The first step of this research focuses on acquiring essential environmental data, including aerial imagery and the corresponding global coordinates of the camera at the time of image capture. This data is critical for converting local pixel positions in the images into global coordinates, a process necessary for accurate spatial analysis. Several camera systems, such as the Sequoia, RedEdge, Micasense, and DJI Zenmuse X7, were considered based on their technical specifications and the resources available for this study. After careful evaluation, the GoPro Hero 4 was chosen due to its ability to capture high-resolution RGB images at a high frame rate. Although this camera lacks near-infrared (NIR) and thermal imaging capabilities, its RGB imagery is well-suited to the image processing algorithms employed in this research. In addition to aerial images, global positioning data is acquired using a Ublox-Neo-6m GPS module, which transmits the camera’s location to the processing unit. To further streamline the system, the camera’s altitude is predefined, rather than measured and transmitted in real-time, allowing for a more straightforward setup without compromising the precision needed for the study.

In response to the need for live waypoint generation in agricultural fields, a hardware setup is required to provide the necessary environmental information. This system has the role of capturing and transmitting data to the software unit, where the processing will take place. In the context of this project, a lightweight camera is crucial to take high-resolution aerial images of the target field which will be the main data source for the image processing algorithm. Several cameras including Sequoia b9-b4-b7-b6, Micasense RedEdge b9-b14-, and DJI Zenmuse X7 b5 were utilized in similar projects. Considering the specifications of these cameras and crop row detection algorithms developed based on their aerial images, it was concluded that having high-resolution RGB images meets the needs of this project. Although the NIR band contains valuable information about the field and can be used for vegetation segmentation, they are too sensitive to environmental conditions such as temperature and might lead to the poor performance of the software. b-5. In conclusion, the Gopro HERO4 camera was acquired for this project. The specifications of this camera including its lightweight, high-quality RGB images, and durability make it a suitable choice for aerial imagery.

Besides the camera, a radio transmission system consisting of power supplies, a transmitter, and a receiver was developed to provide live data transfer between the mounted camera on the UAV and the computer with an image processing program.

Also, the last step of this project, which is the conversion of pixel coordination on the images to global coordination, requires the global coordination of the camera at the time of photo capturing as a reference. A Ublox-Neo-6m GPS module must be mounted on the camera UAV to provide this information.

This section focuses on the crucial task of crop detection within the captured images, which is essential for identifying crop rows and determining the path for subsequent operations. The process begins with a preprocessing step that converts the raw images into a format compatible with the models used for detection. Two crop detection methods, K-means and Unet, are then implemented, with a detailed explanation of each approach. The performance of these models is compared to select the most effective one for this application. Additionally, insights from previous studies using these algorithms inform the analysis.

The main contribution of this paper lies within this section, to develop an image-processing pipeline to determine the position of pixels which are located in the path between the crops. The Figure shows the procedure proposed in this paper. Initially, the aerial images captured with the camera are split into sub-images, and then during a semantic segmentation process, a binary mask is generated for each sub-image showing the positions of vegetation and background. In the next step, using Hough Transform, crop rows are detected. After defining the path line, a desired number of equally spaced points are selected on this line, and their position is recorded for later steps. Finally, the sub-images and their local waypoint coordinates are reconstructed and form the original input image.

High-resolution aerial images covering large areas are typically too large to use in machine learning algorithms directly. To address this, the images are initially split into equal-sized sections, making them manageable for algorithmic processing. The size of these sections is determined by the specific requirements of the algorithms used, ensuring compatibility and optimized performance. Maintaining uniform image sizes across all sections enhances processing speed and efficiency.

High-resolution aerial images covering large areas are typically too large to be used in the image processing algorithms and networks directly. Besides, due to the variation in terrain topologies, the non-uniform shape of crop rows -including curved or irregular shapes- is common in some agricultural fields.

Given this information, the calculation of a straight line for an entire crop row in the original image is not an accurate approach for crop row detection.

To address this issue, the aerial image is initially split into equal-sized sections with a static image size of 512\*512 pixels. These sub-images are named accordingly to be reconstructed after the image-processing procedure is finished and their chosen size ensures compatibility with the algorithms and networks designed in the later steps of the image-processing section.

