CROP ROW DETECTION PROCEDURE USING LOW-COST UAV IMAGERY SYSTEM

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ABSTRACT:

Precision Agriculture (PA) management systems are considered among the top ten revolutions in the agriculture industry during the last couple decades. Generally, the PA is a management system that aims to integrate different technologies as navigation and imagery systems to control the use of the agriculture industry inputs aiming to enhance the quality and quantity of its output, while preserving the surrounding environment from any harm that might be caused due to the use of these inputs. On the other hand, during the last decade, Unmanned Aerial Vehicles (UAVs) showed great potential to enhance the use of remote sensing and imagery sensors for different PA applications such as weed management, crop health monitoring, and crop row detection. UAV imagery systems are capable to fill the gap between aerial and terrestrial imager systems and enhance the use of imagery systems and remote sensing for PA applications. One of the important PA applications that uses UAV imagery systems, and which drew lots of interest is the crop row detection, especially that such application is important for other applications such as weed detection and crop yield predication. This paper introduces a new crop row detection methodology using low-cost UAV RGB imagery system. The methodology has three main steps. First, the RGB images are converted into HSV color space and the Hue image are extracted. Then, different sections are generated with different orientation angles in the Hue images. For each section, using the PCA of the Hue values in the section, an analysis can be performed to evaluate the variances of the Hue values in the section. The crop row orientation angle is detected as the same orientation angle of the section that provides the minimum variances of Hue values. Finally, a scan line is generated over the Hue image with the same orientation angle of the crop rows. The scan line computes the average of the Hue values for each line in the Hue image similar to the detected crop row orientation. The generated values provide a graph full of peaks and valleys which represent the crop and soil rows. The proposed methodology was evaluated using different RGB images acquired by low-cost UAV for a Canola field. The images were taken at different flight heights and different dates. The achieved results proved the ability of the proposed methodology to detect the crop rows at different cases.

1. INTRODUCTION

Agriculture industry plays an important role for the life and development of any community; therefore, it was important to develop a management system to enhance the outcome while controlling the use of the agriculture process inputs for economical and environmental purposes. For such needs, Precision Agriculture (PA) was introduced as a smart management system that aims to distribute the different agriculture inputs as water, fertilizers, herbicides, etc. based on the needs of each spot in the agriculture field while fitting the environmental and economical requirements (Zhang & Kovacs, 2012). To achieve these objectives, PA management system uses different technologies such as navigation and imagery systems to collect different types of data, analyse them, and finally based on the detected needs, the right inputs are distributed at the right time and the right location (Mulla, 2013).

Meanwhile, during the last two decades, UAVs proved to be a special platform for imagery and remote sensing applications. UAVs showed great potential to fill the gap between aerial and terrestrial platforms as they can deliver imagery data with suitable spatial and temporal resolution for different applications. For these advantages, UAV imagery systems were used for different applications including PA applications as vegetation segmentation (Mohamed Hassanein, Lari, & El-Sheimy, 2018), weed management (Guerrero, Pajares, Montalvo, Romeo, & Guijarro, 2012; Hassanein & El-Sheimy, 2018; Peña, Torres-Sánchez, Serrano-Pérez, de Castro, & López-Granados, 2015), and crop row detection (Bah, Hafiane, & Canals, 2018; Comba, Gay, Primicerio, & Ricauda, 2015; Lottes, Khanna, Pfeifer, Siegwart, & Stachniss, 2017; Pérez-Ortiz et al., 2016).

One of the important PA applications is the crop row detection especially that it is used as an important step for other PA applications. The importance of this application is caused by its role in many other applications such as weed detection, mapping, and crop yield prediction (Peña Barragán, Kelly, M., Castro, & López Granados, 2012; Peña & Gutiérrez, 2015; Peña et al., 2015).

Due to such importance, different imagery systems including UAV imagery systems in the recent years, were used for crop row detection. The main objective for such application is to detect the crop rows in the imagery data acquired for the agriculture field. To achieve this objective, different researches were developed and introduced either for the purpose of crop row detection as the final goal or as a main step to achieve another important goal such as weed detection.

