ORB-Based Homography Computation for Progress Mango Orchard Land Monitoring

Ardi Mardiana[1*], Dony Susandi[2], Yani Syafei[3], Trifenaus Prabu Hidayat[4], Indah Latifatun Nissa[1] and Muhammad Dendi Purwanto[1]

1 Department of Informatics, Universitas Majalengka, Majalengka, Indonesia
2 Department of Industrial Engineering, Universitas Majalengka, Majalengka, Indonesia
3 Department of Industrial Engineering, Universitas Komputer Indonesia, Banding, Indonesia
4 Department of Industrial Engineering, Universitas Katolik Indonesia Atma Jaya, Yogyakarta
aim@unma.ac.id

Abstract. Indonesia cultivates mangoes across an average land area of 176,000 hectares, yielding 1.4 million tons annually. Researchers have conducted similar studies to enhance mango orchard management techniques. This study uses OpenCV- based image stitching to assess mango orchard areas and provide accurate data to improve effective management. The research involves collecting captured images in extensive agricultural regions and employing techniques such as feature detection, feature matching, computational homography, image warping, and image stitching to gather valuable data. The researchers have implemented the ORB algorithm for feature detection, enabling the identification of matching points among images. Image warping is conducted using the RANSAC algorithm to estimate image geometry. Finally, the research employs flexible camera calibration for precise image registration. This research contributes significantly to the agricultural industry by offering a non-invasive and efficient approach to preparing land for mango tree cultivation.

Keywords: Agricultural Monitoring, Homography Computation, Image Stitching, Mango Buds, ORB Algorithm

1.0 Introduction

Mango plants come from the family Anarcadiaceae, genus Mangifera, species *Mangifera indica* [1]. The mango tree is a high-level plant whose trunk structure (habitus) belongs to the arboreous group, a woody plant with a stem height of more than 5 m. Mango can reach 10-40 m high [2].

World mango production is spread across 100 countries producing more than 38.67 tonnes of fruit annually [3], with India ranking first among mango-producing countries with an area of 1.23 million hectares with an annual production of 10.99 million tonnes and productivity an average of 8.95 tons per hectare [4], China planted 294,326 hectares of mangoes and harvested 2,414,800 tons [5], Thailand with a planted area in 2006 of 286,697 ha, production of 2,218,262 tons, and a yield of 7,738 kg/ha

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[6], in Indonesia in 2005 it reached 1.4 million tons with a harvested area of 176,000 ha [7]. Based on mango production in the world, mango is a fruit commodity with high economic value, and mango is one of the leading export commodities in the Indonesian horticulture sub-sector, which has excellent potential to be developed [8]. In the production process of agricultural and plantation business, land area is crucial. Land area will affect the scale of business, ultimately affecting an agricultural business's efficiency. In mango farming, ownership or control of narrow land is less efficient than broader land. Greater efficiency and higher yields are achieved when farming operations are carried out on larger plots of land. At the same time, smaller parcels of land tend to result in lower inefficiencies and yields [9]. In addition to land area, managing or caring for plants needs to be considered for maximum results, such as fertilizing, containing plant-disturbing organisms, weed control, pruning, irrigation, fruit thinning, and fruit packaging [8]. The size of the land presents challenges in maintaining cohesion. Therefore, it is necessary to monitor the development of garden crops accurately and efficiently to improve crop management practices and increase productivity [10].

There are several crop monitoring techniques, such as remote sensing [10], and traditional methods for monitoring the growth of mango shoots, such as manual measurement and visual assessment, which are often time-consuming, labor- intensive, and error-prone [11]. These IoT-based technologies can assist in the control and monitoring of plants automatically. Still, there are several areas for improvement, such as no indicators in reading conditions on the tool, orders for giving nutrition to plants still manually via the Android application, and implementing a system that is less than optimal but dynamic in plant management [12].

