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Title: Application of the Hough Transform to Identify Planting Rows and Patterns

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Theoretical Analysis	*0*	*25*	
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System Development and Implementation	*0*	*20*	10
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Aim Formulation and Background Work	*10*	*15*	15
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Total marks		**80**	**80**

Application of the Hough Transform to Identify Planting Rows and Patterns

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ABSTRACT

This paper seeks to investigate the use of the Hough Transform in order to identify planting patterns in orchards. This is done by finding the rows of trees within the orchard, based on Geo-json data and analysing the image representation of this plotted information to extract certain parameters. The paper will highlight the parameters that need to be discovered, the methodology that was followed in order to try and achieve this, as well as a discussion and conclusions on results about which parameters can be identified and issues that arise when trying to determine this information.

1 INTRODUCTION

Food security is a large problem faced globally with many factors influencing it such as high population growth, global warming and poor agricultural systems [1]. As population increases exponentially, the demand for food will follow this trend [2]. Farmers need to ensure that they can keep up with this demand, whilst facing land constraint problems. Thus, they need to take the best approach that will improve their yield. Precision agriculture is the science of improving crop yields and increasing cost-effectiveness by assisting management decisions using high technology sensors [3]. Aerobotics, a South African company specializing in tree crop protection, utilizes unmanned aerial vehicles (UAV) to acquire high resolution images of agricultural land. These are then processed to establish data on productivity of the crops. This information can be used to evaluate yield, soil condition, plant health, fertilizer and pesticide effect and irrigation [3], assisting farmers in keeping a large-scale idea of their crop management and problems.

The focus of the paper is to identify planting patterns for crop/orchard management. These have a major effect on the final yield of the crops for the farmer as different patterns yield different advantages for the farm such as effective cross-pollination, efficient irrigation, and accessibility.

This paper focuses on identifying and classifying planting patterns (Figure 1) such as:

- Square patterns
- Hedgerow or border patterns
- Quincunx/Hexagonal patterns
- Double row planting patterns

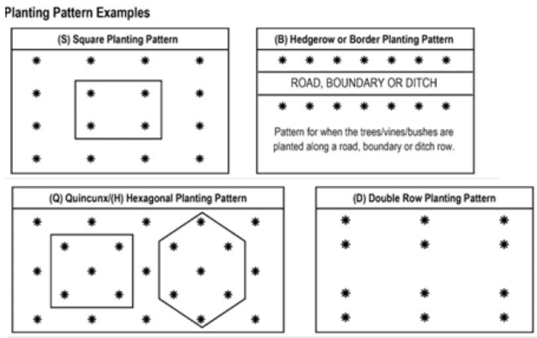

Figure 1. Planting patterns being investigated

Additionally, certain orchard parameters are attempted to be discovered. These are:

- The spacing between rows
- The spacing between trees within rows
- The overall orientation of the two main rows
- The location of a tree at one of the corners of the pattern
- Number of rows in the main row orientations

In order to try to identify both the planting patterns and extract the required parameters, the use of the Hough Transform is investigated in this paper. This is an important computer vision technique that detects lines within an image regardless of how fragmented the line may be [4]. This makes the process a good candidate in order to determine lines in orchards using the tree centroid information, as the tree centroids are not connected.

This paper will give an overview of the Hough Transform along with related work, the methodology used, covering; the data, pre-processing, the application of the HT and post-processing followed by a discussion on results and conclusions.

2 RELATED WORK

The Hough Transform (HT) was initially developed in 1962 (Hough, 1962) and was utilized to find straight particle tracks in high energy nuclear physics. The method he presented was developed further by Duda and Hart in 1972 where it was applied to the detection of lines and curves in digital images.

The HT method follows three main steps (Figure 2): Firstly, the coordinates of a pixel in the cartesian image space is transformed into a sinusoidal curve in the parameter space. Secondly, an accumulator with a cell array (which is equal to the size of the unknown dimensions) is laid on the parameter space and each pixel adds one vote to the cells lying on its sinusoidal curve. Thirdly, cells with global or local maximum votes are selected and the parameter coordinates (p, θ) can be used to determine the line as well as its orientation in the cartesian space [5].

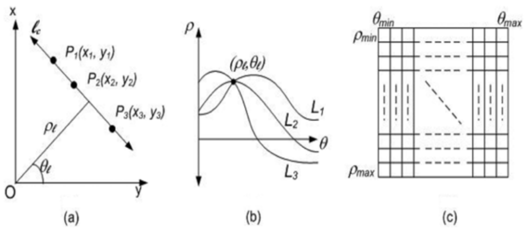

Figure 2. Straight line Hough Transform. (a) Collinear points in the image plane. (b) Intersecting sinusoids in Hough space. (c) Implementation as a two-dimensional array of accumulators

The Hough Transform has been used in a number of studies in the agricultural sector, with the aim of identifying plant rows. These applications will be discussed below in terms of their effectiveness and limitations.