For example, Bah et al., (2018) used the crop row detection as an important step for their work to detect the weed plants. First, the authors performed a vegetation segmentation to differentiate vegetation objects from the background soil, where the output from this process was a vegetation binary image. Then, their methodology used the Normalized Hough transform (Duda & Hart, 1972) to detect the linear objects in the vegetation binary image which are the crop rows. Such procedure to detect the linear objects using Hough transform in the vegetation binary images was highly adopted by other researchers (Peña &

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Gutiérrez, 2015; Tellaeche, Burgos-Artizzu, Pajares, & Ribeiro, 2008). Also, following similar steps, José M Peña et al., (2015) used the concept of Object Based Image Analysis (OBIA) to detect the linear objects in the vegetation binary image. The authors used the OBIA to analyse the segmented region and classify the linear object based on the dimensions of the segmented vegetation objects. Finally, the liner objects are segmented to create the crop rows.

Moreover, different crop row detection methodologies tried to avoid the use of vegetation binary image. For example, Comba et al., (2015) used a combination of Hough and least square to perform a dynamic detection of crop rows to avoid illumination effects. Also, other techniques were introduced to detect crop rows based on Fast Fourier Transform (FFT) (Delenne, Rabatel, Agurto, & Deshayes, 2006; Rabatel, Delenne, & Deshayes, 2008), or based on the difference between the texture properties of crop pixels and the non-crop pixels (Da Costa, Michelet, Germain, Lavialle, & Grenier, 2007). Furthermore, other techniques based on wavelets and multi-resolution analysis were proposed and showed 78% accuracy of crop rows identification (Ranchin, Naert, Albuisson, Boyer, & Astrand, 2001).

Despite the huge potentials showed by using UAV imagery systems for different PA applications including crop row detection, there are still some limitations that affect their use for PA (Erickson & Widmar, 2015; Zhang & Kovacs, 2012). These limitations can be combined in the use of high cost multispectral imagery sensor and the need to perform vegetation segmentation as an initial step.

First, most methodologies used to achieve the objectives of PA applications including crop row detection use multispectral imagery sensors to perform the vegetation segmentation step as accurate as possible using the NDVI vegetation index. Such imagery sensors are considered expensive compared to the RGB imagery sensors. Although there was a lot of efforts to perform the vegetation segmentation process using RGB images, there are still limitations of achieving a consistent accuracy for the generated vegetation binary image in different cases of illumination (Hamuda, Glavin, & Jones, 2016). Such limitation motivated different researchers to recommend the use of multispectral imagery sensors after performing different comparison studies (Peña et al., 2015).

The second limitation is the need to perform a vegetation segmentation process. As the highest crop rows detection accuracies are achieved using techniques that depends on detecting the linear objects in the vegetation binary images, most of the crop row detection methodologies depends on performing a vegetation segmentation process as an initial step. The problem of such need is related to the dependency of the detected crop rows on the accuracy of the vegetation segmentation. Therefore, it is important to note that any miss-segmentation will highly affect the achieved results of the crop row detection.

This paper introduces a new crop rows detection methodology that avoid the need of performing the vegetation segmentation step. Also, the introduced methodology is working on RGB images to avoid the high cost of Multi-spectral imagery sensors. The following sections of the paper are organized as follow: Section 2 describes the proposed crop row detection methodology. Then, section 3 describes the collected imagery data and the implementation of the proposed methodology. Later, section 4 shows the achieved results and provides an analysis for these results. Finally, section 5 provides the conclusions and the limitations of the proposed methodology.

2. METHODOLOGY

The main objective of the proposed methodology is to perform a crop row detection process from RGB images acquired by low-cost UAV imagery systems without the need to perform the vegetation segmentation process. The methodology consists of three main steps, as shown in figure (1), which are: converting the image color space; detecting the crop row orientation; and finally, detecting the crop rows. The following sections provide detailed description for these steps.

