Application of the Hough Transform to Identify Planting Rows and Patterns

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ABSTRACT

This paper gives a review on literature that applies the computer vision method, the Hough Transform, to identify planting patterns and rows in orchard and crop fields. Orchard and crop rows are generally planted according to certain patterns that contain straight lines which makes the Hough Transform an appropriate candidate for the problem space. Of the differing Hough Transform approaches, the Windowed Hough Transform and the Gradient Random Hough Transform are recognized as being the most promising with analytic geometry line filtering in post-processing being identified as necessary.

CCS CONCEPTS

• Computer Vision • Image Processing

KEYWORDS

Hough Transform, Window Hough Transform, Random Hough Transform, Gradient Random Hough Transform.

1 Introduction

With the agricultural sector facing lower margins and earnings, which requires farmers to reduce costs and maximize their output whilst ensuring high product quality [1], the need for implementing a Farm Management Information System (FMIS) is necessary. The inclusion of a FMIS enables success through quicker access to information [2] and allowing farm managers to utilize their resources more effectively. The basis of these systems is the availability of timely high-quality data. This paper looks at a subset of the data that is used by these systems, that being, the automatic detection of planting rows and patterns in agricultural images. Due to various field management factors, orchards and crops are arranged in certain planting patterns as seen in Figure 1. In order to identify these patterns, images are captured by Unmanned Aerial Vehicles (UAV's). These images are ideal candidates for the application of the Hough Transform, which converts a global detection problem in the image space into an easier local peak problem in the parameter space. Using these peaks, lines can then be identified within the image, allowing the identification of planting rows. With the identification of these rows, it will be possible to identify three parameters which this project sets out to measure. Those being Intra-pair spacing, inter-pair spacing and row spacing. This data will be useful to farm managers as it will enable them to adequately plan irrigation and pesticide methods as well as helping them to utilize their resources more appropriately and efficiently.

This paper will firstly, give a high-level view of the Hough Transform. Review how the original HT has been used previously in agricultural areas to identify plant patterns and rows. Extend the HT to the Windowed Hough Transform (WHT) and its potential to recognize curves within orchard rows. A review will then be done on the Random Hough Transform (RHT) and how this is more computationally and spatially efficient than the original HT method. Lastly the importance of line filtering in post-processing after the HT has been applied to further identify the main planting rows within an orchard or crop section.

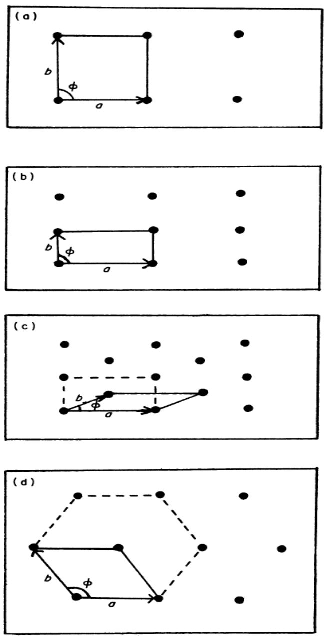

Figure 1. Four types of regular planting patterns. (a) square lattice, (b) rectangle lattice, (c) centred rectangular lattice, (d) hexagonal lattice [3]

2 Hough Transform

The Hough Transform (HT) was initially developed in 1962 (Hough, 1962) and was utilized in order 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. Since then, it has become an important part of image processing. One of the main features of this process, is its ability to detect a line, regardless of how fragmented it is [20].

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 [13].

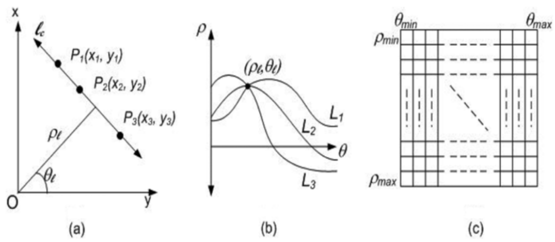

Figure 2. Straight line Hough Transform. (a) Collinear points in the image plane. (b) Intersecting sinusoids in Hough space. (c) Implementation as a two-dimensional array of accumulators

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 [4], 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 [5], 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 in order to find the principal direction of the trees as well as the distances between them (Figure 3).

