost paths than other path planning algorithms because transitions are allowed between two points on adjacent grid cell edges, instead of using only grid corners or cell centres to transverse. Field D* is based on D* Lite (an algorithm based on dynamic A*) and was created to improve upon the paths created and the memory used during execution while updating the graph in real-time. Field D* has capabilities which allow it to dynamically change its path when the environment changes. The results compare these two algorithms on the time to produce a path and the length of the path. On average, the Field D* algorithm produced shorter paths 96% of the time but took 8% longer to compute the paths. These results show that at the expense of extra time a better path can be found.[12] Xu and co-workers (2013) proposed a heuristic search pathfinding algorithm that can identify any-angle paths with fewer turns on a grid map, called Link*. Link* is the combination of three algorithms, namely, Basic Link*, Enhanced Link*, and Weighted Link*. Link* is modelled from the Theta* any-angle path planning framework that is based on the A* algorithm.[13] Link* iterates through the nodes, checking if the neighbouring nodes are visible from the current node and then makes a decision based on the estimated cost to the destination node. Basic Link* is the fast and the simplest variation. Enhanced Link* establishes shorter paths and improves the path quality of Basic Link*. Weighted Link* balances the vertex expansions and the number of turns made from the previous two. Results compared the execution time, the number of turns, and the path length to Theta* and A*. A* has more turns compared to all the others due to its rigid nature but performed quicker execution times than all the Link* variants. Link* found paths that had less than half of the turns at the cost of no more than 122% of the path length of those found by Theta* on random maps.[14]

3.2 Pathfinding in three dimensions

An improved A* algorithm for 3D pathfinding was proposed by Niu and Zhuo (2008) that uses the same core principle of a heuristic search method to find the optimal routes between and source and destination node. The optimal path is described using a culmination of the moving cost from the source node to the current node, and the estimated moving cost from the current grid layout to the destination node.[15] It builds on the industry-standard A* algorithm[7], by increasing the number of moving styles that the algorithm can make at each point and using regions to allow for parallelism within the new algorithm. Regions contain cells that are the 3D basic units in this pathfinding algorithm. The use of regions allows for less storage space as each region runs an independent A* algorithm that each uses less storage. The results compared the normal A* method and the newly proposed method on the same problem set with three metrics. The metrics are the difference in execution time, CPU usage, and storage space used. The new method had better storage use, speed of execution and is more flexible with the use of the Cell structure.[16] Comba and co-workers (2018) proposed an advanced, unsupervised algorithm for vine-rows feature evaluation and vineyard detection using 3D point-cloud mappings that are created from UAV multispectral imagery. The method begins an evaluation of features at each point in the cloud, using a small local radius of 5m, by using the local terrain surface and height evaluation. The by-product of the first step is the orientation parameter (direction of rows) for each local circle. The next is a scoring procedure that uses these evaluations to generate a likelihood map according to height, orientation, and local circle. The last step is the detection of vineyard areas using a simple binary threshold method that determines if it is a vineyard row. This threshold is calculated using the mean, autocorrelation, and normalized frequency distributions from each of the local circles. A by-product of this step is inter-row widths. This algorithm has been proven to be effective even in the case of noise, curved row, steep orchard gradients, and missing plants. The results obtained, on average, were above 90% for good detections with a low misdetection rate and over-detection because of small service paths parallel to vine rows (services rows). The results were obtained from four different instances of the same piece of land, roughly a month apart. The results were not compared to any previous row finding algorithms which may be a potential downfall of this method. This algorithm is overly complex, but the robustness for curvilinear rows and local circle evaluation techniques are fascinating and we would like to try to implement something similar.[17]

3.3 Genetic Algorithms

An improvement on the previous nondominated sorting genetic algorithm (NSGA) was proposed by Deb and co-workers (2002) to address the shortcomings, called NSGA-II. The NSGA-II algorithm finds multiple Pareto Optimal solutions in just a single run due to its diverse set of solutions. The algorithm is sped up by a faster-nondominated sorting procedure, a fast-crowded distance estimation process that then uses a crowded comparison operator for solution selection. The algorithm is tested against the Pareto-archived evolution strategy (PAES) and strength Pareto EA (SPEA) in terms of how close they converge to the true Pareto-optimal set. The diversity of solutions is also compared in the results. The NSGA-II achieved better convergence than the other two algorithms on highly constrained and multi-objective problems while still having a diverse set of solutions. The runtime of NSGA-II is $O(m*n*n)$ where m is the number of objectives and n is the population size.[18] Wei and Lui (2010) proposed a multi-objective path planning genetic algorithm to minimize the distance of a path as well as the maximal curvature between points. The path primitive for waypoints are cubic splines that are piece-wise polynomial functions. The method ensured diversity by using the Island-based Parallel Genetic Algorithm (IPGA), as a path planning framework, which avoids premature convergence. The results compare paths from different structures between the proposed algorithm, Single Objective(distance) GA, and Multi-objective GA. The proposed method successfully produces collision-free, well-constructed paths that reduce the curve between waypoints but still maintain a path of reasonable length.[19] Baron (1998) proposed the use of Genetic Algorithms for line extraction. This algorithm focuses on a two-dimensional space and it uses two free parameters which means it only extracts straight lines but is said to be easily extended by adding more free parameters to capture polynomial equations. It uses robust statistics, based on the breakdown point, to allow generalization for any geometric primitive. This algorithm has a breakdown point of about 95%, which means it can tolerate outliers up to a maximum of 95% in source data and still perform line extraction accurately. For comparison, the Least Squares statistical method has a 0% breakpoint point. Genetic algorithms allow for the search of a large domain and this property is used by a clever manipulation to map every possible line of the image space to a single point in the parameter space. This is done because the parameter space is bounded using a clever transformation of the line equation [20]. A single run of this method extracts multiple lines. The results show that it can produce results equivalent to the Hough Transformation. [21]

