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Real-Time Weed Location Estimation in Cassava Field Using an Aerial Multispectral Camera

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Abstract

This research presents a real-time weed location estimation system for precision agriculture in cassava planting. The widely employed vegetation index known as the normalized difference vegetation index (NDVI) was applied to identify and estimate the locations of the weeds. The multispectral camera mounted on an unmanned aerial vehicle (UAV) with nadir orientation was used to capture the field images. The NDVI values were calculated in real-time using an onboard microcomputer and streamed weed locations in latitude/longitude format to the ground control station. The UAV with the attached camera was controlled to follow a predefined flight path using user-specified coordinates based on the configuration of the planting area. The flight altitude was set at 10 m above ground level. Experimental flight tests were conducted over a cassava field covering an approximate area of 2,500 m^2. The results demonstrated that detected weed locations exhibited errors within the precision bounds of the GPS system. In the future, a spraying system could be implemented on the UAV to eliminate weeds and perform other planting operations.

Keywords: Weed location estimation, Multispectral imaging, Unmanned aerial vehicle, Cassava planting

1. Introduction

Cassava holds a prominent position among the key agricultural commodities in Thailand. In 2018, Thailand's cassava product export achieved an impressive global ranking, securing the third position. As a result, increasing the yield of cassava production becomes an important goal because it not only improves the farmers' financial situation but also greatly boosts Thailand's export revenue. Applying innovation and technology to help solve problems and increase productivity in cassava cultivation is therefore a good choice. Utilizing various methods to reduce the number of weeds that grow in the cassava furrows is an excellent approach to boost productivity.

Optimizing yield in cassava plantations necessitates effective weed control, as weeds have demonstrated the potential to cause substantial yield reductions, ranging from 25 to 50 percent [1]. The weeds in cassava fields comprise various species, encompassing both annual and perennial types. Consequently, several methods exist to address weed infestation, with the choice of approach contingent upon the specific weed species encountered. Traditional weed eradication practices in Thailand entail a manual hoe-up method aimed at eliminating all weeds. However, this technique necessitates a substantial labor force, particularly when managing extensive fields. An alternative method involves the application of herbicides through spraying, which offers an efficient and practical means of long-term weed control while minimizing manual labor requirements.

The advent of Unmanned Aerial System (UAS) technology has emerged as a pivotal development in modern precision agriculture, presenting promising avenues for cost reduction and yield enhancement. Unmanned Aerial Vehicles (UAVs) have been significantly developed in the past decade, leading to their extensive utilization across various domains, encompassing both military and civilian applications. Notably, electro-optical technology has played a pivotal role in reducing the dimensions of high-end cameras, enhancing their portability and operational efficiency. Historically, multispectral cameras were primarily employed in satellites for remote sensing applications, facilitating natural earth observation. However, the limitations of satellite-based monitoring, particularly concerning cloud cover interference, render it less suitable for precision agricultural assessments. Integrating multispectral cameras with UAVs for precision agriculture has been considered a promising novel alternative technique. [2-4]

Another challenge in the realm of precision agriculture development in Thailand pertains to the ability of farmers to comprehend data derived from aerial imagery, particularly in the context of remote sensing technical terminology. To surmount this issue, computer-based remote sensing systems have garnered attention as a compelling and pragmatic solution. These systems offer a user-friendly interface that enables farmers to understand the conditions of their plantations without necessitating expert interpretation. Therefore, this study introduces a real-time weed location estimation system for precision agriculture in cassava planting.

2. Research Scope

This study employed a multirotor UAV equipped with a Raspberry Pi 3B+ and a customized Pi NoIR camera integrated with a blue filter, enabling its functionality as a multispectral camera. The Python programming language, in conjunction with the OpenCV image processing library, was employed for real-time data processing and data recording on the UAV's onboard system. The experimental site for the cassava plantation encompassed an estimated area of 2,500 m^2, located in Amphoe Borabue, Maha Sarakham province, situated in the northeastern region of Thailand.

3. Weed Location Estimation

3.1 The Coordinate Transformation

The requirement for coordinate transformation arises from differences between the coordinate system employed in the UAV navigation system and that corresponding to the detected weed locations represented in image coordinates. The relationship between these coordinate systems is shown in Fig. 1. The coordinate frame denoted as {B} designates the UAV coordinate system, while the coordinate frame designated as {C} corresponds to the camera coordinate system utilized to represent image coordinates specified in pixels. The UAV navigation system utilizes the NED (North, East, Down) [5], which serves as the reference frame for the transformation of weed location coordinates before transmission to the ground control station.