This project's most computationally intensive aspect is crop detection, which is crucial in ensuring accurate outcomes for subsequent procedures. A well-defined layer mask for field images is essential, as the crop detection system must effectively distinguish plants and crops from other objects, including background soil and unwanted vegetation such as grass and weeds.

Semantic segmentation is the most computationally intensive section of this project, while its outcome has a direct impact on the overall accuracy of the system. Given the RGB sub-images, it is important to identify the exact locations where crops exist, which is done by processing the image and generation of a binary mask. In the following section, two semantic segmentation methods are introduced, and implemented and their results are assessed.

By analyzing aerial images of crop fields, the idea emerged of applying color filtering to isolate areas within a specific range of green, corresponding to vegetation. Given that the input images are in RGB format, the initial approach involved using only the green channel to filter out pixels based on their green intensity. However, this method proved unsatisfactory for several reasons. First, white pixels containing high green intensity could not be effectively filtered using just the green channel. Additionally, areas with a more yellowish hue were incorrectly excluded by this filter. To address these issues, the RGB images were converted to the HSV (Hue, Saturation, and Value) format, which allows for more precise color filtering based on hue. The vegetation color range was then defined and applied to the images, resulting in improved segmentation of crops from the soil. The output of this process was a binary black-and-white mask, where white pixels represented areas containing plants.

The initial idea for semantic segmentation of crops in agricultural fields was to apply color filtering methods to isolate the areas having a green color. This method was first applied by analyzing the green channel of the image but performed poorly due to a few reasons. First, the green channel filtering method is not able to filter white pixels, since they also include a large amount of green color. Second, there are sections of crops with color tending to yellow, and they were unintentionally removed from the layer mask. The two issues mentioned were later resolved using a prefiltering for white pixels removal and also by converting the RGB image to HSV format (Hue, Saturation, and Value) so that it would be possible to filter the pixels based on their color considering their Vegetation Index (VI).

Next, to further highlight the areas including crops, a K-means clustering method was applied to the color-based filtered image. The clustering helped in removing sparse pixels identified as crops and uniting the areas where crops exist. The Parameters of the K-means algorithm were defined in an iterative approach, to identify the best-performing setting,

Without a high computational cost, this method can generate an accurate binary mask indicating the areas where vegetation exists. However, examining this method on the images taken from different fields with a variation of crops, it was observed that the method fails when there exists unwanted vegetation like grass and weeds in the field. Since the model filters the pixels based on their color, it cannot isolate crops without including the other vegetation. The same results in b5. FIGURE shows the performance of this method on different sub-images.

Although the color filtering method demonstrated satisfactory performance, it struggled to distinguish crops from other vegetation, such as grass or weeds, present in the field. This limitation arises because the algorithm passes all vegetation through the color filter, disrupting crop detection. These challenges highlight the inadequacy of color filtering for this task and underscore the need to utilize machine-learning models that intelligently differentiate crops from other vegetation.

The limited performance of color-based image segmentation in crop fields indicates the need for an intelligent model that can recognize the crops using more complicated methods. Utilization of machine learning methods to train semantic segmentation models has proven to be a reliable solution for crop detection. In this approach, a Unet network was chosen as the main image segmentation tool and was trained on a dataset developed by b5. This dataset consists of UAV-based aerial images taken from three vineyards with corresponding ground truth images, indicating the location of vines in the vineyard.

To use the annotated aerial images, the original and ground truth images were initially split into sub-images, using a sliding window of size 512 by 512 pixels. The step size of sliding was chosen to be 50 pixels, which resulted in more sample data for training. The resulting dataset consists of 5089 sub-images, which are divided into train, test, and validation sets with the ratio of 80%,10%,10%.

The Unet model was trained in 50 epochs, which reached the early stopping condition at epoch 7 with an accuracy of 96% and a loss value of 0.09. the predictions of this model on test data prove its ability in semantic segmentation of crops in different conditions, even at the presence of unwanted vegetation.

Access to a suitable dataset is essential to train a machine learning model. For this purpose, the vineyard aerial images dataset [REF] was employed, which includes annotated layer masks indicating the positions of plants within the images. The images were initially split into equal-sized segments of 128 by 128 pixels to ensure consistency in the input to the model, eliminating the need for resizing during processing. Subsequently, a Unet model was defined and compiled based on the architecture outlined in [REF]. The model achieved a final accuracy of 96\%\, which was obtained after seven epochs, with early stopping criteria applied. This result confirms that the Unet model can effectively capture image features and accurately segment the crop areas.