Compared to other monitoring techniques, remote sensing is suitable for monitoring mango orchards as remote sensing has evolved dramatically to include a suite of sensors operating at various imaging scales of interest and potential importance to land planners and managers. Coupled with the availability of historical remote sensing data, reduced data costs, and increased resolution from satellite platforms, remote sensing technology seems poised to make an even more significant impact [10]. Therefore, remote sensing technologies, such as unmanned aerial vehicles (UAVs), have emerged as a promising alternative for collecting non- invasive, efficient, and accurate plant growth data [11, 13].

In general, UAVs have many uses, such as land management [14], crop monitoring, plant water [15], mapping [16], etc. One of the processes of maintaining and monitoring the development of mangoes is to use a UAV. UAVs equipped with cameras can provide high-resolution images of mango orchards, which can be used to monitor the growth of mango shoots [17].

Based on the extent of the land, a tailoring process is needed to integrate the various parts of the land into a unified whole. In combining images, several methods can be used, such as image stitching [18], [19], seam carving [20], image mosaicking [21] etc.

Some research examines combining images that utilize different algorithms, including SURF applied in Panorama Image Stitching [22]. Another study examines

Remote Sensing Image Registration Based on Improved KAZE and BRIEF Descriptors [23], while further research is in the form of Feature Detection and Description based on ORB Algorithm for FPGA-based Image Processing [24].

For this study, the method used is image stitching. Image stitching itself is distinguished by several algorithms such as SURF (Speeded Up Robust Features) is a feature detection algorithm that is well-known for its robustness [22], BRIEF is a binary coding string descriptor implemented to improve matching efficiency [23], The Oriented FAST and Rotated BRIEF (ORB) algorithm is a feature detector and descriptor that is widely used in image stitching, the ORB algorithm is built based on the FAST corner detection algorithm and BRIEF description. Multi-scale features and feature point orientations increase scale and rotation invariants [24].

The algorithm to be used is ORB because the ORB algorithm is the fastest, most accurate, and with higher performance. Additionally, Exposure Compensation is the highest-quality splicing mixing method [25]. The added benefit of ORB is that it is free from the limitations of the SIFT and SURF licenses [26].

This study investigates the potential of using image stitching with OpenCV to monitor mango shoot growth in commercial orchards. The research will focus on collecting daily imagery of mango orchards using UAV processing images using OpenCV, and the image stitching process involves several steps, including feature detection, feature matching, homography calculations, and image stitching.

2.0 Method

2.1 Data Collection

The data collection stage encapsulates the initial and foundational phase within the research framework. This pivotal step entails the meticulous gathering of pertinent information, facts, and descriptive details from sources that directly align with the defined objectives of the ongoing research endeavor. As the bedrock upon which subsequent analyses are built, data collection orchestrates a series of intricately interconnected steps, encompassing key facets such as location selection, comprehensive planning, meticulous implementation, and meticulous documentation. The success of this stage lays the groundwork for informed and insightful research outcomes.

Central to the data collection process is a series of systematic steps that collectively pave the path toward comprehensive and meaningful results. The location selection involves a reasonable choice of environments that facilitate the desired data acquisition. This is followed by rigorous planning, ensuring that data collection is well-structured and systematic. Guided by these thoughtfully laid out plans, implementation ensues with precision, capturing the intended data points with accuracy. Crucially, each step is meticulously documented, forming a transparent record of the entire process enhancing the credibility and reproducibility of the research.

Table 1. Key specification of UAV and image.

Figure	Detail	Specification
	DJI MavicPro	700 g weight, 27 min hoveringtime, 7 kg flight range, camera 12.3 MP, 1/2.3" CMOS

Table 1 contains detailed specifications governing the information on the main Unmanned Aerial Vehicle (UAV) and an in-depth exploration of the associated image parameters. As UAVs become increasingly integral across various industries, including surveillance, photography, and disaster response, these specifications—covering flight endurance, payload capacity, and communication range— provide essential insights into their operational capabilities.

