A Novel Geometric-Descriptor Based Algorithm for Individual-Level Crop Monitoring using UAVs

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Abstract

Consistent, individual-level crop monitoring enhances yields and crop health by providing farmers with relevant insights for each plant, boosting overall productivity and minimizing waste. Traditional methods are time-consuming, labour-intensive, error-prone, and unreliable, making automation necessary. UAVs equipped with cameras are popular for farm monitoring and can capture images over time for further analysis. However, processing these images proves challenging due to varying lighting conditions, changes in scale due to height differences, orientation shifts based on the drone operator's skill, and fluctuating image quality depending on the camera. For effective monitoring, it's crucial to map individual crops across different images taken at various times, achieving a 1:1 crop matching over time. Traditional feature-matching algorithms fail here due to the significant visual changes caused by crop growth, weather, and farm activities. GPS offers a potential solution by tagging each crop with a unique coordinate feature for mapping, but GPS-based systems like Real-Time Kinematic and Post-Processed Kinematic are costly, complex, and struggle on uneven terrains. To address these challenges, we introduce a novel computer vision algorithm that handles variations in image quality, scale, orientation, and terrain by converting crops into 2D points for consistent matching. This method leverages the spatial relationships between crops to create unique geometric descriptors for each crop, enabling precise temporal 1:1 crop matching. Tested with UAV-acquired images, our algorithm achieved 0.84 accuracy in crop matching over time, and by incorporating Lowe's ratio test, the precision was improved to 0.94, making the method a reliable, cost-effective, robust, and user-friendly solution.

1. Introduction

Agriculture is a cornerstone of India's economy, accounting for 18% of GDP (PIB, 2023) and employing 46% of the workforce as of 2023 (Sansad.in, 2023). Looking ahead to 2050, India will need to feed nearly 1.7 billion people with limited resources, as the net sown area has stagnated around 140 million hectares (Naas, 2022). These challenges demand a shift towards technology and data-driven, evidence-based methods to optimize and enhance farming efficiency, and help us navigate the evolving ecological challenges we face today.

Precision agriculture emerges as a promising solution in this context. By using advanced technology to optimize the use of resources like water, fertilizers, and pesticides, it offers a means for farmers to optimize yield and maximize profits. In contexts like India, where the average landholding is small (Kareemulla et al., 2021), generic insights are less beneficial, making individual crop monitoring far more valuable. Therefore, there is a need for more precise crop monitoring and mapping at the individual crop level to effectively track changes over time. Such "1:1" crop matching would involve identifying and following the same crop across different images taken at various time frames.

Leveraging techniques from precision agriculture to provide accurate and automated individual-level crop monitoring would enable precise application of pesticides and fertilizers, ensuring each plant gets exactly what it needs without waste. Early detection of issues like pests or diseases would also become much easier, enabling timely interventions that protect yield and quality. It would help with irrigation management, as it helps deliver the right amount of water to each crop, preventing both drought and waterlogging. For small-scale farmers, this means more efficient resource use and less waste, while large-scale farms can achieve optimal productivity and maximize returns.

Traditionally, farmers relied on labor-intensive and time-consuming manual methods for crop monitoring, such as field surveys and pen-and-paper data logging (Teucher et al., 2022, Tian et al., 2020). Attempts to automate these methods using tractors and robotic platforms remain resource-intensive, struggle with complex field operations (Fountas et al., 2020), and do not scale well for larger fields as they still involve manual inspection.

Aerial sensing, particularly with drones or unmanned aerial vehicles (UAVs), offers a promising solution for such crop monitoring. Due to the widespread availability of commercial UAVs, farmers are now able to consistently obtain field image data without requiring expert assistance. UAVs offer numerous advantages: they are cost-effective, easy to operate, capable of vertical take-off and landing, and fly under cloud cover and other atmospheric barriers.