A paper by John A. Merchant and Renault Brivot [6], discusses the real time tracking of plant rows by applying the HT to rows of cauliflowers. In their experiment they were able to identify the row structure of the cauliflowers by using the maximum peaks in the Hough space. Although the paper showed interesting results in identifying rows, it is much limited by the fact that the images that were processed were taken with the camera at 1200mm above the ground and thus not aerial views. An interesting observation from this paper however was that even though one of the rows was not complete and missing plants, the HT algorithm was still able to detect the row as a whole.

A study by Luis A. Ruiz et al [7], where the HT was used on a cross section of citrus trees from an aerial position did produce positive results. In this study the HT was able to yield individual trees within the cross-section image and the results were then utilized to find the principal direction of the trees as well as the distances between them (Figure 3).

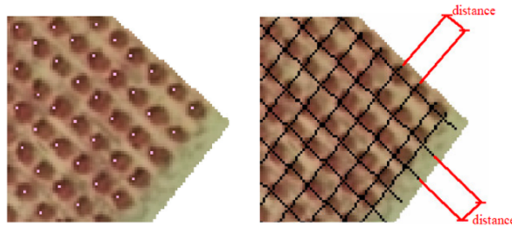

Figure 3. (left) Detail of identification of tree positions overlaid on image, (right) Extraction of the two principle directions of tree alignment and the regular distance between trees.

In a later study [8], an investigation is done by a plot-based approach of identifying the number of trees and planting patterns using aerial images. In this paper, the authors highlighted the importance of characterizing planting patterns and the usefulness of such in crop management. The patterns that were identified in citrus orchards were square, rectangular diamond and triangular. This is much the same as the planting patterns that this project will try and differentiate between. The first steps described were using the HT to identify the main tree alignments. This information was extracted by finding the most frequent directions of the lines in the range of directions from 0 to 179 degrees (θ). Once this was found, the median of the distance between the lines was calculated to find the row spacing. From this process, the parameters extracted from the HT to describe the planting pattern were the separation between tree alignments in the two main directions and the angular difference between the directions, which was done to obtain information on the orthogonality of tree alignments (Figure 4). This information was able to be used to determine spacing between the rows and the trees themselves.

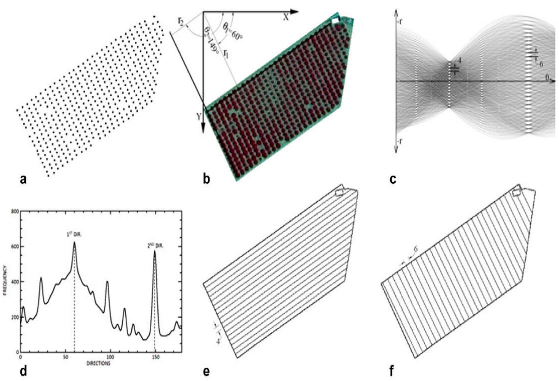

Figure 4. Steps for characterization of planting patterns: (a) tree centroid locations, (b) parameters of tree alignments, (c) Hough Space, (d) histogram of directions, (e) alignments in main direction, (f) alignments in secondary direction

There were factors that negatively affected the results from this paper. These were: the tree cover area where the delimitation of trees may be affected by tree overlap and the quality of the output of pre-processing which determines the individual locations of trees. In terms of identifying planting patterns, it is seen that the estimation of independent planting patterns is accurate. This can be negatively affected however where plots are narrow making it harder to identify principal row directions. It must be noted, that only single planting patterns were considered on a plot where in practice there may be more than one in each area.

The importance of post-processing is highlighted in [9], where analytic geometry techniques are described to distinguish crop rows from the output of the HT used due to many false positive lines being introduced. It states that the number of false positives is due to the HT returning points in the spatial domain that are allocated coordinates outside the plane of the image. The paper highlights a number of formulas that are applied in order to filter out the relevant crop rows from the images used. Figure 5 highlights the benefits of the post-processing process.

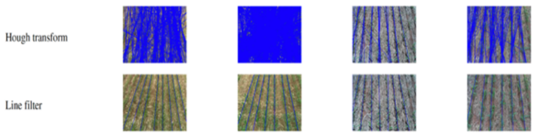

Figure 5. (Top Row) Results of line identification after applying the HT, (Bottom Row) Identified crop rows after post-processing line filter applied.

Although these results look promising, the type of data used is fairly different to the geojason data inputs that are used in this study which meant the same process of line noise elimination could not be fully followed.