3.4 Swarm Algorithms

A modified Ant Colony Optimization algorithm was proposed by Sangeetha and co-workers (2019) to determine the optimal path, called the Modified Gain based Ant Colony Optimization (MGACO). MGACO uses satellite images from the International Society for Photogrammetry and Remote Sensing (ISPRS) as the input. These images are used to produce a thematic map, that is a map of the traversable areas, utilizing SegNet. SegNet semantically segments the input images through a deep convolution encoder-decoder architecture to produce a thematic map. The MGACO algorithm is then run on the thematic map to produce a path. The path is altered using the Bezeir spline approximation for a smoother path. The results are compared with the A* algorithm and Ant Colony Optimization. The MGACO algorithm outperforms these two in terms of the speed and the length of the optimal route produced. [22] Xu and Tie (2013) proposed a method for straight line detection based on the particle swarm optimization (PSO) algorithm. Each particle in this algorithm represents a straight line initialized between two edges points. The fitness function of the PSO algorithm is the number of edge points (nodes) that lie on the line for any instance of a particle. This method is compared to the HT and Random Hough Transformation (RHT) on simple and noisy images. The results show the method is equivalent to the HT and RHT but with a much lower computational time.[23]

3.5 Image segmentation

Zhang and co-workers (2018) proposed an automatic and robust crop row detection method for maize fields based on images acquired from a vision-based system. The vision-based system captures images from the front of a tractor. This method is intended for straight row detection with minimal angle changes and crop rows with heavy weed pressure. The three steps in the method are image segmentation, feature point extraction, and crop row detection. The crop row method is implemented by separating the input image into horizontal and vertical segments, thereafter, Floyds shortest path algorithm and a position clustering algorithm are applied to identify crop rows. The results obtained are comparing the proposed algorithm and Hough Transform on detection accuracy of angle and the line parameters of crop rows produced. The proposed algorithm slightly outperforms HT and produces more accurate lines in the presence of heavy weeds. The take away from this method is the crop row detection algorithm after the feature points have been extracted.[24]

Currently, there is a plethora of academic literature for crop row detection using image segmentation. These methods use input images from various sources as input to their solution mechanism. The different techniques usually differ according to their detection principle, namely, Hough Transform[25-27], Linear Regression[28, 29], Horizontal strips[30, 31], blob analysis[30, 32], stereo vision[33, 34], vanishing point[35, 36], and filtering[37, 38]. Unfortunately, all of the methods above solve the crop row problem while using an inequivalent input mechanism (ground-based imagery) or do not transform the source image into a graphing problem. Therefore, we do no analyse these methods further.

4 Discussion

The critical analysis table (Table 1) includes a 2D or 3D capability column because if the Digital Elevation Map is included in the problem instance, every (x; y) value has a corresponding z value which would enable us to use 3D pathfinding methods. The ratings are out of five, one being the worst and five being the best.

Table 1: Critical Analysis Table

Algorithm	**2D/ 3D**	**Execution Time**	**Straight/ Curved lines**	**Algorithm Relevance Ratings**
PEaRL [11]	2D	< 60 seconds	Straight	3
The Field D* Algorithm [12]	2D	< 4 seconds	Any-angle straight lines	3
Link* [14]	2D	< 3 seconds	Any-angle straight lines	3
3D A* algorithm [16]	3D	< 1 second; Parallelizable	Both	3
Vineyard detection using 3D point-cloud [17]	3D	Not specified	Both	3
NSGA-II [18]	3D	$O(n^2)$	Both	5
Cubic Spline MOGA [19]	2D	Parallelizable	Both	4
Genetic Algorithm for Line Extraction [21]	2D	Parallelizable	Straight	2
MGACO [22]	2D	< 1 second	Both	3
PSO [23]	2D	< 1 second	Straight	3
Crop row detection for maize fields [24]	2D	$O(n^3)$	Straight	3