However, UAV-captured images present several challenges. Research indicates that UAV photogrammetry in low-light or artificial lighting conditions is unreliable for surveying or cartographical applications due to factors such as camera type, brightness, and post-processing analysis (Burdziakowski et al., 2021). Additionally, the height and position from which drones capture images can vary, depending on the operator's skill and training (Gugerty, 2004), leading to changes in the scale and rotation of images, even for the same plot of land. Furthermore, the type and quality of the camera have been shown to significantly affect the resolution and overall quality of the images (Kim et al., 2024).

Traditional feature matching algorithms that rely on consistent features across images to match the target objects, face additional challenges such as changing crop shapes due to growth, varying weather conditions, inconsistent lighting, and diverse terrains which further makes it difficult to accurately monitor the crops in images.

GPS technology offers one potential solution to this problem, where drone images are geotagged using onboard GPS processors, offering a unique location-based descriptor to each crop which can further be utilized for 1:1 crop matching. However, commonly used drones like the DJI Phantom 4 struggle with poor GPS resolution (Coptrz, 2024). To resolve this issue, they rely heavily on Ground Control Points (GCPs). GCPs are calibrated markers used to subtract out the accumulated errors. However, they are expensive and difficult to maintain over time as they can be displaced or obstructed by farming debris.

Achieving meaningful accuracy requires up to 12 GCPs on farms as small as 7 hectares (Yu et al., 2020), each incurring installation and upkeep costs. The need for additional GCPs increases in hilly or uneven terrains.Real-Time Kinematic (RTK) and Post-Processed Kinematic (PPK) methods enhance crop monitoring accuracy by using a base station for precise positioning, reducing the need for numerous GCPs (Tomastik et al., 2019). However, RTK drones need to stay within range of the base station to maintain a constant internet connection (Sitemark, 2024) and can face challenges due to signal interference and altitude variations (Rokaha et al., 2020), making them suitable mainly for flat terrains (Sitemark, 2024). RTK drones also need to fly slowly to maintain accuracy, which increases operational costs and time (Geodetics, n.d.). PPK drones, while more versatile across terrains, need complex and costly post-processing software and specialized training (Propelleraero, n.d., Dinkov et al., 2020).

Addressing these key challenges, this paper introduces a novel method for precise individual crop-level monitoring by combining computer vision, geospatial analysis, and image processing to register UAV images of an agricultural field over time. The system generates a unique geometric descriptor for each crop, based on its spatial relationships with other crops. By comparing and matching a given crop’s descriptor across the same farm images across timeframes, it establishes one-to-one crop correspondence over time. Our approach bypasses the need for large numbers of GCPs and avoids the complexities and costs of GPS-based systems.

In this paper, the prior research is reviewed in Section 2. Next, the novel geometric-descriptor based approach is introduced in Section 3. Section 4 outlines the experimental methodology using a real farmland image dataset. In Section 5, results are discussed, and key conclusions are presented in Section 6.

2. Literature Review

With the increasing use and prevalence of remote sensing tools, there has been substantial progress in automated robotic applications and techniques in precision agriculture. Researchers have introduced several methods using ground and aerial vehicles for automated field monitoring (Bryson et al., 2010). One group used a modified vegetation index to differentiate crops from weeds, enabling targeted weeding (Zhang et al., 2018), while (Rocha et al., 2023) used orthomosaic aerial images of sugarcane fields and assessed multiple machine learning algorithms to identify crop row gaps, aiding in yield estimation. Authors in (Ramprasad et al., 2024) developed a Mask R-CNN segmentation approach for monitoring farms, focusing on detecting diseased crop areas and estimating crop yields at a farm level.

Efforts to utilize automated computer vision-based algorithms for temporal image mapping face significant challenges due to variations caused by seasonal changes, noise, and issues with image quality. For instance, researchers in (Valgren, 2010) found that classical feature matching techniques achieved only 30% accuracy for panoramic images of buildings taken in different seasons. By adding constraints to maintain consistent distances between matched features, they improved accuracy, but high noise levels still required multiple images for reliable matching. Other researchers have explored post-processing techniques to achieve lighting invariance, such as combining RGB channels into a grayscale image based on camera and scene elements (Arroyo, 2018, Yang et al., 2021, Clement et al., 2020) or using gamma correction to enhance low-light images for better day-to-night matching (Sun et al., 2021). Traditional machine vision methods like Hough transform (Slaughter et al., 2008), linear regression (Montalvo et al., 2012), and Theil-Sen estimator (Guerrero et al., 2013) have been attempted for use in crop-row and weed detection, but these methods often produce false matches due to high weed density and gaps in crop rows.