3 METHODS/METHODOLOGY

To determine if the HT was suitable to be used for the detection of patterns and the extraction of other row parameters in orchards, both generated test data and real data was used. To identify the overall pattern within the orchard structure, both the main and secondary direction alignments are required.
With these alignments identified correctly the other parameters such as orientation, distance between rows, distance between trees and corner points of the structure can be found.

In order to be able to identify these main alignments, the data needed to be pre-processed, have the HT applied at different thresholds and post-processed. This output was then used to identify further parameters that are required. Images of points overlaid with detected rows were inspected, as was generated data, such as number of actual vs detected rows and distance changes between these rows to draw results.

Data

The data used is separated into two classifications: Sample Data and Real Data.

<u>Sample Data:</u>

The sample data was created in order to test the use of the Hough Transform in order to tackle the problem of pattern/row detection as well as extracting the required parameters. It was useful having data of fixed parameters to highlight areas where error margins or ulterior approaches may be needed
This data covered the four patterns being investigated with variability in both number of columns and rows in order to see the effect of the HT on different data sizes. This information is made to mimic the centroid information of the real data consisting of tree polygon centroids. (Figure 6).

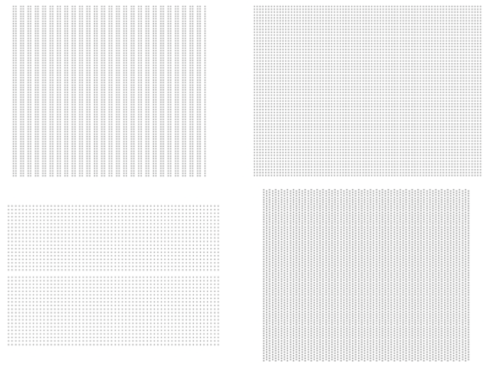

Figure 6. Test Data set examples: (top left) 70x46 double row, (top right) 60x80 square, (bottom left) 38x60 hedge-row, (bottom right) 70x139 Hexagonal

During testing, rotation was applied to the test data sets to see the potential effect on row, orientation and pattern detection.

<u>Real Data:</u>

The real data is based off aerial images of orchards where tree polygon information has already been discovered (Figure 7). This data is provided in geojson files which includes the points making up polygons of the trees at different confidence levels. These confidence levels set the amount of points that make up the dataset, with points having a higher confidence more likely to be a valid. Real data is explored at different confidence levels of 0.2, 0.4, 0.6 and 0.8. Access to real data has been limited with no Hexagonal data set present.

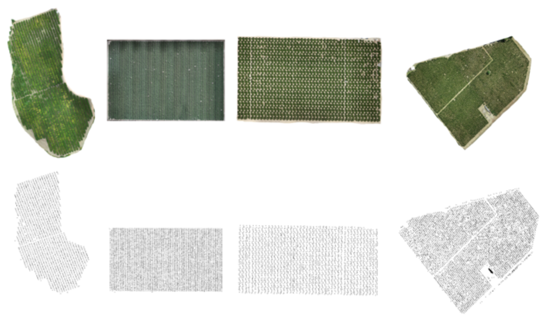

Figure 7. Real Dataset examples; (top) Image of orchards. (bottom)Plotted polygon centroids

Pre-Processing:

As real data is in the form of a list of tree polygons, the centroids for each polygon is calculated. The determination of the centroid for each polygon is done by taking all the coordinates for that polygon and calculating the average. This information is then stored within an array to be plotted. The confidence level for the data is between zero and one, where closer to one means more accuracy (higher confidence) but less polygons detected and closer to zero means more polygons are detected (with less confidence).

For both sets of data, the aspect ratio of the image is set to equal. Without this modification the distance between points on the x-axis and y-axis are not the same which lead to some distortion and incorrect plotting of the data.

Prior to applying the Hough Transform, the edges needed to be detected. This was done using the Canny Edge detector (Figure 8).

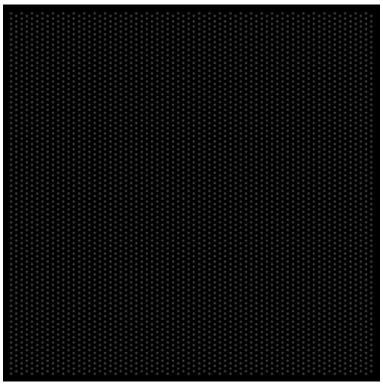

Figure 8. 70 x 70 Hexagonal Pattern after applying Canny Edge Detection on test data

This data is contained in a 2D array the size of the images length and width dimensions. The results of the edge detection process result in points not being single pixels but covering a 3x3 pixel range. In order to see the effect this may have in detecting lines from points, these 3x3 pixels are reduced to being singular within the edge map (Figure 9).