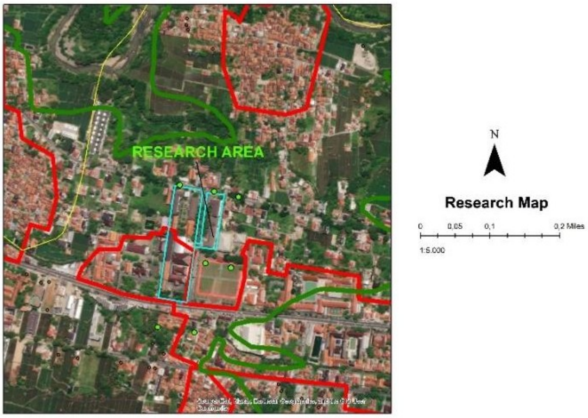

Fig. 1. The flight path of the UAV.

Figure 1 illustrates the flight path of the UAV, offering a dynamic representation of the aerial trajectory that serves as the conduit for data acquisition. The combined utilization of tabular and graphical representations ensures a holistic understanding of the research's foundational elements, reinforcing the meticulous approach undertaken to gather high-quality data.

2.2 Feature Detection

Currently, the ORB (Oriented FAST and Rotated BRIEF) algorithm is utilized for the purpose of detecting features in a collection of photos depicting mango orchards. The ORB algorithm demonstrates a high level of effectiveness in accurately detecting and describing significant visual features.

The detection mechanism uses a Bresenham circle with a radius of three, consisting of 16 pixels, to categorize potential pixels as corner points. Bright points refer to pixels that have a higher brightness value compared to the candidate pixel, above a predetermined threshold. Conversely, dark points are pixels with a lower brightness value than the candidate pixel, falling below the threshold. A pixel is considered a corner candidate when it exhibits a substantial presence of adjacent bright or dark pixels, hence demonstrating its ability to effectively capture complex details and localized characteristics inside images.

To achieve scale invariance, a rapid corner detection algorithm is employed at every level of the image pyramid. The image pyramid is generated by applying a Gaussian filter to the image, resulting in both smoothing and subsampling of the image. The size of each pyramid level is reduced by a ratio of ½.

Prior to creating the BRIEF descriptor, the orientation of the feature point is computed, and the sampling pairs utilized for the descriptor are subjected to rotation in order to enhance rotational invariance. The estimation of the corner's focus is determined by calculating the moment of the area surrounding the feature point. This calculation takes into account both the horizontal (mx) and vertical (my) components, as well as the weighted summation of intensities.

$$\begin{cases} m_x = \sum_{x=-r}^{r} xI(x,y), \\ m_y = \sum_{y=-r}^{r} yI(x,y), \end{cases} \tag{1}$$

Where I (x, y) is the intensity of the pixel at the coordinate (x, y). The orientation of the corner is determined by:

$$\theta = \arctan\left(\frac{m_y}{m_x}\right) \tag{2}$$

The next is BRIEF descriptor, bit of the descriptor is computed by comparing the intensity of two pixels p(a) and p(b) sampled from the image patch centered at the feature point.

$$\tau(p; a, b) = \begin{cases} 1, p(a) < p(b), \\ 0, p(a) \geq p(b), \end{cases} \tag{3}$$

where $r\ (p\ \ a\ \ b)$ is the comparison result between p(a) and p(b). The coordinates of the sampled pairs are rotated according to the orientation of the feature point. Because the rBRIEF descriptor is sensitive to noise, the source image has to be smoothed by Gaussian filters.

2.3 Feature Matching

During this phase, we conduct feature-matching across multiple images capturing different stages of the mango orchard. The goal is to connect key points in adjacent images in the time sequence. This process creates a coherent link between similar vital points, allowing for meaningful associations between pictures taken at different times.

By aligning key points in neighboring images, we comprehensively depict the interconnections among prominent features within the orchard. This web of correlations provides insights into the relationships between significant elements across various snapshots in the time series. This deeper understanding of patterns and variations enables a more informed analysis of the orchard's development.
Overall, feature-matching is a pivotal phase, establishing a cohesive narrative of the evolving orchard. It reveals the interplay of salient features across successive images, providing a foundation for a comprehensive exploration of the orchard's growth dynamics and a more insightful comprehension of its transformation over time.