Feature-detection algorithms such as Scale-Invariant Feature Transform (SIFT) (Lowe, 2004), Speeded Up Robust Feature (SURF) (Bay et al., 2006), and Oriented FAST and Rotated BRIEF (ORB) (Rublee et al., 2011) are commonly applied in image matching tasks due to their ability to handle scale, rotation, and certain viewpoint changes. These algorithms excel in identifying unique keypoints—distinctive spots within images—that remain relatively stable under various transformations. However, in agricultural applications, the landscape evolves over time due to crop growth and farming activities, which significantly alter these visual features. This makes it challenging for these algorithms to consistently match keypoints across different images, as the distinct features they rely on may not remain stable.

A similar challenge arises with deep learning approaches which rely on finding distinct features in large amounts of data for efficient object detection and tracking. In agricultural contexts, crops are often highly similar in appearance and planted simultaneously, resulting in minimal visual diversity. This uniformity limits deep learning’s effectiveness, as it depends on recognizing unique, distinguishing features in the data to achieve reliable training outcomes, and ultimately predicting crop pairs spread across different timelines, as it lacks the necessary distinguishing cues for accurate temporal matching.

To increase robustness to significant lighting and seasonal fluctuations in images taken over a long period, researchers in (Griffith et al., 2017) combined visual data with GPS and compass measurements to match images from different surveys. However, they are still prone to failure when visual appearance changes drastically, such as during rain, flooding or plant growth.

There is a marked gap in works that focus on crop monitoring over time, particularly at the individual crop level. A robust methodology that can facilitate individual crop-level monitoring within precision agriculture and that can handle the complexities and diversity of real-world farmland datasets is needed.

3. Approach

The geographic position of the crop remains static throughout, irrespective of terrain, crop growth, weather, time of the day or any other constraints that have remained as a challenge so far for individual level crop monitoring. The proposed novel algorithm harnesses these fixed spatial locations of the individual crops to create unique geometric keypoints or descriptors for each individual crop. As discussed earlier, these distinct descriptor values get matched across images and hence needs to be stable. Now since the crop position is independent of the growth of a crop, these values serve as a reliable keypoint.

When comparing two UAV images of the same farm area, the intra-variance of the descriptor values for each individual image (1 and 2) needs to be high. This ensures that each crop has its unique identity which is very different from others in order to identify them easily, despite their similar visual appearance. Additionally, the inter variability should be low to enable efficient crop matching.

For this, the Hungarian algorithm is used, which is an optimal assignment method that pairs each crop across images by minimizing the calculated difference between descriptor values of potential matches. By selecting pairs with the smallest differences, the algorithm ensures each crop is accurately matched to its counterpart in the other image. Meeting these criteria is essential to generating robust geometric descriptor values for consistent crop identification across farm images taken at different times.

Subsections 3.1 to 3.4 ahead detail the steps for generating geometric descriptors and creating the corresponding mappings. Subsection 3.5 provides a comprehensive example that walks through the entire workflow.

3.1 Raw Image Processing Pipeline

To achieve our goal of generating crop matching pairs across images, we begin with raw data – a sequential collection of farmland images captured over time. These images then undergo a pre-processing pipeline to ensure they are compatible with the algorithm assigned for generating the final crop mappings. This involves obtaining bounding boxes around each unique crop detected in the farmland. The centroid of a given crop's bounding box is used as the crop's location identifier in cartesian (x, y) coordinates.