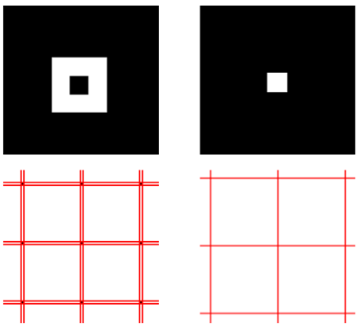

Figure 9. (top left) Point representation in edge map as 3x3 block. (top right) result of reduction to a single pixel points. (bottom left) Lines detected for 3x3 blocks. (bottom right) Lines detected for single pixel points

The reduction to single pixels does add additional processing time which is proportional to the size of the edge image.

Hough Transform (HT) Application

Once the edge image is created, the HT can be applied to the data in order to identify the main orientation and lines that are associated with it.

The HT uses a number of parameters that need to be specified; The edge image, the distance resolution of the accumulator in pixels (rho), the angle resolution of the accumulator in radians (theta) and the accumulator threshold parameter (only lines getting more votes than this threshold are included).

The first step taken was to identify the correct main direction alignment of the data used as input. This is an important step as this main direction is used to derive the secondary direction and is used in finding the other parameter requirements. This is done by running the HT at increasing threshold levels, and using a dictionary data structure to store the count of the amount of lines detected for each theta. The top theta value associated with the highest count is then extracted. Additionally, the threshold value where the main line direction is in the top two count categories is also recorded.
A problem was noted with diagonal lines being detected in the orchard data as the main direction when in fact it was not. This occurred in rare occasions as diagonals in the data set were prevalent, although the count of these were less than that of the main direction. In order to account for this, a measure of the amount of lines needed for a direction to be considered the most prominent was introduced. This measure ensured that a prominent direction had to have a certain count in order to be considered as the main direction. (Figure 10).

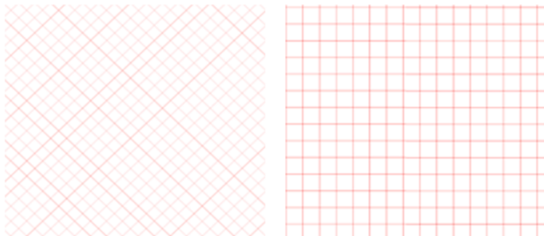

Figure 10. (left) Square Pattern with incorrect diagonal line as main direction based on longest line approach. (right) Square Pattern with correct main directions due to count threshold implemented.

Once the main direction (appropriate theta value) is determined, the HT is then applied once to the data set. This determined all the possible lines through the points within the image of centroids at various theta values. The number of lines associated with the main direction theta previously calculated were stored in a dictionary structure and sorted from largest to smallest in terms of line count.

To determine the secondary direction the theta value of the main direction is changed to degrees and the dictionary of stored values is explored to find the theta with the highest count that is 90 degrees to the main direction. As the secondary direction is not necessarily always 90 degrees of the main direction, a margin of error in degrees is introduced. The sorted dictionary of theta values and counts is then searched to identify the secondary theta with the highest amount of lines within this margin of error. The theta value of the secondary direction is then stored.

Using the main and secondary theta values, the rho values associated to these angles are found and stored in two separate lists and represent the lines through the points associated with the main two directions.

Post-Processing

As each theta value is associated with many rho values, post-processing is needed in order to remove unnecessary lines which may occur due to either points being too close together along one of the two main directions or due to multiple lines being detected for the same points.

The lists of rho values associated with the two main theta directions are sorted, resulting in the rho values being in descending order. To filter out lines that are close together, a margin of error in terms of pixels is introduced. These rho values for each direction are then checked to see if they fall within the error margin and if this occurs the rho values are combined and replaced with the computed average of their distances and stored (Figure 11). This results in a final list of rho values for each of the directions, which can be used along with their relative theta values to determine lines within the orchard structure.

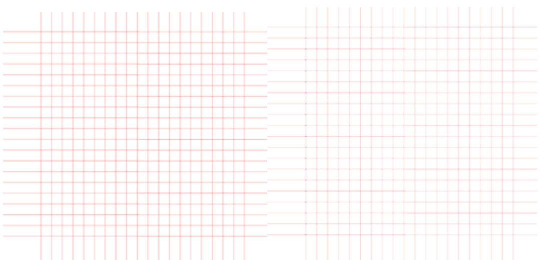

Figure 11. (left) multiple lines detected for the same point. (right)Reduction of lines within Line filtering Error Margin

The theta and rho pairs are then converted into pairs of (x,y) coordinates that represent two points on a line and stored in an array of lines. To achieve this the sine and cosine values of theta are calculated. These values are then multiplied by the rho value to get (x_0, y_0). This point is used to determine two points on the line, which are grouped together. This process is highlighted in Figure 12.