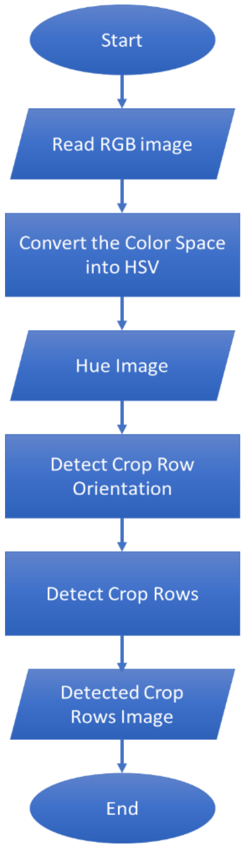


Figure 1. Methodology main steps.

2.1 HSV Color Space

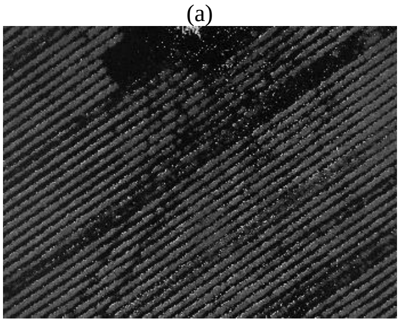
The first step in the proposed methodology is to convert the color space of the acquired image from the RGB color space into the Hue channel of the HSV color space. The main motivation for this step is to provide a different representation for the objects' colors in the acquired image without any effect from illumination conditions.

Generally, in RGB color space, any pixel in the image has three values which are the saturation levels of Red, Green, and Blue colors. The combination of these three values represent the pixel's color. Such representation of color has high correlation between the three values of R, G, and B channels. Moreover, the illumination values are impeded in the three values of R, G, and B which might affect the color or the chromatic representation. Therefore, separating a specific color in RGB images is considered a challenging problem especially for PA applications (Tang, Chen, Miao, & Wang, 2016). Due to these limitations of RGB color space, the proposed methodology depends on using HSV color space to represent the objects' colors.

Hue, Saturation, and Value or HSV color space provides a different representation for the pixels/objects' color. HSV color space consists of three channels, where each one of them is responsible for different representation. The Hue channel represents the color or the chromatic of the object, while Saturation channel represents, as it can be told from its name, the saturation level of the color. Finally, the Value or the Vibrancy channel represents the brightness of the color. As the chromatic value of the objects/pixels is represented away of the illumination effect, HSV color space was adopted by different methodologies for different PA applications (Hamuda et al., 2016; Hassanein & El-Sheimy, 2018; Hassanein et al., 2018).

Therefore, the first step in the proposed methodology is to convert the color space of the acquired image into HSV. Then, the Hue values of the image are extracted and separated in another image, as shown in figure (2). Such extracted Hue image is providing a grayscale image representation for the RGB image, which provides a color representation for the objects in the image separated from any illumination conditions or effects.

(a)



(b)

Figure 2. image for a canola field. (a): RGB image, (b): Hue image.

2.2 Crop Row Orientation Detection

The second step in the proposed methodology is the crop row orientation detection. The main objective in this step is to detect the orientation angle (θ) of the crop rows in the acquired image, as shown in figure (3). To detect the correct orientation angle (θ), the proposed methodology takes the advantage of the concept of row planting which is widely adopted.