2.4 Homography Estimation

During this step, our attention is directed towards the process of perspective transformation, which involves aligning and merging two photos captured from varying perspectives within the mango orchard. The fundamental concept at play in this context is homography, which facilitates the calculation of the complex transformation between these images, enabling their alignment despite variations in perspectives. The utilization of homography is of utmost importance in the establishment of exact and geometrically accurate correspondences within the panoramic view of the mango plantation. By employing meticulous calculations of homography matrices, we get insight into the perspective transformation that connects neighboring images, taking into account the alterations in geometry resulting from variations in viewpoint, as well as the distortions arising from imaging settings and scene attributes.

The utilization of homography is crucial in examining alterations in perspective between adjacent photographs, enabling the quantification of these transformations and facilitating a more comprehensive comprehension of the visual dynamics inside the developing mango orchard. The utilization of this technique facilitates the identification of patterns, variations in scale, and distortions in spatial representation within the imagery. Consequently, it offers a complete approach to analyzing the interconnections among individual frames in the temporal sequence.

For an image point P, the 3x3 transformation matrix H transforms this point P to P' using P' = HP where H is represented in the homogeneous coordinates system as follows:

$$H = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \quad (4)$$

$P = \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$ and $P' = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}$ in homogeneous coordinates. Then can write

$$c \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \quad (5)$$

By eliminating c, we can formulate the above equation in the form Ah = 0, where

$$A = \begin{bmatrix} -x & -y & -1 & 0 & 0 & 0 & ux & uy & u \\ 0 & 0 & 0 & -x & -y & -1 & vx & vy & v \end{bmatrix} \quad (6)$$

$$h = [h1 \quad h2 \quad h3 \quad h4 \quad h5 \quad h6 \quad h7 \quad h8 \quad h9]T \quad (7)$$

Knowing A, we can find the values of h by solving the above equation. It is to be noted that we need at least four such point correspondences in order to estimate the homography matrix [28].

2.5 Image Stitching

The process of image stitching involves the merging of many overlapping photos in order to generate a segmented panorama. The process consists of two primary stages: image registration and blending. Image registration is a process that aims to align photographs by minimizing discrepancies in adjacent pixels. On the other hand, blending is employed to obscure image borders, resulting in a visually pleasing composition.

The efficacy of picture stitching is contingent upon preceding phases, namely feature detection, feature matching, and homography estimation. The aforementioned stages serve to discover crucial characteristics, establish connections, and quantify spatial changes, laying the foundation for the process of stitching.

The interplay among feature detection, matching, and homography is of paramount importance. The process orchestrates a seamless integration of pictures, resulting in the creation of a gripping narrative that surpasses the boundaries of individual frames. The aforementioned stages serve as a platform for the demonstration of the technical skill and artistic prowess involved in the process of image stitching, contributing to a more comprehensive comprehension of the dynamic and ever-changing visual environment.

3.0 Result and Discussion

3.1 Data Collection

Empirical data was systematically gathered inside a regulated mango orchard setting, employing unmanned aerial vehicles (UAVs) for the specific aim of training. The unmanned aerial vehicles (UAVs) were calibrated to maintain a flight altitude of 25 meters, which was determined to be the most advantageous position for capturing detailed information about the orchard. The data collection was conducted on May 23, 2023, between the time frame of 15:30 to 16:30, taking advantage of optimal lighting conditions.

The duration of each Unmanned Aerial Vehicle (UAV) flight was around three minutes, during which it acquired high-resolution photographs of the orchard. Ten separate data sets were obtained, each representing the spatial and temporal features of the orchard. The aforementioned photographs served as the basis for the future phase of research, which is further upon in Table 2.

Table 2. Image data.

Figure	Detail	Specification
	Image Data	Dimensions 4000 x 3000, width 4000, height 3000, horizontal resolution 72 dpi, vertical resolution 72 dpi, bit depth 24, resolution unit 2, color representation sRGB, compressed bits/pixel 3.98610066666666674

3.2 Feature Matching

During the feature-matching step, the brute-force matcher approach demonstrates exceptional performance in the identification and correlation of crucial features in neighboring images. The inclusion of this stage is crucial in order to develop significant relationships among images. The procedure entails the selection of appropriate feature pairings through the utilization of the distance ratio metric, which effectively eliminates pairs that are not compatible.