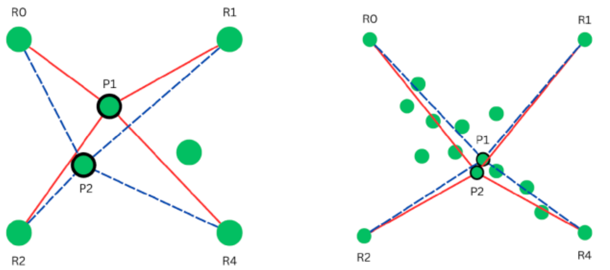
3.2 Reference Crop Selection

Unlike traditional feature-based descriptors which rely on the static nature of a given object's features, geometric descriptors capture the spatial relationships between crops, specifically the distance and orientation relative to designated reference points. These relationships remain stable regardless of individual plant size or shape variations, making them ideal for tracking crops over time. By comparing these unique geometric descriptors across a series of images, the algorithm can establish a one-to-one correspondence between individual crops over time.

Our investigation into reference and pivot crop selection for the geometric descriptor-based crop detection algorithm explores four methods. The first method uses K-nearest neighbours (KNN) as reference points for each crop, with the farthest of the K neighbours as the pivot crop. This is to identify crops based on spatial proximity, aiming to capture the unique geometric relationship each crop has with its immediate neighbours. However, given that most fields have uniform, grid-like planting patterns, there may not always be enough variability in crop placement to generate sufficiently unique geometric descriptors. Hence, the remaining methods utilize the concept of fixed reference points in various ways (see Fig 1), which is inspired by the use of stationary GCPs as discussed in Section 1 (Baseline Equipment, n.d.).

As aerial images of fields typically appear like polygons, the second method, Corner Points (CP), involves manually annotating the corner or extreme edge points of the field in each image as references, with one of the points randomly chosen to be the fixed pivot. This method aims to produce more unique geometric descriptors for each crop due to the increased variability in crop positions relative to these fixed references (Figure 1 (a)).

For the third method, K-Specific Points (KSP), we hypothesized that when applying CP, crops in the innermost region of the farm might be considerably distant from the crops at the farm boundaries, potentially leading to negligible variations in distances between them (Figure 1 (b)). Therefore, KSP uses K reference crops positioned halfway between the outermost boundary and the center of the farm. One of these middle points is arbitrarily selected as the pivot. Random selection is acceptable because the unique crop placement in each farm ensures that any consistent selected reference point would provide a comparable basis for measuring distances.



(a) (b)

Figure 1. Distance variations between crops and reference points in sparse versus dense farms.

This approach is based on the hypothesis that by choosing reference crops that are, on average, close to all the crops in the field, the variability in crop distances can be enhanced. The fourth method, CP-KSP is a combined approach that incorporates both the corner crops and K points from the interior of the field as references, with one of the outer extreme corner crops designated as the pivot, in an attempt to synergize potential advantages from CP and KSP. Another rationale for this method is to assess whether increasing the number of reference points leads to more distinct descriptor values, thereby enhancing the reliability of the mappings. This would ensure that each crop is better differentiated from one another.

The approaches to reference point selection for all the methods can be visualized in Figure 2, where the grid represents a crop field, the unfilled dot is the crop point of interest, the triangle icon is the pivot crop, and the square icons are the reference points chosen for the given method.

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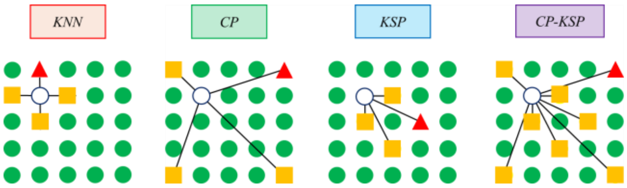

Figure 2. Reference and pivot point selection across KNN, CP, KSP and CP-KSP methods.

3.3 Geometric Descriptor Computation for 1:1 matching

For a given crop, we need a unique geometric descriptor based on its relative position and orientation with respect to the reference and pivot points chosen as discussed in subsection 3.2. These descriptors can then be compared across images to determine a match. To generate this descriptor, the distances and angles to the reference points for each crop are normalized and aggregated into a single resultant descriptor for each crop.

We explored several methods for aggregating the normalized angles and distances, including simple addition, multiplication, and weighted averages. Ultimately, we found that simple addition produced the most unique descriptors and the best mapping accuracy, making it the preferred aggregation method. This is illustrated in Figure 3.