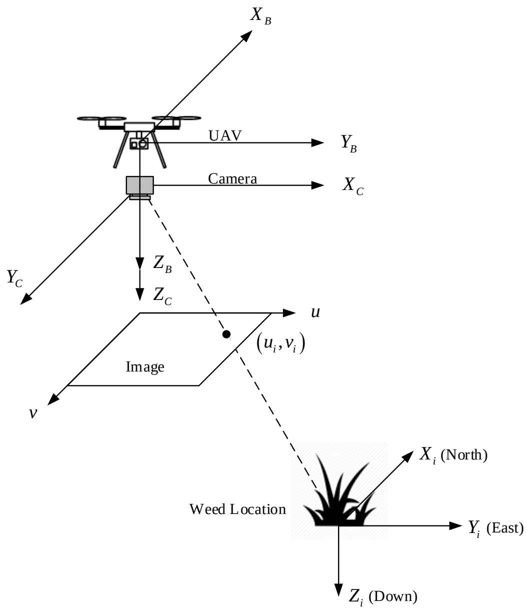


Fig. 1. Coordinate transformation from image coordinates to latitude/longitude coordinates.

The process of coordinate transformation involves a series of equations, as shown in Equations (1) to (4). In Equation (1), the detected weed location coordinates in the image frame coordinates (pixels) are transformed to physical units (m) using the relationship between pixel size and footprint size in physical units that are related to the scaling factors T_1 and T_2, FP_x and FP_y are footprints in x and y directions, respectively. Following that, Equation (2) is applied to transform the coordinates in physical units to reference with the true north using the heading of the UAV platform obtained from the GPS module as specified by θ. Then, the x and y in NED (North, East, Down) coordinates are transformed to the LAT and LON using Equation (3) and (4), respectively.

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix}_{meter} = \begin{bmatrix} T_1 & 0 & -T_1 FP_x / 2 \\ 0 & T_2 & -T_2 FP_y / 2 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}_{pixel} \tag{1}$$

$$\begin{bmatrix} x \\ y \end{bmatrix}_{NED} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}_{meter} \tag{2}$$

$$LAT = LAT_1 + \left(y_{NED} * 0.00001/1.1132\right) \tag{3}$$

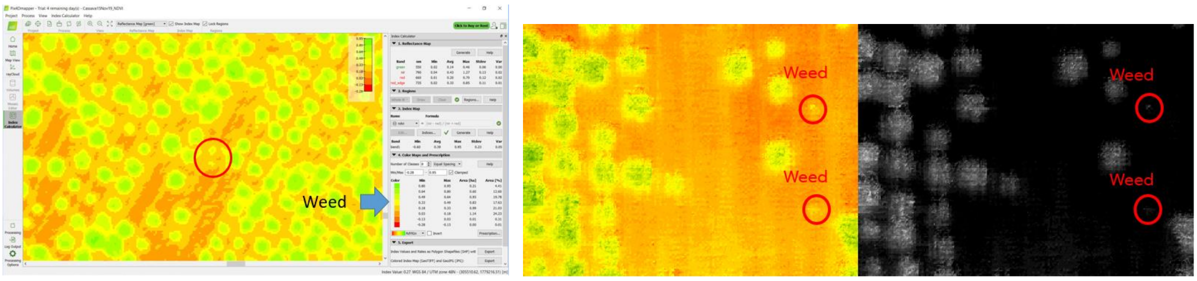
$$LON = LON_1 + \left(x_{NED} * 0.00001/1.1132\right) \tag{4}$$

LAT_1, and LON_1 are the latitude and longitude of the center of the camera system. These LAT and LON values will be sent to the ground control station.

3.2 Weed Classification Algorithm

Various techniques have been explored for weed classification [6-8]. This study employed the NDVI values acquired from the Parrot Sequoia, a commercially available off-the-shelf multispectral camera, for the purpose of calibrating the NDVI values, as illustrated in Fig. 2. Subsequently, the calibrated NDVI values were employed in a dedicated weed detection algorithm. The outcomes of this algorithm demonstrated that the NDVI values effectively enabled the difference between cassava crops and weeds by considering both the difference in NDVI values and the diameter of the detected weeds, which were processed using an edge detection algorithm. The classification of weeds from cassava crops was accomplished based on a specific condition using Equation (5).

$$\text{(NDVI value} < 0.3\text{) and (Diameter of NDVI blob} < 10\text{ cm)} \Rightarrow \text{Weed} \tag{5}$$



(a) (b)