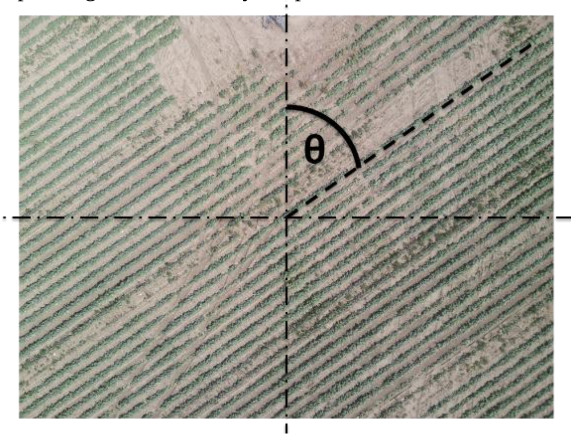
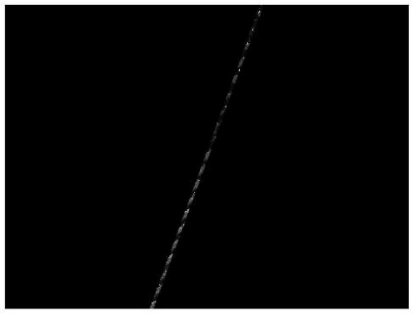
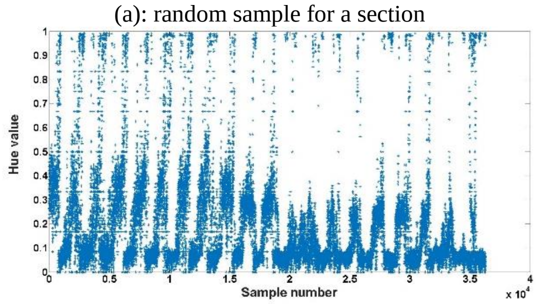


Figure 3. Crop rows orientation angle (θ).

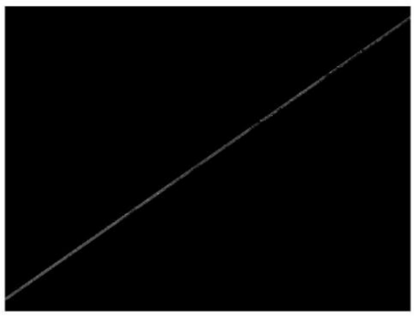
The concept of row planting is considered a very attractive planting approach for many farmers. The main motivation for row planting is the advantages related to maximizing the light exposure for the plants, providing wind passage along the inter-rows to enhance the gas exchange, enhancing the movement between plants especially for cultivations or weeding operations, and enhancing the counting process for the plant population in the farm. Therefore, it is common for different crops to be planted in linear rows. These rows or straight lines have the same orientation, as shown in figure (3). Therefore, as the agriculture field is planted in parallel rows, there are two types of objects in the agriculture field, which are the vegetation object, or the crop, and the non-vegetation object, or the soil. All these rows are parallel and share the same orientation angle.



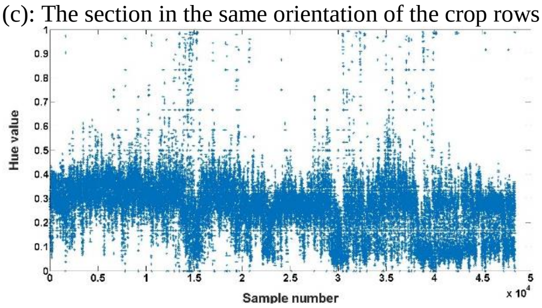
(a): random sample for a section



(b) The Hue values for the points in the random section



(c): The section in the same orientation of the crop rows



(d): The Hue values within the right section

Figure 4. Two cases for sections in the Hue image along with the distribution for the Hue values within these sections

Using such information, the proposed methodology is creating a longitudinal section with small width (d), as shown in figures (4.a) & (4.c). Through performing an evaluation or assessment for the homogeneity of the Hue values within each longitudinal section or profile, an indication if the objects within this section belong to the same type or not can be achieved. If the homogeneity of the Hue values proved that the pixels in the longitudinal section belongs to the same type of objects, the methodology assumes that the orientation of this section is the same orientation of the crop rows. To evaluate the homogeneity of the Hue values with the section, the Principle Component Analysis (PCA) is used (Wold, Esbensen, & Geladi, 1987).

PCA procedure provides the ability to detect the dominant direction of a data represented in the Principle Component 1 (PC1) along with its perpendicular direction, the Principle Component 2 (PC2). Generally, for any data, PC1 detect the dominant direction of the data, while PC2 indicate how scattered or the variance of this data. Therefore, with the use of PCA for the Hue values in the longitudinal section, PC2 can indicate if the pixels in this section belong to the same type of object or not, as shown in figure (4).