The parameter of distance ratio, which has been precisely determined, functions as a threshold for the assessment of feature pairs. In this study, a threshold value of 0.6 is employed to determine the validity of a feature pair. Specifically, a feature pair is deemed legitimate if the distance to its nearest neighbor (m) is found to be less than 60% of the distance to its second nearest neighbor (n). The utilization of this specific criterion guarantees the inclusion of only the most pertinent feature matches in the set classified as "good matches," hence eliminating any potential outliers.

In conclusion, the utilization of the Brute-Force Matcher technique, along with the application of a distance ratio value of 0.6, successfully detects and establishes meaningful correspondences between significant characteristics present in neighboring photographs. This parameter serves the purpose of ensuring that only feature pairings that are highly compatible are taken into consideration, hence contributing to a more refined and accurate list of "good matches". The following are the outcomes of feature matching:

Fig. 2. Feature detection from 2 image data.

3.3 Feature Detection

Within the domain of mango orchards, a significant advancement in the feature recognition method was made through the use of the ORB (Oriented Fast and Rotated Brief) algorithm. The system demonstrated exceptional performance in the detection and annotation of significant features inside photos of mango shoots, hence highlighting its high level of precision in capturing subtle details from various perspectives.

The ORB algorithm plays a fundamental role in the examination of mango orchard photos, deciphering intricate topography, and augmenting our research of botanical structures. The study significantly enhances our comprehension of mango orchards, uncovering previously undisclosed facts.

The successful incorporation of the ORB algorithm into our feature detection methodology represents a significant advancement in our research endeavors. The precision exhibited in the process of revealing intricate shapes and angles significantly enhances our comprehension of mango shoots, enabling the detection of a remarkable number of 2000 features with each execution of equation (1). The following are the outcomes of feature detection conducted on two sets of image data:

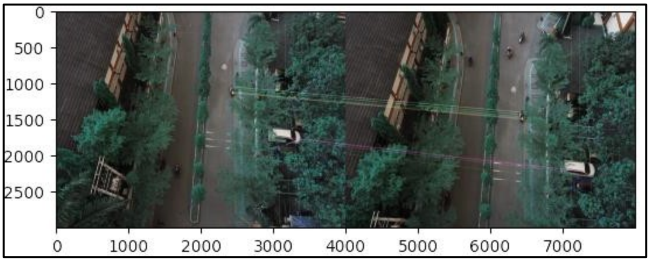

Fig. 3. Feature matching from 2 image data.

3.4 Homography Estimation

In this phase, our goal is to find a homographic matrix that satisfies equation (4) using the RANSAC (random sample consensus) technique. RANSAC effectively produces a homographic matrix, representing the perspective change between related images, and it excels at handling outliers and noise in the dataset. The resulting homographic approximations are robust and coherent, essential for subsequent image processing and analysis.

The researcher's choice of a threshold value of 5.0 is pivotal to RANSAC's success. This threshold distinguishes inliers, which conform to the model, from outliers, which deviate from the expected pattern, significantly influencing the precision and reliability of homography matrix estimation. The researcher's careful examination of this threshold value demonstrates the pursuit of optimal outcomes.

RANSAC's robustness in accurately estimating the homographic matrix, even under challenging data conditions, underscores its importance in modern image analysis. It ensures consistency and reliability in homography estimates by effectively handling outliers and noise, enabling precise mapping of feature relationships between two photos. The researcher's dedication to enhancing algorithm performance is evident in the thoughtful choice of threshold values, strengthening the accuracy and dependability of subsequent image modification procedures.

The homographic matrix mathematically describes the relationship between source and destination image points through linear equations. Techniques like RANSAC are employed to minimize viewpoint transformation errors and determine the optimal homographic matrix. Below are the outcomes of homography estimation using the RANSAC algorithm:

Fig. 4. Homography estimation from 2 image data.