Input: Theta, rho
A = cosine(theta)
B = sine(theta)
*X_0 = A * rho*
*Y_0 = B * rho*
*X_1 = x_0 + int *(-b)*
*Y_1 = y_0 +int * (a)*
*X_2 = x_0 - int *(-b)*
*Y_2 = y_0 - int * (a)*
Output: Line points = (x_1, y_1), (x_2, y_2)

Figure 12. Conversion of Theta, Rho pairs to sets of x, y coordinates

The generated points are used to calculate the distances between the lines in each of the main and secondary direction using a line distance formula.

These distances are analysed in order to find the distance between rows (moving across one direction) and the distance between trees (moving across the alternate direction) which can be used to see a correlation to a specific pattern. There is a slight. error differential when comparing these distances, which needed to be taken into account with a pixel distance error margin.
The changes in distances and how often they change are then used in order to determine the planting pattern for the direction being analysed.

Planting pattens are then checked in the order of Double Row, Boundary Road, Square/Rectangle and then Hexagonal. For the double row pattern, distances should change uniformly with a large distance followed by a smaller distance. The boundary road pattern has a majority of equal distances occurring with one distance being larger than the others. The square pattern has all uniform distances with no other distance occurring. If a square pattern is found, this could mean that the pattern is actually Hexagonal. Therefore a further check needs to be done to check for this, which would require the intercept points of the two main directions for at least the border edges of the orchard space.

The interception points of the lines going in the main and secondary directions are determined through the use of the interception formula:

$$(P_x, P_y) = \left(\frac{(x_1 y_2 - y_1 x_2)(x_3 - x_4) - (x_1 - x_2)(x_3 y_4 - y_3 x_4)}{D}, \frac{(x_1 y_2 - y_1 x_2)(y_3 - y_4) - (y_1 - y_2)(x_3 y_4 - y_3 x_4)}{D} \right)$$

where the denominator is:

$$D = (x_1 - x_2)(y_3 - y_4) - (y_1 - y_2)(x_3 - x_4)$$

These intercept points are stored in a 2D array of intercepts.

The use of the intercept points between the main two directions can be utilized to determine if the pattern is Hexagonal and not just Square. Hexagonal pattern are similar to Square patterns except for the fact that only every alternating intercept point relates to a pixel being present, whereas in the square pattern the majority of intercepts along a line should relate to a pixel location.

To allow for the fact not all pixel points may be in the exact location of intercepts, a grid of points around the intercept position is checked.

The secondary function of both the intercept points and grid search around those points, is to identify another required parameter which is determining one of the orchard border edges.

4. Results and Discussion

Results from testing the HT on both the sample data and real data have been varied and have highlighted both positives and negatives with using the HT to identify planting patterns and the parameters required.

Test Data

The test data was initially run over the four planting patterns of various dimensions. A subset of this data can be found in Appendix A. The test data was run in order to see the potential effectiveness of applying the HT in order to identify planting patterns. As all the parameters around this data were known beforehand, it was useful as it helped to identify where potential problems may arise.

The main parameters that were being assessed over these tests were; the effect of pixel reduction to reduce the amount of lines being detected, difference in the HT threshold value that is used to determine the longest length of a line to be determined, the effect of line filtering in removing excess lines caused by points being too close together or the same points being registered twice, the size in the image space needed in order to detect if a pixel exists at corner points, if the main orientation of the data set is determined and if the main and secondary direction patterns are correctly detected.

It was observed for all patterns that if no pixel reduction or line filtering was implemented that excess lines were apparent. The amount of lines that were observed were double of what they should have been. This is true at both higher and lower threshold levels, with this not having an impact on results. This did not however have an impact on the detection of the main orientation of the pattern which was correct across all cases. The introduction of these false-positive lines did effect the identification of the correct pattern within the structure, with the patterns not being correctly identified for both directions. The double row pattern did observe one correct classification in the main direction. This was due to the double row pattern being very similar in nature to the effect that multiple lines caused.

Pixel reduction was applied to the data sets with improved results. The incorporation of pixel reduction correctly identified the correct number of rows in both the main and secondary direction at different HT threshold values for unrotated data. Showing increased accuracy due to this decreased pixelization. However, tests on rotated data led to incorrect row and pattern identification in at least one direction for all pattern cases due to excess lines being detected when they should not have been.