The proposed methodology creates different section with small width (d) at different orientations starting from angle (θ) equal to 0^0 to angle (θ) equal to 180^0 with small step of 1^0 or less. Through comparing the PC2 values of each section, the crop row orientation (θ) is detected as the orientation of the section that provided the smallest value of PC2, as can be noticed through comparing figures (4.b) & (4.d).

2.3 Crop row Detection

The third and final step in the proposed methodology is to detect the crop rows. In this step the proposed methodology creates a line scanner with the declination equals to the detected crop row orientation (θ). The line scanner scans through the Hue image and the average of the Hue values of each line are represented in a graph, as shown in figure (6). In this graph, each of the peaks and valleys represents either a crop row or a soil row, while the slopes between the peaks and the valleys are the translation between the crop and soil rows. Through averaging the peaks and the valleys values, the crop rows are detected with comparing these values and the green color representation in Hue channel.

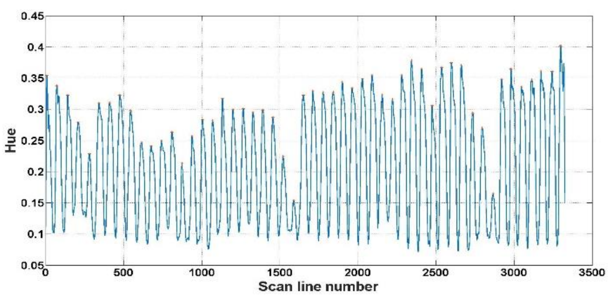


Figure 6. Average Hue value for each scan line.

3. METHODOLOGY IMPLEMENTATION

To evaluate the proposed methodology, a low-cost imagery system was used to collect different RGB images for an agriculture field at different altitudes and dates. In the following parts, a description for the used UAV, Imagery sensor, agriculture field, and the acquired images will be provided. Then, different figures, showing the achieved results using the proposed methodology, are presented.

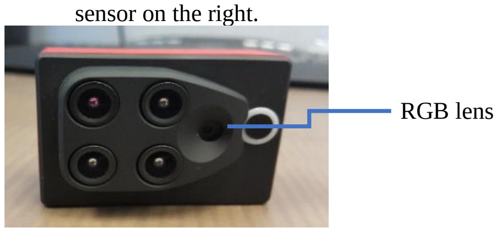
3.1 Data Acquisition

As mentioned, to evaluate the proposed crop row detection methodology, different RGB images were collected using a low-cost UAV imagery system. As shown in figure (7), the used UAV was the 3DR Solo UAV, while the attached imagery sensor was the Sequoia imagery sensor from Parrot, as shown in figure (8). Although the Sequoia Camera is classified as a multi-spectral imagery sensor, it provides the user with the ability to collect the imagery data with different lenses, as shown in figure (8-b). Therefore, the authors collected the imagery data with the RGB lenses only, without any use for other images acquired by other multispectral lenses.

Figure 7. 3DR Solo UAV equipped with the Sequoia Imagery Sensor.

The described UAV imagery system was used to collect different images for an agriculture field planted with Canola. The images were acquired at different altitudes to evaluate the ability of the proposed methodology to detect the crop rows at high altitudes. Moreover, the imagery data were collected at two different dates to evaluate the proposed methodology to detect the crop rows even at early stages where the crop rows width are too small. Table (1) provides detailed description for the used images in the evaluation process.

(a): The Sequoia camera on the left, while the GPS /IMU sensor on the right.



(b): RGB lens in the Sequoia Camera

Figure 8. The Sequoia imagery sensor.