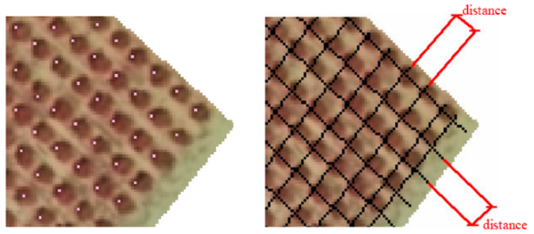

Figure 3. (left) Detail of identification of tree positions overlaid on image, (right) Extraction of the two principle directions of tree alignment and the regular distance between trees.

These are quite promising results, especially in terms of identifying distances between rows. It must be noted that the cross section that was used is fairly basic with not much background noise within the image. As we are also wanting to investigate the potential of various patterns within an image, the results of just applying the HT to a single pattern type can be misleading.

In a later study [6], an investigation is done by a plot-based approach of identifying the number of trees and planting patterns through the use of 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 in order 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.

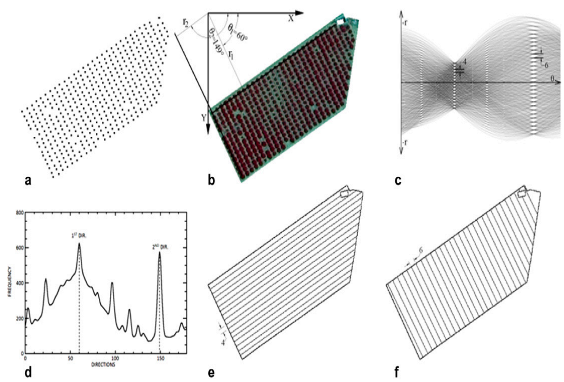

Figure 4. Steps for characterization of planting patterns: (a) tree centroid locations, (b) parameters of tree alignments, (c) Hough Space, (d) histogram of

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 a given area.

A limitation that can be noted from these studies are that the majority of planting rows used have been in fairly straight lines. As noted in [7], planting patterns may not be straight due to geological restrictions. As the HT works best on items that are in straight lines, an altered approach may be needed where curvature may exist within the rows.

3 Windowed Hough Transform

The Windowed Hough Transform (WHT) is the use of a sliding window in the image in order to compute the HT of smaller subsections where local maxima are extracted [8].

As planting patterns follow certain shapes for effective plant management [3] and more than one pattern may exist in a region due to geographical restraints, breaking up an image into smaller windows and applying the HT to each of these regions may help to identify if there is more than one planting pattern used.

In [9] the detection of rectangles is investigated using the WHT. Although this paper relates to detecting rectangles in images with solid lines, it may have use in the problem space of orchard rows when they are discovered as well as being able to be applied to other shapes. It is stated in the paper, that the technique used works for rectangles with unknown dimensions and orientations and can be applied directly to an edge map which would be the input for the HT.

A major configuration that would need to be considered in this approach is the determination of the window size as it would need to be able to accommodate different planting patterns for which the size is not known beforehand. It is also highlighted that duplication of the same shapes may be detected [9]. A method that is proposed to deal with removing duplicated shapes is to compute an error measure for each detected shape and then choosing the shape where the error is smallest (Figure 5).

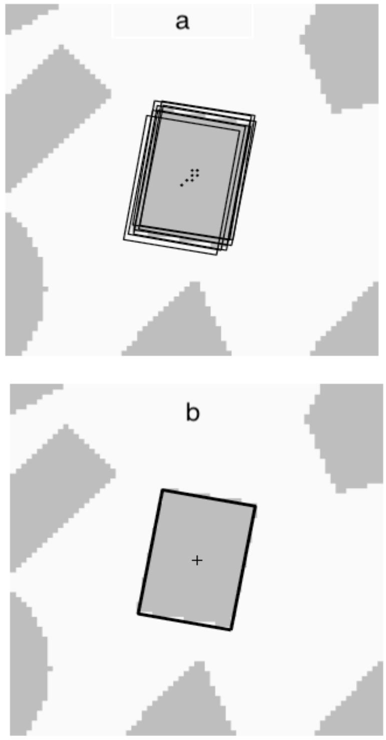

Figure 5. (a) Multiple detection of the same rectangle, (b) Reduction to single rectangle with minimal error.

A paper by G. A Soares et al [7] addresses the use of tiling (using smaller windows) within an image to correctly identify rows in coffee crop fields. An interesting observation that is made about the limitation when identifying rows of crops from UAV's is that the actual planting rows are not straight. If the image is segmented into smaller windows, then the lines within these windows will be perceived as straight, upon which the HT can be applied (Figure 6). The results from these smaller windows, when combined, could show curvature within the planting rows.