Crop row detection involves assigning a line with a defined slope and intercept to each crop row. Based on the binary mask of segmented crops obtained in the previous step, lines must be fit to the pixels to minimize the least square error from the line. This study analyzed and implemented two approaches—linear regression and the Hough Transform—for this purpose.

The crop row detection process aims to assign a straight line with a defined slope and intercept to each group of white pixels annotated as crops in the binary mask. This study analyzed and implemented two approaches—linear regression and the Hough Transform—for this purpose.

This experiment used the binary layer mask of segmented crops to assign each pixel to its corresponding crop row. The first step involved determining the optimal angle of the crop rows through an iterative algorithm, assuming that all rows are parallel and share the same slope. Once the slope was defined, the x and y coordinates of the white pixels were rotated to align the crop rows vertically, simplifying the clustering process.

The idea for implementing linear regression in crop row detection is based on the similarity of this problem to line fitting to data points. Given the white pixels related to each crop row, it is possible to find a line passing through each group of white pixels that has the least square distance from all the pixels. Fitting this line, its slope and intercept can be stored for further steps.

To implement this method,

At this stage, the K-means algorithm was applied with a customized loss function designed to minimize the least square error of the distances between the white pixels and a vertical line. Unlike standard loss functions that measure the distance from a centroid point, this approach considered each cluster centered around a line, not a point.

Given the variability in the number of clusters across different images, the clustering algorithm is initiated by grouping nearby pixels. When a pixel was too distant from the existing group, it was treated as the center of a new cluster. However, this approach led to the formation of numerous unwanted clusters. To address this, adjacent clusters were merged in a subsequent step. Finally, the initial rotation of the pixel coordinates was reversed to visualize the resulting clusters. As illustrated in the results, even after merging close clusters, the method failed to accurately identify crop rows, leading to complications in the later stages of the project. To conclude the experiment, linear regression was applied to fit a line to the pixels within each cluster. However, the results indicated that this clustering and linear regression approach is ineffective for defining crop rows, necessitating exploring alternative methods.

A widely used solution for crop row detection is the Hough Transform. This computer vision technique is primarily designed to identify geometric shapes in images, making it particularly effective for detecting lines and curves. In this study, the Hough Transform was employed as an alternative to the linear regression model for predicting crop rows. Implementing this method requires significantly less preprocessing and image manipulation, mainly due to the availability of related packages in the OpenCV Python package. Applying the Hough Transform to the images, multiple lines are detected for each crop row, as illustrated in the results. It is observed that these lines successfully cover the crop rows, indicating the method's effectiveness in line detection. To refine the results and assign a single line to each crop row, the detected lines were merged using their average slope and intercept. The final results are presented in FIGURE.

Defining waypoints becomes straightforward once the crop rows have been established. Initially, a path is defined as a line parallel to the crop rows and equidistant from two neighboring crop rows. A predefined number of equally spaced points are selected along each path line. The coordinates of these points are recorded for use in subsequent steps. FIGURE

As stated in previous steps, the most computational parts of this study are image segmentation and crop row detection. The determination of crop rows as lines with defined slope and intercept makes it straightforward to calculate a line indicating the path. The path is defined as a line parallel to two neighboring crop rows at an equal distance from each.

Waypoints can be defined by choosing a specific number of equally spaced points selected along each path. The local coordination of these waypoints is stored to be used in the later steps of the study.

Following the image splitting described in section B.1, the image processing tasks outlined earlier will be applied to each segment of the leading aerial image. The goal is to determine and record the waypoint coordinates within each segment. Once the waypoint coordinates are computed, the initial image must be reconstructed and assembled. Subsequently, the waypoint coordinates need to be converted to align with the coordinates of the newly assembled image.