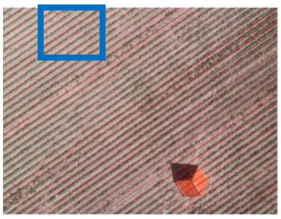
Case #	Acquisition Date	Flight Height (m)
1	July 4	10
2	July 4	10
3	June 24	10
4	July 4	20
5	June 24	30
6	June 24	40
7	June 24	60
8	June 24	80
9	June 24	100
10	June 24	120

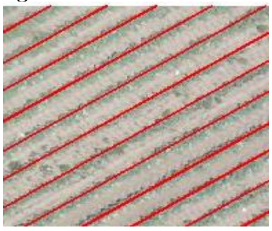
Table 1. List of the used images to evaluate the proposed methodology.

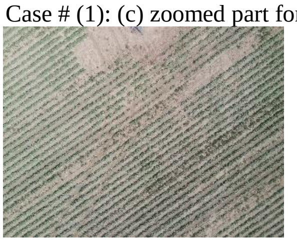
3.2 Results

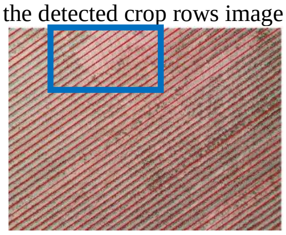
Each one of the described images in table (1) went through the proposed crop row detection methodology. Figure (9), shows the RGB inputs images along with the detected crop rows in each image. For more explanation for the achieved results with implementing each step of the proposed methodology, figure (10) shows the results of each step for one image.