Fig. 2. Weed detection algorithm: (a) The NDVI value < 0.3 (b) Diameter of NDVI blob < 10 cm

4. Methodology

Fig. 3 illustrates the weed-targeting operation developed in this research. A quadrotor UAV featuring vertical take-off and landing capabilities was utilized to capture the image. The acquired images were processed by an onboard computer, a Raspberry Pi 3B+ equipped with a multispectral camera. The UAV flew autonomously with a predefined flight path using the Pixhawk flight controller and ArduPilot ground control software. It can carry any sensors that weigh less than 1.0 kg mounted under its structure. The images were captured with a multispectral camera and a Pi NoIR camera with a blue filter. The software was developed to calculate the NDVI and perform weed classification between cassava and weeds in the cassava field in real-time.

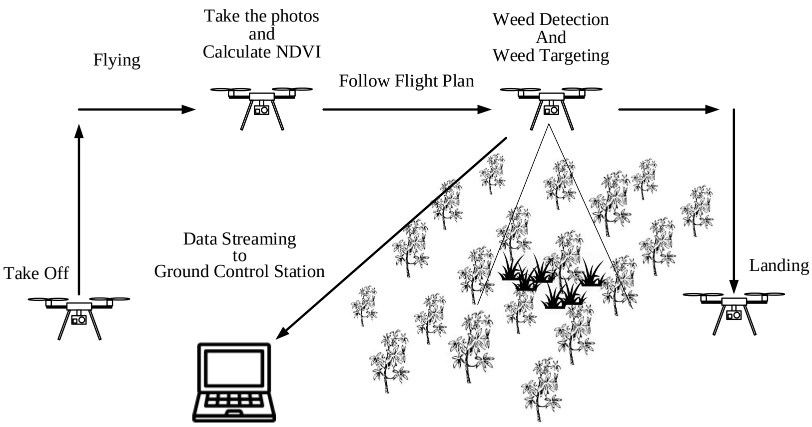


Fig. 3. Overview of the weed-targeting operation using the developed system

The UAV, ground control station, and communication scheme are shown in Fig. 4. The airborne unit consisted of an onboard computer with a GPS module for location estimation of the weed. This design choice was necessitated by the fact that the algorithm employed for weed detection was operated within the image coordinate system, while the position and orientation of the UAV were referenced in latitude/longitude format. The coordinate transformation is necessary to align the weed coordinates with a global coordinate system. Its details will be described in the next section.

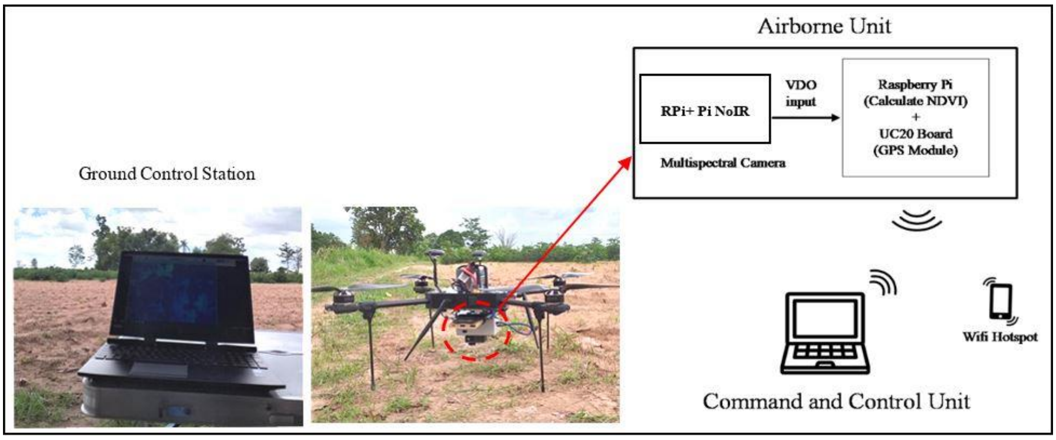
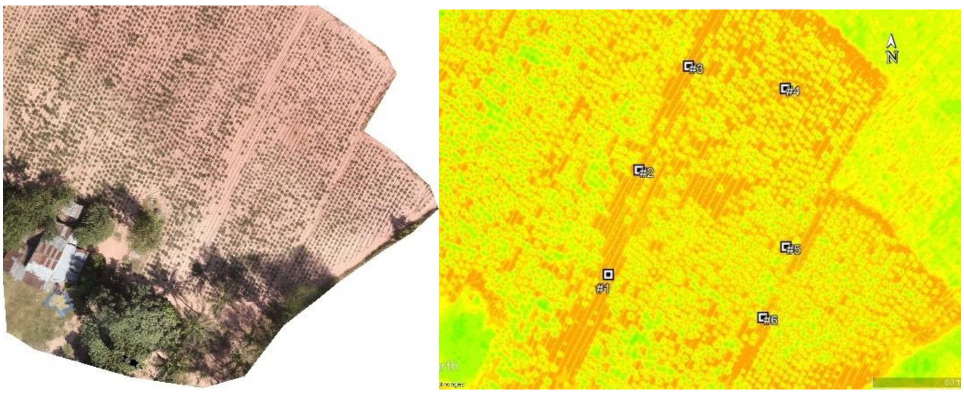