In response to the increasing demand for autonomous agricultural systems, there is a critical need for accurate and reliable waypoints for navigation. This paper presents a solution involving a comprehensive live image capturing, processing, and waypoint generation system. The system is divided into three main sections: data acquisition, which captures and transmits aerial images; image processing, which identifies crops, determines crop rows, and assigns waypoints; and global coordinate conversion, which translates local waypoint coordinates into global coordinates. This approach ensures that the waypoints are precise and suitable for use by mobile robots or other devices requiring accurate navigation within agricultural fields.

In response to the increasing demand for accurate navigation systems utilized by autonomous agricultural mobile robots, this paper presented a hardware setup in conjunction with an image processing procedure to acquire live aerial images of agricultural fields and identify the global coordination of the waypoints placed on the path in the field, which can be used as the reference for mobile robot navigations systems. Using high-resolution RGB aerial images acquired by cameras mounted on UAVs, and the global coordination of the UAV acquired by GPS modules was chosen to gather the required environmental information of the field. Data transfer from the UAV position to the processing unit was achieved by implementing a radio transmission system. The procedure to extract global coordination of path from the acquired aerial images was defined as an image processing algorithm including image segmentation, crop row detection, and waypoint generation.

At this stage, the aerial image was initially split into equal-sized sub-images to ensure uniform inputs were fed to image processing algorithms. Two image segmentation methods (Color-filtering-based and Unet-based) were considered to identify the position of the crops in the resulting sub-images. It was proven that both methods can perform image segmentation tasks, while the color filtering approach failed in the fields having other unwanted vegetation such as grass and weeds. Conversely, The trained Unet model could achieve an accuracy of 96\%\ and generate satisfying predictions of the plants in different types of fields. Thus, this research chose the Unet-based method as the main image segmentation tool.

Given the binary mask of crop position in the image segmentation step, linear regression and Hough Transform methods were analyzed for crop row detection. The investigations showed that the complexity of the linear regression method which includes pixel clustering and line fitting, makes it a hard solution for this task, while the results showed non-satisfactory crop row detections. Thus, Hough Transform was implemented as an alternative approach for crop row detection, which resulted in more accurate estimated lines. Waypoints were defined as equally spaced points on the path, which are calculated as parallel lines between two crop rows.

The global coordination of defined waypoints is achieved after the reconstruction and mapping of the local coordination found in each sub-image to the local coordination of the original image. The global coordination is then calculated based on the local position of pixels and the global coordination of camera at the time of image capturing and stored for further usage.

As autonomous agriculture evolves, using wheeled mobile robots for various tasks necessitates precise waypoint generation to define the robots' paths accurately. This paper introduces a method that leverages aerial imagery to detect crop positions and determine waypoints. A specialized hardware setup, consisting of a high-resolution camera, wireless transmitter, and receiver, is developed to capture and transmit live images of the agricultural field. In the image processing stage, crops are identified through two parallel techniques—Unet and K-means clustering. Subsequently, the integration of linear regression and Hough Transform is to detect crop row lines, refined through filtering to ensure that a single, accurate line represents each row. Finally, by selecting specific points on the paths between these rows and converting them into global coordinates, the system facilitates real-time crop detection and precise waypoint generation, supporting autonomous navigation for agricultural robots.

System implementation

In correspondence to the main objective of this research which was to develop an integrated system to acquire live aerial images and calculate global coordination of path waypoints, an experimental setup consisting of camera and radio transmission system was designed and implemented. The wireless connection of camera and pc was established using RC805 radio transmission system to transfer live images acquired by Gopro Hero4 camera. This setup is presented in figure

The image processing features explained earlier were also integrated into a single program with a graphical user interface (GUI) to be fed offline aerial images by loading locally existing images on pc, or be fed online by receiving the live stream imagery data of the camera. Finally, the results achieved from each part of the image processing is presented in the output of the program, to visualize the logic behind the generated waypoints.

Contribution

In this paper, a system is developed to meet the growing demand for precise navigation in autonomous agricultural robots, focusing on capturing live aerial imagery and waypoint generation for navigation. The hardware setup involves a UAV-mounted camera to capture high-resolution RGB images of agricultural fields, and a radio transmission system to relay both the images and the UAV's global GPS coordinates to the processing unit. The captured images are processed using an integrated image processing algorithm, which begins by dividing the aerial images into equal-sized sub-images to ensure uniform inputs. Two methods are explored for segmenting the images to identify crop positions: a color filtering approach and a U-Net-based model. Following segmentation, crop row detection is implemented, with linear regression and the Hough Transform being evaluated as potential techniques. Finally, the waypoints are calculated as evenly spaced points between the detected crop rows, with their global coordinates derived by mapping local pixel data from the sub-images to the UAV's GPS coordinates at the time of image capture. These coordinates serve as critical reference points for the navigation systems of mobile agricultural robots.