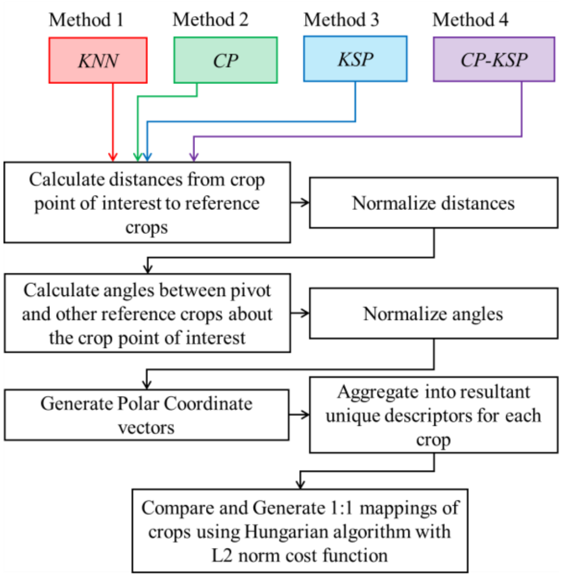

Figure 3: Block Diagram of Algorithm Steps.

3.4 Filtering Incorrect Matches

To ensure the algorithm's reliability and confidence in its matching, apart from direct comparison of descriptors, there is a need to filter out false positives—matches that the algorithm may produce that are incorrect, which could be worse than not predicting a match for the crop. Mismatched crops might receive inappropriate treatments, leading to damage or stunted growth. This not only wastes valuable resources like water, fertilizers, and pesticides but also directly impacts crop yields and quality.

Thus, instead of focusing on the accuracy of the algorithm, i.e., the ratio of the number of correct matches to the total number of crops to be matched, there is a crucial need to account for and enhance the precision of the algorithm, i.e., the ratio of correct matches or ‘true positives’ to the total matches generated by the algorithm.

This effect can be observed in Figure 4. Although the image pair on the left yielded more correct matches (marked as solid lines) in absolute terms, the matches generated for the image pair on the right are more desirable due to a higher ratio of correct matches among the total matches provided, resulting in increased precision in the predictions due to fewer false positive matches (marked as dotted lines).

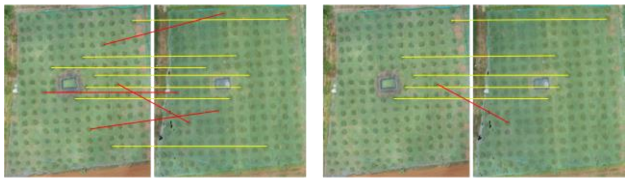

Figure 4. Comparison of two hypothetical crop matching results with varying precision.

To improve the precision of our algorithm’s results, we utilize the Lowe’s ratio test (Lowe, 2004). This test helps distinguish correct matches from false positives by comparing the ratio of distances between the nearest and second-nearest neighbors, and eliminating matches that are too close to each other to be conclusively distinct. While this test improves the performance outcomes of the model by eliminating mismatches, it also results in some true matches being missed. However, this tradeoff is justified by the increased confidence in the matches resulting from this filter, which outweighs the data loss incurred.

3.5 Example Walkthrough of Geometric Descriptor Algorithm using CP Method

To illustrate the entire methodology, we can walk through an example with artificially generated images of farmland. Each image is first preprocessed to create bounding boxes around each crop, and the centroids of each crop are found and labelled. Let a crop of interest be labelled *P*. For reference point and pivot selection, we arbitrarily choose to use the CP method. As shown in Figure 5, we first record the distances from *P* to each of the four corner crops. To compute the angles, we designate R1, R2, R3 as reference crops and R0 as the pivot to compute angles about *P*. As per our convention, the angles are computed in the anticlockwise direction.