Fig. 4. The UAV system and communication scheme

5. Experimental Results

Thailand has a variety of weed species, which can be classified into two main types based on their characteristics: cover weeds (e.g., grasses) and tiny bush weeds (e.g., Billy Goat Weed). This project focused on the tiny bush weeds, as they offered ease for conducting the experiment. The experiment started with data collection from the cassava plantation, where six distinct weed locations were selected. The locations were recorded in latitude/longitude format, as depicted in Figs. 5 - 6. The UAV equipped with the Parrot Sequoia multispectral camera was programmed to follow a predefined flight path at a height of 10 m above the plantation. Upon completion of the data acquisition, post-processing analysis yielded both RGB and NDVI indexes. The study's focus lay in locating weeds, which were readily identifiable by the UAV, as demonstrated in Fig. 7.



(a) (b)

Fig. 5. The experimental cassava plantation. (a) RGB format (b) NDVI format

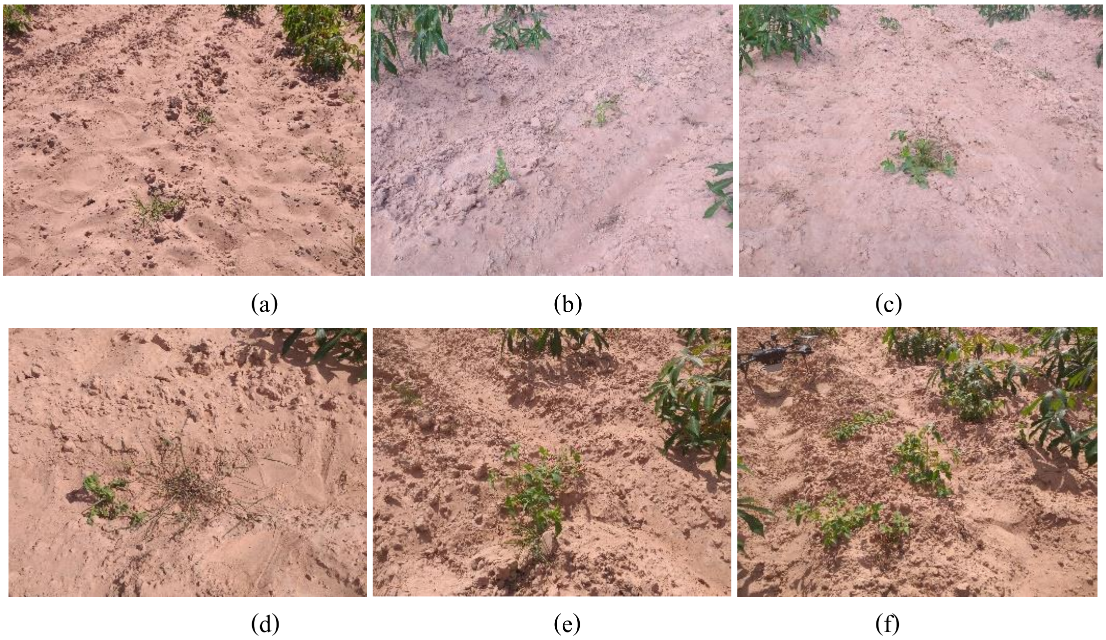


Fig. 6. The weed images in the field (a) to (f) for weed numbers (1) to (6) respectively