Integrating advanced technologies, such as artificial intelligence, sensing systems, and autonomous robots, is crucial in addressing global food challenges by enhancing agricultural productivity and sustainability \cite{b2,b3}. Precision Agriculture (PA) has emerged as an intelligent management system that optimizes input distribution, such as water and fertilizers, based on site-specific needs, thereby improving crop yield and resource-use efficiency while minimizing environmental impact \cite{b5,b6}.

Mobile robots in precision agriculture have been utilized in various field tasks, such as fertilization, irrigation, weeding, harvesting, and crop picking \cite{b2,b3}.

In precision agriculture, traditional GPS-based path planning for agricultural machinery remains common. However, it presents challenges, such as the risk of seedling injury due to deviations between the ideal path and the actual crop rows \cite{b1}. To address these issues, machine vision-based crop row detection on unmanned agricultural machinery has gained attention, allowing for real-time, precise path planning that minimizes crop damage \cite{b1,b8}. However, the unstructured agricultural environment complicates accurate navigation and autonomous operations, necessitating the integration of onboard sensors, such as scanning lasers and machine vision cameras, to enhance the robot's ability to sense and interact with its surroundings \cite{b2,b3}. Despite these advancements, ground-based platforms face challenges, including soil compaction and vibrations from uneven terrain, which can be mitigated by utilizing UAVs for high-resolution, low-altitude aerial sensing \cite{b10}.

Unmanned Aerial Vehicles (UAVs) have increasingly become a vital tool in precision agriculture, offering a flexible, cost-effective platform for high-resolution remote sensing \cite{b9,b12}. UAVs can capture detailed imagery under different conditions, providing satisfactory spatial resolutions and covering significant areas, essential for monitoring crop variability and supporting temporal analysis \cite{b10,b12}. These platforms excel in vegetation segmentation, weed management, and crop row detection applications, filling the gap between terrestrial and satellite-based remote sensing \cite{b7,b13}. Despite certain limitations, such as flight endurance, the ability to conduct self-automated flights and provide timely data collection makes UAVs indispensable in modern agriculture \cite{b11,b13}. However, aerial image post-processing is necessary to differentiate crop rows from soil and weeds, highlighting the complexity of their integration in precision farming \cite{b6}.

The initial step in crop row detection is semantic segmentation of aerial images to determine the positions where vegetation exists. Previous works experimented with different approaches to achieve a trusted and accurate segmentation model.

The literature on crop row detection encompasses a range of approaches, each employing distinct methodologies to enhance precision in agricultural applications. Vegetation indices (VIs) like NDVI, ExG, and SAVI are frequently utilized as inputs for various detection methods, including thresholding algorithms, K-means clustering, and the Minimum Distance to the Mean (MDM) classifier. These methods are instrumental in segmenting vegetation from soil backgrounds and effectively identifying crop rows \cite{b1,b6,b13}. Fusion approaches, which combine RGB and NDVI data, are also explored to improve segmentation processes, particularly for autonomous robotic navigation in agricultural fields \cite{b5}.

AI-based approaches have gained prominence, particularly deep learning models, which have significantly improved detection accuracy. For instance, CRowNet, which combines a convolutional neural network (CNN) with the Hough transform, demonstrates robust detection capabilities across various crop types and field conditions, achieving high detection rates even in complex scenarios like curved or intersecting rows \cite{b8,b14}. Additionally, networks like U-Net, SegNet, and ModSegNet are used with traditional and deep learning-based semantic segmentation methods. These networks have shown varying degrees of effectiveness, with deep learning models generally outperforming classical approaches, particularly in challenging conditions where traditional methods may falter \cite{b5,b13}.