Line filtering was then introduced. This was tested without pixel reduction and also in conjunction with pixel reduction and pattern rotation. Results from line filtering were positive. The impact of line filtering (without changing pixel sizes) reduced excess lines that were detected into single lines. This led to the correct classification of patterns, orientation, outside corner points and numbers of rows. Line filtering was not negatively effected by any rotation in the data. The combination of line filtering with pixel reduction is seen as a must as accuracy is increased. Although not prevalent in the test data, line filtering is also used to combine multiple detections of the same line due to points on that line not being fully aligned. A possible negative to the line filtering process however is it may remove separate lines that are close together if the line error margin is set too high. This could especially occur with variable sized image resolutions as it is based on pixels between points. Combination with pixel reduction does reduce negative effects of the error margin being too low.

The hexagonal pattern and corner detection are dependent on identifying pixels within the image. As the number of pixels representing a point is reduced to one, incorrect results can occur if only the pixel at the point of intersections is checked. The pixel grid value does mitigate this problem in test data when set to checking the circumference of two pixels wide in all direction around the interception points. It is important to note that only 50% of all corner points are able to be detected for the Hexagonal pattern due to the nature of the pattern. As we are only looking for at least one corner point, this is considered a good result.

Results have been promising with the inclusion of pixel reduction, line filtering and pixel grid checking across all pattern types for the min and max (program generated) HT threshold values. The main orientation of the patterns have been successful for all testing scenarios. Corner point detection has been successful for all results but a note is made that all actual corner points may not be present in real data, which would lead to this not being able to be obtained. Rotation effects on the data have been successfully overcome which holds promise.

Real Data

After acquiring results from the test data, the methods were applied to four real datasets. A subset of the results of this data can be found in Appendix B.

The real data used is classified as Double Row, Boundary Road, Square/Rectangle and Square/Boundary Road. Out of these data sets, the Square/Rectangle and Square/Boundary road sets are the only ones where at least one direction is able to be successfully classified.
The unsuccessful classification of the second direction is due to the sporadic nature of the data points making up the rows in that direction. This led to both false positive

lines as well as false negatives (lines not being identified when they should). As both directions are needed in order to identify the planting pattern as a whole, this was not able to be accomplished fully for any of the sets of data.

Datasets were run across various HT threshold values in order to establish the main orientation. This did prove successful over all the real data at all confidence levels inspected and the count value used in order to not incorrectly identify diagonal lines did successfully achieve its purpose as only the main orientation was discovered. This further led to the secondary direction being identified.

Once the main orientation was found, setting the correct HT threshold for the datasets was needed. A problem that was encountered was setting the HT threshold too high. As real data orchard shapes are not standard in their dimensions, with some parts of the orchard being thinner than others. This is especially the case for the Boundary Road and Square/Boundary Road patterns. With the threshold being set too high, the rows in the narrower portions of the orchard gave false negative results, meaning that rows that should have been identified were not. This was seen across all confidence levels, although at higher confidence levels this was more profound due to less centroids being identified within the orchard. Decreasing the threshold value to a minimum did help account for false negatives.

Low threshold drawbacks occurred due to the nature of the real data polygons. Lines of points within these datasets do not have high degrees of accuracy, even at low confidence levels, meaning that points along the lines within the image are not in straight rows. If the HT threshold is low to account for smaller edges of the orchard, these variations in the lines have the impact of extra lines being identified within the image where they should not be, although partial mitigation of this can be achieved through line filtering.

It was found having a lower threshold value and identifying more false positives was preferrable to having a higher threshold value which led to more false negatives. This is due to the fact that the majority of these false positives were able to be removed with line filtering whereas not correctly identifying lines had the detrimental effect of rows being excluded. This was especially the case with confidence levels below 0.4. The additional benefit of having a decreased threshold value was that missing centroids within the image did not affect the outcome of line recognition.

Line filtering was able to account for some variations within the same line, but only when these differences were not large. This could mainly be due to points being reduced to single pixels. As distances between points along the same rows varied both within datasets and across different ones, identifying the correct line filtering error margin was difficult. The effect of the filtering error margin being too low meant more false positive lines were identified. It was found that having a higher error margin combined with a low HT threshold was preferable. This was especially true in the case of the Boundary Road and Square/Boundary Road data sets where portions of the orchard were much narrower than other sections. This combination had success at a 0.4 confidence level for the Double Row dataset, 0.2 and up confidence level for the Square/Boundary set, 0.4 confidence level for the Boundary road. This is similar for the Square/Rectangle orchard but this dataset did do better up to a 0.6 confidence level.

When one of either the main or secondary directions were identified, it was then possible to extract the distances between rows. As both directions were never accurately found in any of the data sets, distances between trees could not be extracted.