The pathfinding algorithms previously presented are usually run on a uniform square grid where each node has a single (x, y) pair. However, the format of tree objects that we have does not meet the standard grid requirements. The row finding problem can be transformed by using the centroids of each object as a single node with an (x, y) value that can be plotted on a standard grid. After this transformation, all of the pathfinding algorithms can be used to solve the row finding problem. The Link*[14] and Field D*[12] algorithms are both any-angle path planning algorithms that work on a two-dimensional space. These algorithms are applicable to the tree row problem if the height data is not used. These algorithms produce adequate outputs and are considered for the solution. When the problem instance includes the height data, we can apply the 3D A*[16] algorithm. It enables the traditional A* algorithm to branch out in three dimensions while using Regions to allow parallelization. Using precise mathematics, PEaRL[11] has accurately identified straight lines. This algorithm does not require the number of lines to be classified a *priori*. It is robust in handling outliers however it does not work for curved lines. Fortunately, this makes it a good candidate for an initial algorithm. Similar to PEaRL, the crop row detection for maize[24] can detect straight lines with great accuracy in two dimensions. The disadvantage of the crop row detection for maize is that the time complexity is $O(n^3)$ which means it takes longer than PEaRL but obtains similar results. Therefore, we shall only consider PEaRL for straight-line detection. The point-cloud processing algorithm[17] is not usable directly, as it makes use of the source image of the data which is not allowed in the solution mechanism. However, we do believe that similar steps could be performed without the source image and valid results would still be obtained. The idea of using a smaller radius, with height data, to capture all the information in a given area should add inspiration to the tree row detection algorithm. We can, therefore, consider the whole algorithm unfeasible for tree row finding but we will take in this new isolated detection principle of using a small radius. The evolutionary algorithms we have reviewed have indicated that Genetic Algorithms have very good, feasible solutions. The NSGA-II[18] and cubic spline MOGA[19] are both multi-objective Genetic Algorithms that have excellent results. The NSGA-II is more general but if we apply it, we can use the same objective functions as the cubic spline MOGA. The results show that the minimax-curvature MOGA produces good paths with no sharp turns by ensuring a larger radius is used for turns. This is a candidate for the row finding algorithm as it allows more natural curves which may mimic the way curved tree rows follow the contour lines on a Digital Elevation Map. Using smoothed splines also protects against unnatural curves which could be triggered by noise from the uncertainty of the classified trees in a problem instance where there are many overlapping tree objects. We believe that the NSGA-II might be volatile with the transitions between nodes, and the cubic spline could smooth out the curves to fit the crop rows more naturally. These two algorithms can handle both curved and straight lines unlike the Genetic Algorithm for line extraction[21] method which can only handle straight lines. The genetic algorithm for line extraction extracts multiple lines from one execution which encourages the use of this algorithm as the initial straight-line algorithm. The swarm algorithms performed well for their respective objectives. The PSO[23] is a good candidate for the initial straight-line algorithm because of the quick execution time matched with suitable results for straight lines. The Genetic Algorithm for line extraction, PEaRL, or PSO could be used as an initial algorithm to identify the tree rows that are easily classifiable as a row. The Genetic Algorithm for line extraction and PEaRL work well with noisy data. This property is useful because of the uncertainty of the clustering of tree objects that arises in difficult problem examples. Based on the ratings of these three methods, we believe PEaRL or PSO is the best options to explore for the initial straight-line algorithm. The MGACO algorithm[22] has a competitive execution time and can be used to classify straight and curved lines. In addition, it uses a similar input to the row finding problem's input, but the generation of the thematic map is using the source image. The input mechanism would have to be altered, but we still believe this is a good candidate solution for the row finding problem.

5 Conclusions

In this review, there has been a comprehensive amount of research conducted into the different methods of row detection. The problem is to associate detected trees to individual rows in an orchard which contains an internal structure of trees planted in coherent rows. Following this, to identify patches in those rows which contain missing trees. This problem can be reduced to a directed graph where each node is a tree and each edge is the distance between the trees. Row detection, on this directed graph, can be completed by finding disjoint subgraph structures that represent tree or crop rows. These subgraphs are found using various optimization procedures that are single or multi-objective. The main avenues investigated are pathfinding and evolutionary algorithms as they can be used for efficient multi-objective optimization. The literature review suggested that line detection could be used as an effective solution to tree row identification. We have covered algorithms that can conclusively identify straight rows of trees, but for heavily curved lines we are uncertain of the accuracy that can be achieved. We have concluded that using a dedicated straight-line algorithm in the initial stages to identify the straight rows benefits the main row detector as it provides a good starting point to try to classify the difficult tree rows. The best candidates for the straight-line initial algorithm are PEaRL and PSO. NSGA-II has announced itself an ideal algorithm for the main robust algorithm, but the cubic spline could rival it based the natural curve it produces. The next step is to try and integrate the knowledge from previous academic works into a single specialized tree row detection algorithm for curved and straight lines.

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