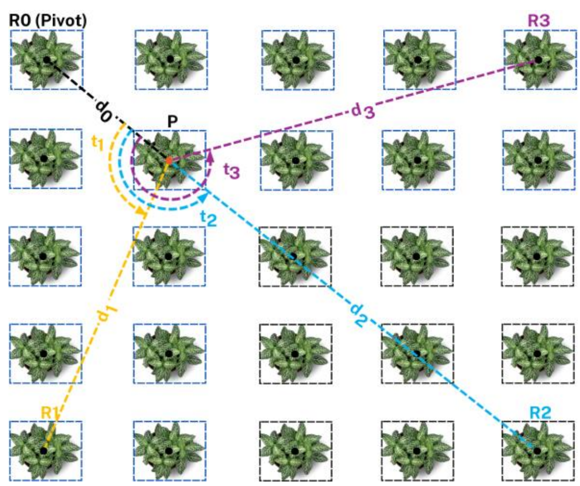

Figure 5. Representative farmland image with annotations.

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Now, the distances (d_1 , d_2 , d_3) are normalized by dividing the distance between P and R0 (in this case d_0) to get normalized distance vectors (D_1, D_2, D_3). Similarly, we normalize the angles (t_1, t_2, t_3) by converting to radians and dividing by 2π to get a corresponding normalized angle vector (T_1, T_2, T_3). Together the polar coordinate pairs of the form (D_i, T_i) where i = 1, 2, 3 uniquely identify the position of crop P with respect to its reference points.

We then convert the polar coordinate pairs to cartesian coordinates of the form (x_i, y_i where i = 1, 2, 3) to obtain (x_1, y_1), (x_2, y_2), (x_3, y_3). We then aggregate them by adding the x and y coordinates to get ($x_1 + x_2 + x_3 = X$, $y_1 + y_2 + y_3 = Y$), and converting this aggregated cartesian coordinate back to polar form to get (D_{aggr}, T_{aggr}).

We then simply add the D_{aggr} and T_{aggr} raw values to get a singular geometric descriptor value G for crop P. We repeat this for every crop in the image, and for each image in the dataset of the farmland over the time period of interest. We can now compare the geometric descriptors of each crop to every other crop using the Hungarian Algorithm (Kuhn, 1955) with L2 norm as the cost function.

To mitigate the influence of spurious matches, the Lowe's ratio test is then applied. This test operates by comparing the absolute difference between a descriptor in one image of a given crop and its potential matches in another image. The ratio L_{best} / L_{second} is calculated, where L_{best} represents the distance to the nearest matching descriptor and L_{second} denotes the distance to the second-nearest match. If this ratio is less than or equal to a predefined threshold of 0.8, the match is considered reliable and retained for further processing. Conversely, matches exceeding the threshold are discarded due to ambiguity in their correspondence, suggesting a weak geometric relationship between the features.

Thus, by applying the methods discussed above, we can extract unique geometric descriptors for each crop from raw field image data acquired over time.

4. Experimental Results

4.1 Image Processing

4.1.1 Data Acquisition: The dataset for this study is a collection of RGB images obtained from a 3.5-acre pomegranate orchard in Tiptur, Karnataka, India, using an unmanned aerial vehicle (UAV) equipped with a high-resolution camera. The UAV captured 4k resolution images of the farmland at a speed of 2.3m/s during a 11-minute flight.

In this image dataset, the shape of the farm was roughly a quadrilateral, and none of the bounding boxes around the crops overlapped with each other. To capture the variability in the crop's appearance for effective crop monitoring, images were taken at different stages of the crop cycle.

4.1.2 Image Data Preprocessing: Orthomosaic stitching was performed on the drone images of the farm using Pix4D tool to obtain high-quality .tif files. However, these large file sizes posed challenges for efficient upload and processing. To address this, the images were converted to .png format, ensuring they remained manageable for subsequent image processing tasks.

4.1.3 Image Annotation: The ground truth annotations for the pomegranate orchard were generated using the Roboflow tool, creating bounding boxes around each crop (see Figure 6), and the labelled bounding box data was saved in .json format. These annotations were utilized to construct a dataset adhering to the Visual Object Classes (VOC) format.