Traditional computer vision techniques are widely employed in crop row detection, with the Hough Transform being a prevalent method for line detection \cite{b2,b15}. Despite its extensive use, the Hough Transform has inherent limitations, such as high computational complexity and sensitivity to noise, which compromise its suitability for real-time applications \cite{b2}. To address these issues, various adaptations, including the Probabilistic and Multi-scale Hough Transforms, have been developed \cite{b2}. Moreover, combining the Hough Transform with deep learning has been shown to improve detection accuracy \cite{b8}. Linear regression is another commonly used technique, valued for its simplicity and computational efficiency, especially when integrated with preprocessing steps like image segmentation and feature extraction \cite{b2,b3}. Other methods, such as the Horizontal Strips Method and Blob Analysis, are also utilized in crop row detection. The Horizontal Strips Method enhances computational efficiency by bypassing additional segmentation steps but may suffer from accuracy issues due to factors like camera angle and missing rows \cite{b2}. Blob Analysis, which groups connected pixels into blobs to generate crop rows, can struggle in environments with high weed density \cite{b2}. The Random Sample Consensus algorithm is another approach that provides robust row detection by estimating mathematical models from data with outliers. However, its effectiveness depends on factors such as the quality of extracted feature points \cite{b2}. Machine learning methods, including clustering techniques like K-means and deep learning models such as Faster R-CNN, YOLOv3, and SegNet, are increasingly being applied in this domain \cite{b2,b5}. These methods offer significant advantages, although challenges remain, particularly in handling varying field conditions and limited annotated data \cite{b2,b5}.

In precision agriculture, extracted crop row and inter-row information serves as a foundation for various tasks, such as guiding autonomous ground vehicles by defining navigation paths between rows, which are crucial for tasks like automatic path computation and the development of vigor maps for field partitioning \cite{b11}. For aerial images, the navigation path is identified as the line between two crop rows, while for unmanned agricultural vehicles, it is defined by the central angle between two rows\cite{b1}.

In this section, methods to acquire live aerial images from a camera and the process

\subsection{Image Coordination to Global Coordination Conversion}\label{Image Coordination to Global Coordination Conversion}

An analytical approach and mathematical algorithm are required to obtain the corresponding global coordinates of the points identified in the images. This process involves using the global coordinates of the camera at the time of image capture, along with the camera's height. The conversion process is broken down into two phases: first, converting pixel coordinates into meter distances, and second, converting these meter distances into the global coordinate system.

\begin{figure}[t]

\centering

\includegraphics[width=0.7\linewidth]{waypoint\_geometry}

\caption{Geometrical representation of waypoint generation}

\label{fig:waypointgeometry}

\end{figure}

\subsubsection{Pixel to Meter Conversion}\label{Pixel to Meter Conversion}\leavevmode

Assuming the camera is positioned at the center of the image at a height of \( h \), and given the angle \( \theta \)

\[

\tan \theta = \frac{x}{h} \implies x = \tan \theta \cdot h

\]

Where \( x \) is the distance from the projection of the camera’s position to the edge of the image.

If the image length in pixels is denoted as \( L \), then:

\[

1 \text{ (pixel)} = 2h \cdot \frac{\tan \theta}{L} \text{ (m)}

\]

Using these equations, the position of a pixel with coordinations \((x, y)\) in the image can be determined relative to the camera's position on the ground.

\subsubsection{Meter to Global Coordination Conversion}\label{Meter to Global Coordination Conversion}\leavevmode

The final step involves converting the meter distances obtained from the previous calculations into global coordinates. The relationship between meters and degrees of latitude or longitude is given by:

\[

1 \text{ (m)} = 0.00001^\circ

\]

This conversion factor enables the translation of local pixel positions, measured in meters, into global coordinates.

Results:

Image Segmentation: Kmeans worked well but failed on grass. Unet was awesome, 96%, 83 IOU ( Images)

Crop Row Detection: Linear regression implementation was not successful, but Hough was great. Needed post processing.

Waypoint generation algorithm, which is a novel approach is able to compute the coordination successfully, but was not tested and implemented

Experimental Setup: The prototype proved the functionality of this system. While its performance was not measured in real situation. The implementation of discussed system is suggested for future works.

In this section, the performance of the aforementioned methods is evaluated, and the visual and statistical outputs of the image processing algorithms, including semantic segmentation and crop row detection, are presented. Subsequently, the results obtained from the experimental setup are analyzed and discussed.