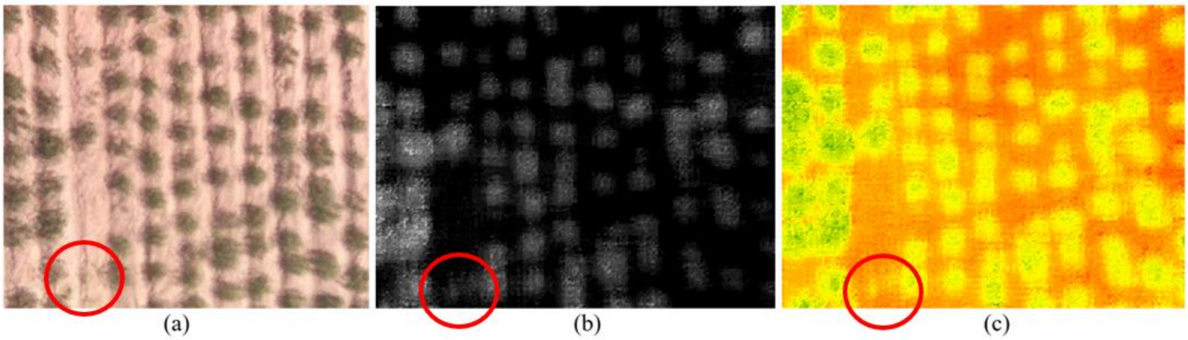


Fig. 7. The aerial image captured: (a) RGB, (b) Real-Time NDVI image, and (c) NDVI colormap post-processing.

After the calibration of the weed detection algorithm, both the NDVI value and the diameter of the NDVI blob were computed using Python programming and an image processing library. The processing tasks were executed on a Raspberry Pi 3B+ integrated with a Pi NoIR camera. The UAV was repeatedly flown along the designated flight path to detect the locations of the weeds. These detections enabled the estimation of weeds' positions in the latitude/longitude format. Subsequently, a comparative analysis was performed by juxtaposing the estimated weed locations with the measured positions, as presented in Table 1 and Fig. 8.

Table 1. The comparison of the measured weed locations and the estimated weed locations.

Target No.	Measured Weed Position		Estimated Weed Position		Heading (degree)	Error (m)
	LAT	LON	LAT	LON		
1	16.085352 N	103.181491 E	16.085308 N	103.181458 E	40.52	5.9
2	16.085446 N	103.181521 E	16.085411 N	103.181473 E	200.45	5.1
3	16.085535 N	103.181585 E	16.085510 N	103.181534 E	32.45	5.4
4	16.085448 N	103.181624 E	16.085453 N	103.181625 E	66.46	0.1
5	16.085328 N	103.181655 E	16.085314 N	103.181633 E	145.54	2.3
6	16.085268 N	103.181649 E	16.085247 N	103.181602 E	158.15	5.5

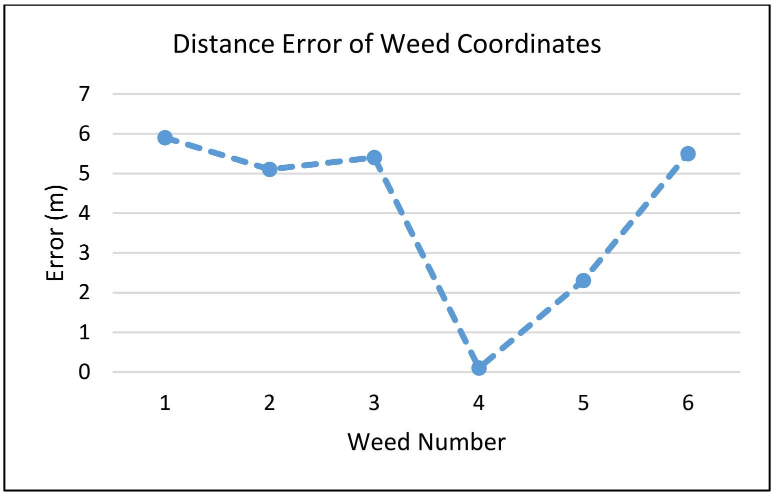


Fig. 8. Distance errors of weed coordinates for 6 weed locations.

6. Conclusion

This research is part of an unmanned aerial vehicle for precision agriculture to calculate NDVI in real-time. The NDVI was calculated using an onboard computer, a Raspberry Pi 3B+, integrated with a Pi NoIR camera equipped with a blue filter. The calibration of the NDVI values for the weed detection algorithm was achieved using data from the Parrot Sequoia, a commercially available multispectral camera. During real-time test flights, the Pi NoIR multispectral camera mounted on the UAV, along with the onboard computer, could estimate weed coordinates within the cassava field. Furthermore, the system recorded the latitude and longitude values of the detected weed locations for subsequent analysis. The flight tests encompassed a predefined flight path at an altitude of 10 m, traversing over designated weed locations in six distinct areas at a speed of 3 m/s. The weed location estimation errors ranged from 0.1 to 6 m, which can be reduced using higher-performance GPS with real-time kinetics and a ground reference point.

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