3.5 Image Stitching

The process of combining or stitching photos is a critical element in the production of a cohesive and uninterrupted panorama derived from a collection of meticulously captured mango shoot images. The complex procedure encompasses the identification of distinctive attributes, the comparison of these attributes, and the calculation of the transformation across images, ultimately leading to a cohesive visual depiction of the mango orchard.

The process of image stitching is of utmost importance in integrating the results obtained from preceding steps. The utilization of information obtained through feature detection significantly improves the precision of computer vision algorithms in accurately identifying and tracking objects within intricate surroundings. The process of feature matching involves the identification of common spots and patterns in photographs, thereby establishing significant links between them. The aforementioned procedure is consistent with the estimation of homography, a technique used to establish correspondences between features in neighboring images and capture perspective alterations.

The successful integration of feature recognition, matching, and homography techniques culminates in the process of image stitching, wherein several individual photographs are combined to create a panoramic representation that effectively captures the visual intricacies of the mango orchard. This visual depiction facilitates a thorough examination, offering extensive perspectives on the subject of mango shoots and demonstrating the capabilities of sophisticated image-processing methodologies. The following results are presented:

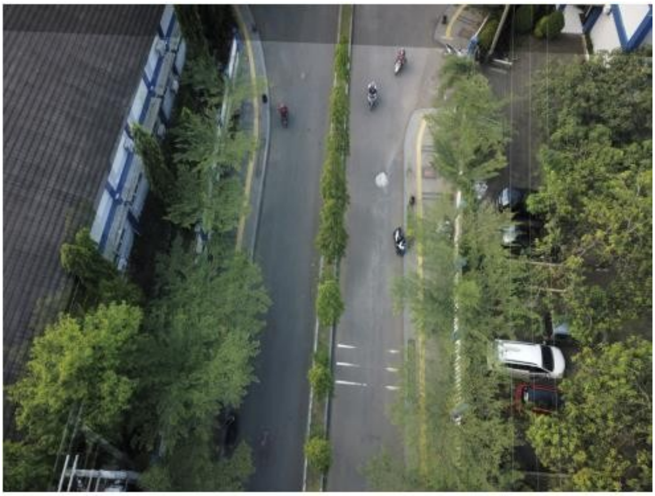

Fig. 5. The result from 2 image data.

3.6 Final Result

Each step in this method is carried out on two image data first, and the results of the stitching of the two data above are then used in the next stage. This process continues along with the addition of increasingly advanced image data.

In more detail, the initial stage involves merging the first and second image data. After getting the results of this merger, the resulting image will be used with the third image data in the next stage.

This approach is continued until all ten-image data are entered into the series of stages of the same method. This image merging process involves feature detection using the ORB method, feature matching to map the relationship between adjacent images, homography estimation to calculate the perspective transformation, and image stitching to produce a more significant and continuous panorama.

This method makes monitoring the development of mango orchard lands more effective. Using UAVs and image stitching techniques significantly assists farmers in regularly monitoring the progress of mango orchard lands. Data can be collected weekly or monthly as needed, allowing for a clear view of the development of mango trees through this image- stitching technique. The following is the result:

Fig. 6. Final result.

4.0 Conclusion

The research successfully implemented the ORB algorithm for image stitching in mango orchards, creating panoramic views for monitoring orchard development. OpenCV's integration streamlined feature detection, matching, and homography estimation, producing coherent panoramas. The ORB algorithm excelled at recognizing orchard features, enhancing agricultural image analysis. RANSAC improved homography estimation, ensuring accurate transformations between images. Additionally, a related study demonstrated ORB's superiority over SURF and SIFT.

In summary, this research showcases the potential of advanced image processing techniques in agricultural monitoring, offering valuable insights into complex landscapes. The integration of these methods demonstrates the feasibility of leveraging technology for informed decision- making. ORB, with a 60% accuracy rate, emerges as a crucial tool for orchard monitoring.

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Conflict of Interest. The authors have no competing interests to declare that are relevant to the content of this article.

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