Figure 6. Coffee plantation following geographical features. Inset: illustration of segment where curves can be approximated to straight lines.

It is noted in the paper, that after dividing up the image into smaller segments, applying the HT to these segments and combining the results may lead to gaps within row identification. It thus proposes that a parameter of overlap be introduced. Paper [7] suggests that the optimal overlap of the windows be 25% although this would need further analyses in order to determine if this is actually optimal. Some results from this paper can be seen in Figure 7, where the application of an overlap between the tiles removes gaps in row detection albeit not all of these are removed, leading to the belief that a 25% overlap may not be optimal.

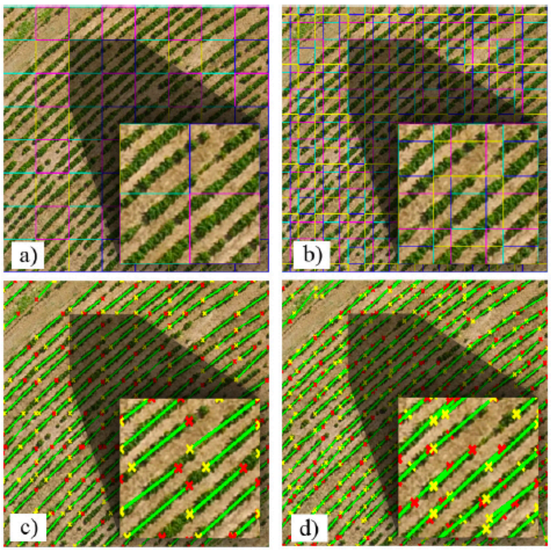

Figure 7. Overlap Strategy: (a) imaged window without overlap, (b) image window with overlap of 25%, (c) Processed image windowed without overlap, (d) Processed image windowed with 25% overlap.

Although this method reduces line discontinuity of lines within the broader image, it does also produce extra lines due to background noise within the smaller windows. This induces the need for further post-processing of the image where background noise is removed. It is proposed in this paper, that this happens in two stages. Firstly, removing noise within the small windows and secondly using larger tiles which are proportionally bigger to the smaller ones (known as the denoising index). The denoising index would need to be tested in order to find the most favorable proportion.

With images being broken down and processed as smaller windows which are overlapping, computational efficiency may be compromised. It is stated by the authors however, that a biproduct of the windowing strategy is that the problem could be parallelizable, thus making the process more computationally efficient, due to the independent nature of the windows being analyzed suggesting that a divide and conquer approach may be a possibility.

The idea of parallelization is explored in [17], using a variant of the HT named the Additive Hough Transform (AHT), in order to speed up computation time. This is done by a similar approach to the WHT by dividing the edge map into uniform blocks of k-by-k grids. It was found that this reduced the computation time by at least k-squared times whilst giving the same Hough profile as the traditional HT (Figure 8). The benefits of trying to achieve this speed-up however may only be relevant for future work. It seems this approach could be a synonym for the WHT.

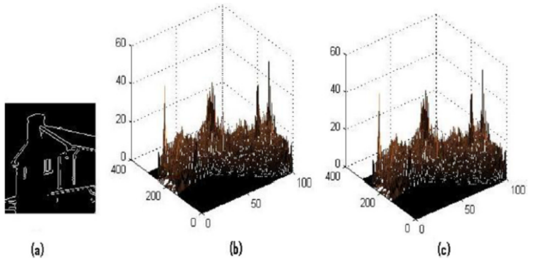

Figure 8. (a) Edge map of image, (b) Hough Transform using conventional method, (c) Hough Transform using AHT

Further to address the computational and spatial costs of the HT, investigation into the use of the Random Hough Transform (RHT) is necessary as this is seen as less computationally and spatially costly. The benefits of the RHT and its potential application to detecting crop rows compared to the standard HT is further discussed.

4 Random Hough Transform

Although the HT has had success in detecting rows of crops in images, it does come with both computational and space costs. [11, 12].

The HT has several drawbacks that are posed as being critical in terms of its performance [11]. The main reason for this comes from the fact that the HT is a one-to-many diverging mapping from the image space to the parameter space. The RHT conversely is a many-to-one converging mapping (Figure 9).