The last issue is the identification of a corner point within the image. This was negatively affected by threshold values being too high as outside lines are then not detected and corner points are incorrectly identified. The occurrence of missing data points at the corners of the orchards especially at higher confidence levels also had a negative effect.

Overall, the data generated was not uniform in being able to identify specific error margins that can be used for all datasets. The variability of the orchard centroids and shapes led to different margins needed for different sets of data. Among the data sets, the Square/Rectangle pattern had the most success across one direction. This is due to it being the most uniform of all the patterns investigated. Patterns such as the Double Row, had embedded It must be noted that duel patterns within the same orchard structure could not be determined.

4 Conclusions

The results of the HT in order to identify different planting patterns, though good when using sample data, fell short when being used on more complex real world data. One of the major issues with the HT is variability of points within a row. Additionally using a threshold value that is too high, results in not identifying all the potential rows. The usage of a threshold value that is low can to a certain degree be combined with a higher line filtering error margin, although this could also result in potential lines that are different being merged together. On a positive note however, the HT does seem to correctly identify the major row direction (orientation) in all cases and it is believed that this fact could lead to the HT being used as a prerequisite for other pattern matching techniques such as template matching in order to reduce runs times.

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Appendix

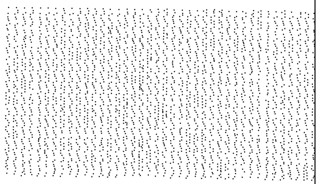
A.

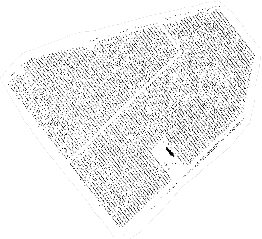
Type	Dimensions	Total Lines Detected	Main Direction count check	Pixels Reduced	Lines detected in main direction	Lines Detected in Secondary Direction	Hough Transform Thresholds*	Line Filtering (size)	Main Lines Post Filtering	Secondary Lines Post Filtering	Pixel Grid Check size	Corner Points Detected	Main Orientation identified	Pattern Rotated	Pattern Identified in Main Direction	Pattern Identified in Secondary Direction
Double Row	70 x 46	58500	10	No	92	140	5, threshold value	Na	Na	Na	2	Yes	Yes	No	Yes	No
	70 x46	58500	5	No	92	140	5, threshold value	3	46	70	2	Yes	Yes	No	Yes	Yes
	70 x 46	3030	5	Yes	46	70	5, threshold value	Na	Na	Na	2	Yes	Yes	No	Yes	Yes
	70 x 46	7398	5	Yes	57	70	5, threshold value	Na	Na	Na	2	Yes	Yes	Yes	No	Yes
	70 x 46	7398	5	Yes	46	70	5, threshold value	3	46	70	2	Yes	Yes	Yes	Yes	Yes
Boundary	38 x 60	64464	10	No	76	120	5, threshold value	Na	Na	Na	2	Yes	Yes	No	No	No
	38 x 60	64464	5	No	76	120	5, threshold value	3	38	60	2	Yes	Yes	No	Yes	Yes
	38 x 60	1472	5	Yes	38	60	5, threshold value	Na	Na	Na	2	Yes	Yes	No	Yes	Yes

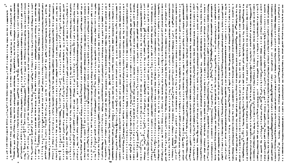
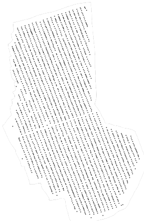
	38 x 60	1889	5	Yes	38	70	5, threshold value	Na	Na	Na	2	Yes	Yes	Yes	Yes	No
	38 x 60	1889	5	Yes	38	75	5, threshold value	3	38	60	2	Yes	Yes	Yes	Yes	Yes
Square	60 x 80	74541	10	No	120	160	5, threshold value	Na	Na	Na	2	Yes	Yes	No	No	No
	60 x 80	74541	5	No	120	160	5, threshold value	3	60	80	2	Yes	Yes	No	Yes	Yes
	60 x 80	7508	5	Yes	60	80	5, threshold value	Na	Na	Na	2	Yes	Yes	No	Yes	Yes
	60 x 80	23327	5	Yes	60	113	5, threshold value	Na	Na	Na	2	Yes	Yes	Yes	Yes	No
	60 x 80	23327	5	Yes	60	113	5, threshold value	3	60	80	2	Yes	Yes	Yes	Yes	Yes
Hexagonal	70 x 139	63923	10	No	140	278	5, threshold value	Na	Na	Na	2	50%	Yes	No	No	No
	70 x 139	63923	5	No	140	278	5, threshold value	3	70	139	2	50%	Yes	No	Yes	Yes
	70 x 139	9624	5	Yes	70	139	5, threshold value	Na	Na	Na	2	50%	Yes	No	Yes	Yes
	70 x 139	32681	5	Yes	113	139	5, threshold value	Na	Na	Na	2	50%	Yes	Yes	No	Yes
	70 x 139	32681	5	Yes	113	139	5, threshold value	3	70	139	2	50%	Yes	Yes	Yes	Yes

*Threshold value is the Hough Transform Threshold variable where the main theta direction is either the first or second highest value according to line count across multiple threshold variables being tested.