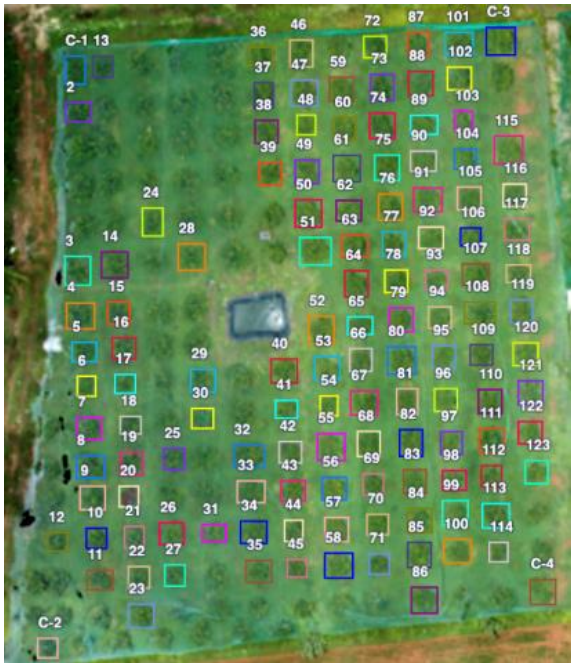

Figure 6. Annotated image of the UAV-captured farmland with bounding boxes.

Upon receiving the bounding box coordinates for each crop from the annotation process, the next step involved calculating the center coordinates for individual crops using the centroid formula. These center coordinates serve as the location of each crop within the farmland.

4.2 Geometric Descriptor Calculation

Our investigation focused on achieving accurate matching of individual crops in images captured at different times using four methods to generate geometric descriptors for the matching. We tested these on the pomegranate field dataset using two images of the same farmland from different time frames. For the first round of testing, we used a section of the image with 25 labelled crop points as the ground truth for testing our methods. After testing with various values of K, we found that K=4 provided the best performance for the methods.

The performance of the methods was evaluated using two metrics – accuracy and precision – with the following formulae:

$$Accuracy = \frac{Number\ of\ correct\ matches}{Total\ number\ of\ crops\ to\ be\ matched} \quad (1)$$

$$Precision = \frac{Number\ of\ correct\ matches}{Number\ of\ crops\ left\ after\ filtering} \quad (2)$$

Accuracy was computed as the percentage of correct matches to total number of crops after applying Hungarian algorithm to produce matches. Then, after applying the Lowe's test filter on the matches produced, precision was computed on these matches, as is captured in Table 1.

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Method	No. of crops	Accuracy	Initial Match	Precision after Lowe's test	Match after Lowe's test
KNN *(K=4)*	25	24.00%	6/25	37.50%	3/8
CP	25	80.00%	20/25	94.73%	18/19
KSP *(K=4)*	25	76.00%	19/25	92.30%	12/13
CP-KSP *(K=4)*	25	76.00%	19/25	90.00%	18/20

Table 1. Crop Matching Performance Across Methods

As can be seen, CP significantly outperformed the other three methods on both the accuracy and precision metrics. To explore the limits of CP, we increased the number of analyzed crop points (see Table 2). Performance steadily improved, reaching a peak precision of 94.73%. However, as the number of points continued to rise, precision began to decline and the data loss after applying Lowe's test began to increase.

No. of crops	Accuracy	Initial Match	Precision after Lowe's test	Match after Lowe's test
25	80.00%	20/25	94.73%	18/19
50	84.00%	42/50	94.73%	36/38
75	73.33%	55/75	86.36%	38/44
100	67.00%	67/100	80.70%	46/57

Table 2. CP Method Performance with Increasing Crops

5. Discussion

Even the most advanced smart farming techniques, including deep learning and artificial intelligence (AI), face challenges with individual-level crop monitoring due to the high similarity among crops and visual changes over time. Even in applications when these methods prove effective, they often come with high costs or require expert operation. In contrast, the proposed algorithm effectively addresses this challenge while remaining simple, interpretable and operationally cost-effective. Additionally, this method is immune to scale, orientation, and even external factors like lighting conditions.