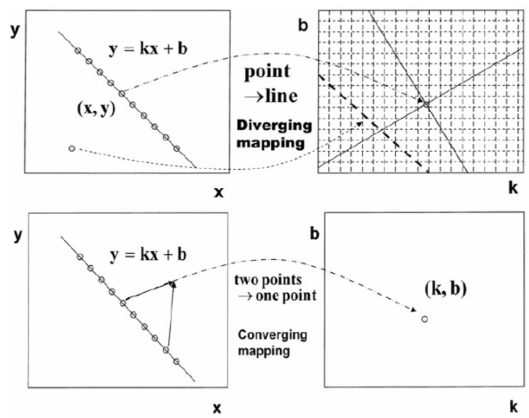

Figure 9. Difference of mapping between HT and RHT: (Above) Hough Transform, (Below) Randomized Hough Transform

This has the effect of both enabling random sampling in the place of costly pixel scanning, reducing the storage space of the Accumulator arrays and adaptive detection in place of the enumerating over all the pixels [11]. It is stated that this results in reducing the time and space complexity as well as the benefit of increasing detection accuracy. The statement of increasing detection accuracy however is contradicted in other articles, as the RHT is still affected by ground noise conditions.

It is noted in [11, 18, 19] however that the type of pixel background noise is important to consider as this may lead to inaccurate line detection. It was determined that although the RHT was computationally quicker, it may not be able to detect lines adequately where images are contaminated by noise and errors. N. Kiryati et al [18], proposed that in this case a different variant of the HT, the Probabilistic Hough Transform (PHT), which is based on a one-to-many mapping is more suitable.

The benefits of the RHT in terms of computation and spatial efficiencies are more easily identifiable visually as can be seen in Figure 10, which shows a comparison of consumed times of the RHT compared to those of HT with an equal amount of line segments discovered [13].

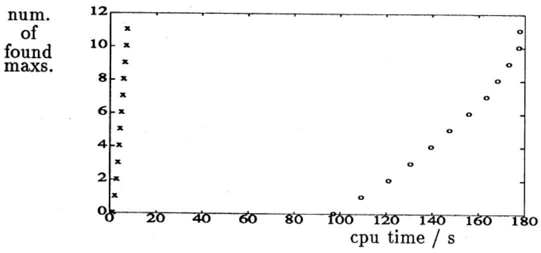

Figure 10. A comparison of consumed times of HT (marked by o's) vs consumed time of RHT (marked by x's)

Figure 11 further highlights the benefits of the RHT [14] showing the 2D histograms of the RHT compared to that of the HT with peaks A and B more defined with less points mapped (meaning less computations) within the parametrized space. This, however, is applied to lines that are very distinct and background noise is very random. This most certainly will not be the case in orchard and crop fields where individual items will be closer together.

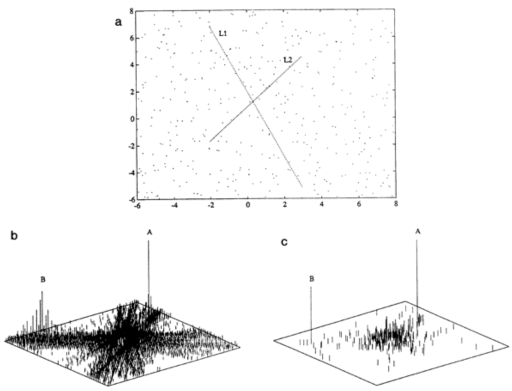

Figure 11. A comparison experiment on an image with string outlier noise: (a) An Image containing two lines L1 and L2, (b) Resulting 2D histogram using the HT with the maxima A, B denoting the two lines detected, (c) The resulting 2D histogram using the RHT with the maxima A,B denoting the two lines detected.

In [10], the HT and a modified version of the RHT are used in crop row detection. This modification is the Gradient Random Hough Transform (GRHT). This version of the RHT uses gradient information about points being detected, where local gradients were used to decrease noise within the image to enable better line identification [10, 15]. The use of this gradient information may be very helpful in the problem space that will explored due to the fact that rows in orchards are generally straight. Table 1 shows comparative results between the standard HT and the GRHT for different plant row densities in terms of computation speed.

Table 1. Comparison of detection speeds using the HT and RHT for different crop sparsity's

Plant density	Sparse		General		Intensive	
Method	RHT	HT	RHT	HT	RHT	HT
Speed(s)	0.802	1.715	0.823	1.8103	0.831	1.8209

The papers so far have emphasized improved performance of the RHT over the HT. This may be the case in the literature that has been seen, but it is not clear if the regular HT was parallelized in any way. It could be seen in previous sections that this is a potential possibility and could bring added benefits in terms of computation speed.