B.

Type: Tree Dimensions	Confidence Interval: minimum	Total Centroids Detected	Main Direction count check	Lines detected in main direction	Lines Detected in Secondary Direction	Hough Transform Thresholds *	Line Filtering (size)	Main Lines Post Filtering	Secondary Lines Post Filtering	Pixel Grid Check size	Corner Points Detected	Main Orientation identified	Pattern Identified in Main Direction	Pattern Identified in Secondary Direction
														
Double Row: 88 x 61	0.2	3372	5	96	69	Threshold= 6	3	74	62	5	No	Yes	No	No
	0.2	3372	5	112	287	1	3	62	92	5	No	Yes	No	No
	0.2	3372	5	112	287	1	**7**	53	89	5	No	Yes	No	No
	0.4	2891	5	89	68	Threshold= 6	3	68	53	5	No	Yes	No	No
	0.4	2891	5	106	265	1	3	71	112	5	1	Yes	No	No
	0.4	2891	5	106	265	1	5	59	90	5	1	Yes	No	No
	0.4	2891	5	106	265	1	6	46	87	5	No	Yes	No	Yes

	0.6	2184	5	63	9	Threshold= 6	3	41	9	5	No	Yes	No	No
	0.6	2184	5	90	274	1	3	59	104	5	1	Yes	No	No
	0.6	2184	5	90	274	1	5	45	88	5	No	Yes	No	No
	0.8	1104	5	27	1	Threshold= 6	3	23	0	5	No	Yes	No	No
	0.8	1104	5	81	195	1	3	45	95	5	1	Yes	No	No
														
Boundary Road 76 x Indeterminate	0.2	7951	5	88	71	Threshold= 18	3	71	16	5	No	Yes	No	No
	0.2	7951	5	115	202	5	3	77	98	5	No	yes	No	No
	0.2	7951	5	181	82	1	3	248	121	5	No	Yes	No	No
	0.4	4280	5	134	94	Threshold= 6	3	75	66	5	No	Yes	No	No
	0.4	4280	5	180	249	1	4	79	124	5	No	Yes	No	No
	0.4	4280	5	130	240	1	6	77	83	5	No	Yes	No	No
	0.6	1633	5	99	52	Threshold= 3	3	65	41	5	No	Yes	No	No
	0.6	1633	5	158	210	1	3	77	105	5	1	Yes	No	No

														
Square: 79 x 65	0.2	8531	5	79	49	Threshold = 15	3	79	44	5	2	Yes	Yes	No
	0.2	8531	5	80	187	5	3	79	124	5	2	Yes	Yes	No
	0.4	7028	5	79	79	Threshold= 12	3	79	60	5	2	Yes	Yes	No
	0.4	7028	5	80	165	5	3	79	113	5	2	Yes	Yes	No
	0.6	4992	5	79	89	Threshold =9	3	79	62	5	2	Yes	Yes	No
	0.6	4992	5	79	149	5	3	79	99	5	2	Yes	Yes	No
	0.6	4992	5	80	157	1	3	79	105	5	2	Yes	Yes	No
	0.8	2132	5	67	49	Threshold = 6	3	66	41	5	No	Yes	No	No
	0.8	2132	5	87	95	1	3	79	95	5	1	Yes	No	No
														
Square/Boundary: 28/29 x Indeterminate														
	0.2	2522	5	N/a	N/a	Threshold= 9	3	N/a	N/a	5	N/a	N/a	N/a	Na
	0.2	2522	5	60	32	5	3	32	8	5	No	Yes	No	No
	0.2	2522	5	63	273	1	4	30	121	5	No	Yes	No	No
	0.2	2522	5	63	273	1	6	28	98	5	No	Yes	Yes	No
	0.4	2490	5	63	275	1	3	32	136	5	No	Yes	No	No
	0.4	2490	5	63	275	1	6	28	99	5	No	Yes	Yes	No

	0.6	2412	5	55	266	1	6	28	97	5	No	Yes	Yes	No
	0.8	2116	5	60	271	1	6	28	98	5	No	Yes	Yes	No

* Pixels reduced for all tests