5.1 Precision versus Accuracy Metrics

In assessing the methods' performance, our evaluation considers not only accuracy, which represents the percentage of correct matches out of the total crops to be matched, but also precision, indicating the number of correct matches within the predictions made. Relying solely on accuracy can obscure the algorithm's confidence in its matching. Therefore, despite the data loss incurred, utilizing Lowe's test as a filter helped improve our confidence in the algorithm, and the resultant precision scores provide a more complete picture of the algorithm's performance. For all methods, the precision significantly improved after applying the Lowe's test compared to the accuracy derived from the direct comparison of geometric descriptors.

5.2 Performance Comparison of KNN, CP, KSP and CP-KSP

We started matching the crops across two images from different time frames using KNN. Despite trying multiple K values, KNN was ineffective in generating sufficiently unique descriptors for the crops. This was demonstrated by the significant data loss when applying Lowe's test, reducing the number of crop matches generated from 25 to 8. This limitation might be attributed to the inherent uniformity of the crop field. With crops planted in a grid-like pattern, most crops have neighbors at roughly the same distance, leading to a lack of distinctiveness in the KNN-generated descriptors for each individual crop.

As the farmland captured was in the shape of a quadrilateral, we utilized the four corner points as references for CP. This produced a matching precision of 94.73% for cases with 25 and 50 points. However, this went down to 86.36% when we increased the points to be matched to 75 points.

KSP attempted to improve on CP by choosing reference points within the interior of the field, and while the accuracy for matching 25 points was 92.30%, this method suffered from data loss after applying the Lowe's test. KSP retained 13 matches while CP retained 19 out of the total of 25. CP's superior performance could be attributed to the isolated nature of the corner crops, making them consistent and reliable references.

As CP-KSP introduced more reference points, it outperformed the simpler KSP method by incurring less data loss after applying Lowe's test. This is demonstrated by the better retention of crop matches after applying Lowe's test: CP-KSP retained 20 matches with 18 correct, whereas KSP retained only 13 matches with 12 correct.

The investigation culminated in CP emerging as the most successful method with the highest precision score of 94.73% for 25 and 50 crops, with the least data loss after filtering with Lowe's test.

Thus, this work successfully demonstrates individual-level crop monitoring using geometric descriptors to identify crops across images. This algorithm is robust to changes in visual appearance as it relies on stable planting locations to generate accurate mappings.

The unique contribution of this algorithm is to focus on individual crop matching rather than broad farm-level insights, which is essential for precise farm management tasks like targeted pesticide application and resource allocation. Additionally, the integration of Lowe's ratio test significantly enhances the algorithm's performance by helping to differentiate correct matches from false positives, providing greater confidence in the results.

5.3 Future Scope

As noted, the accuracy of the algorithm declines when dealing with a larger number of crops. The primary issue we encountered was that as the field size increased, the distance between crops near the center of the image and those at the edges became negligible. This caused the descriptors to be too close together, ultimately reducing accuracy. To address these limitations, future work could explore ways to intelligently segment the farmland. We observed that accuracy was very high with lesser number of crops, indicating that if the large farmland could be segmented into sufficiently smaller sections with fewer crops, a similar performance could be achieved. The algorithm could determine the optimal segmentation, ensuring that each segment is accurately matched, even in larger fields with a higher number of crops. Further exploration can be done to find other descriptor-based methods for 1:1 crop matching.

6. Conclusion

This research work presents a novel approach that leverages the convergence of computer vision, geospatial analysis, and remote sensing to address the critical need for precise individual crop-level monitoring in modern agriculture.

The investigation first established the efficacy of geometric descriptors as an effective means to identify unique matches for individual crops within sequential field imagery, with an excellent precision of 94.73% on UAV-acquired images of a pomegranate farmland. The algorithm incurs minimal data loss after filtering out potentially false matches using Lowe's ratio test. The selection of reference crops had a measurable influence on matching accuracy, with CP leading to the most optimal results.

This work showcases the potential of geometric descriptors as a viable approach for precise 1:1 crop matching. This paves the way for the development of a comprehensive farm management system that equips farmers with granular data and insights into the health and status of their crops over time, ultimately empowering them to optimize yield and resource allocation.

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