5 The importance of Post-processing

Thus far, emphasis has been made on defining HT variants and cases in which they have been used in the realm of crop row or pattern identification. Indications are that it is a feasible approach to this problem. Information that has not been mentioned as of yet, is necessity of post-processing.

This is highlighted in [16], where analytic geometry techniques are described in order to distinguish crop rows from the output of the HT used due to a large number of 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 filter out the relevant crop rows from the images used. Figure 12 highlights the benefits of the post-processing process.

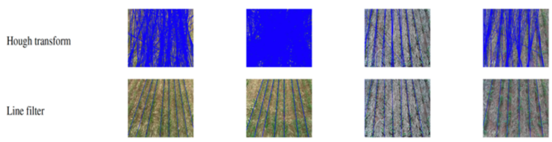

Figure 12. (Top Row) Results of line identification after applying the HT, (Bottom Row) Identified crop rows after post-processing line filter applied.

The use of these analytic geometry techniques seem impressive, but one must also keep in mind that statistical approaches in post processing can also help in row determination.
In terms of identifying crop rows, there is an expectation of ground noise with a potential for the HT, in any form to identify lines in multiple directions. Upon inspection of the image after filtering is done, it shows the importance of post-processing in identifying crop rows.

6 Discussion

This review has discussed how the HT and some of its variations can be applied to identifying rows within crops and orchards. It is generally noted that how pre-processing of images is done is important for the use of the HT technique.

The first method identified is the basic form of the HT. In [5] it is stated that if polygons are missing in rows, the HT will still be able to identify the line where the majority of objects are visible, which we believe will be the case. In [6] it is indicated that missing objects in a row as well as geological features of the landscape may negatively affect pattern identification, but it is not stated if this will affect the actual identification of a row. Using the information generated by the HT, distances between rows as well as individual items that make up that row have been seen to be computed. These can be seen as very promising results that justify the use of this method.

An extension to the HT, the WHT [7,8,9,10], has been proposed in images where inherent curvature in planting rows is identified. Here a sliding window can be used on an image, breaking it down into smaller windows. Within these smaller windows, straight row lines can be identified, and then the windows can be reassembled to show rows even where curvature exists. The use of the WHT was discussed in terms of addressing curvature but should also be able to be used in images with straight line rows as it behaves in the same way as the HT. We believe that this approach and the use of a Denoising Index will also aid in finding the principal row directions. Limitations of the standard HT and WHT approach however could be high computational and spatial requirements, although it is suggested that these methods can be parallelized, thus reducing computational complexity. This should not be a core focus however, as it is far more important to firstly address the identification of primary rows and patterns. The use of HT in general may be more efficient than other techniques used to address this problem, such as pattern matching and graph theory. This means that the reduction in computation efficiency may not be a needed approach in this stage of the problem space. Before computation benefits can be realized, it would be more beneficial to show that the HT approach will work in identifying primary rows and overall patterns.

The RHT is a method that can address issues of computation efficiency. [10, 11, 12, 13, 14]. This uses a many-to-one converging mapping as opposed to a one-to-many diverging mapping that the HT and WHT uses. This has the benefit of increasing the computational speed and reducing the space complexity. A limitation that has been seen with this approach, is the effect of background noise in detecting lines from points due to less points being selected in the cartesian image space. It is suggested however, that using the GRHT may be able to reduce this problem by using local gradients to remove the background noise. The use of gradients does seem prudent, and this has the potential of being applied to the WHT. The implementation of this approach may be more complicated to implement than the WHT, leading to the belief that investigating the use of WHT may be more beneficial. A perceived problem with the implementation of the RHT that must be taken into consideration and is not imperatively revealed in the literature reviewed is the potential lack of support seen on coding platforms.

A technique that has also shown promise and should be able to be applied to all forms of the HT, is the use of line filtering in post-processing with the use of analytic geometry [16]. This will have the benefit of reducing unneeded lines within the image and let us have better determination of the main crop row features.

7 Conclusions

This review has investigated different forms of the Hough Transform to apply to the orchard row detection problem. The approach of using the RHT along with gradient information may be efficient for orchard row detection as this method has less computational and spatial requirements in comparison to the traditional HT. However, a limiting factor for the use of the RHT method is the potential scarcity of code availability and library support on coding platforms, increasing the difficulty of implementation. The use of the WHT alternatively may be a more prudent approach to take as the HT on which this is based has supporting code libraries on a far broader range of coding platforms and has had success in previous work. The analyses of gradient information may further improve this approach. In either case, the need for post-processing is essential, with line filtering based on analytic geometry showing promising results.

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