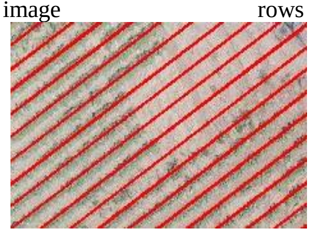

Case # (1): (a) original RGB input image


Case # (1): (b) Detected crop rows image

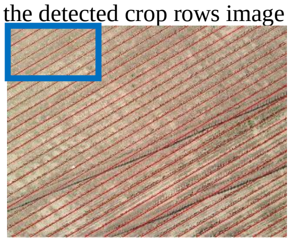

Case # (1): (c) zoomed part for the detected crop rows image

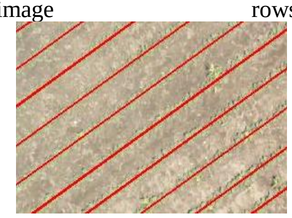

Case # (2): (a) original RGB input image


Case # (2): (b) Detected crop rows image


Case # (2): (c) zoomed part for the detected crop rows image

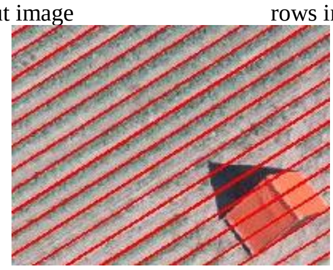

Case # (3): (a) original RGB input image

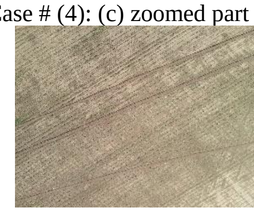

Case # (3): (b) Detected crop rows image


Case # (3): (c) zoomed part for the detected crop rows image

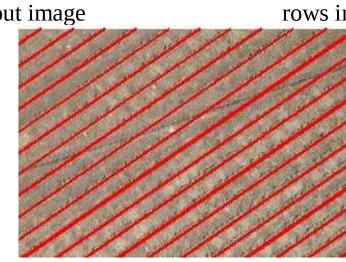

Case # (4): (a) original RGB input image

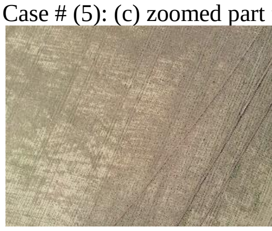

Case # (4): (b) Detected crop rows image

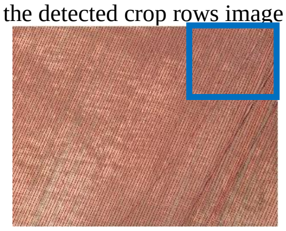

Case # (4): (c) zoomed part for the detected crop rows image

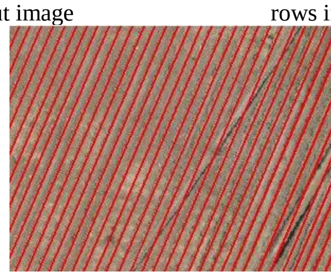

Case # (5): (a) original RGB input image


Case # (5): (b) Detected crop rows image


Case # (5): (c) zoomed part for the detected crop rows image


Case # (6): (a) original RGB input image


Case # (6): (b) Detected crop rows image


Case # (6): (c) zoomed part for the detected crop rows image


Case # (7): (a) original RGB input image


Case # (7): (b) Detected crop rows image

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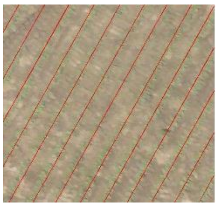
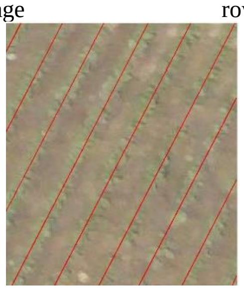


Case # (7): (c) zoomed part for the detected crop rows image

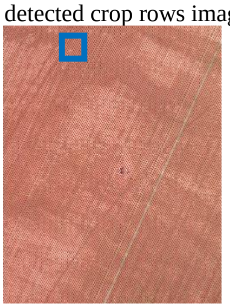
Case # (8): (a) original RGB input image

Case # (8): (b) Detected crop rows image

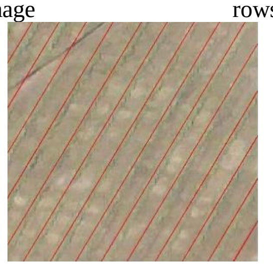


Case # (8): (c) zoomed part for the detected crop rows image

Case # (9): (a) original RGB input image



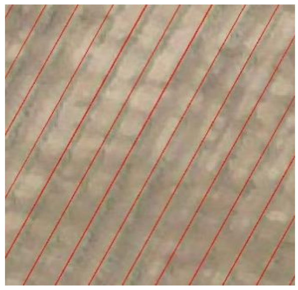
Case # (9): (b) Detected crop rows image



Case # (9): (c) zoomed part for the detected crop rows image

Case # (10): (a) original RGB input image

Case # (10): (b) Detected crop rows image



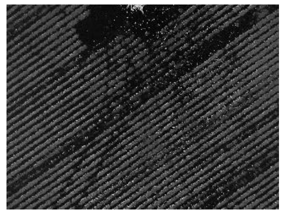
Case # (10): (c) zoomed part for the detected crop rows image

Figure 9. The achieved crop rows detected images from the proposed methodology.

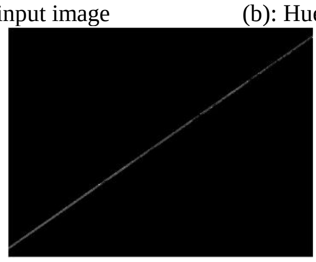
4. RESULTS ANALYSIS

The achieved results, as shown in figure (9), proved the ability of the proposed crop row detection methodology to detect the crop rows in the RGB images acquired by low-cost UAV imagery system. The crop row detection process was able to detect the crop rows even with the change of the images' altitudes, as can be noticed in cases (3, 5, 6, 7, 8, 9, and 10) in figure (9).

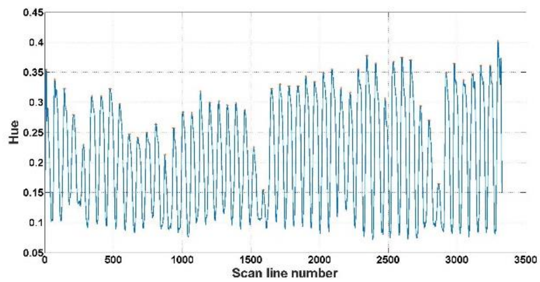
(a): RGB input image



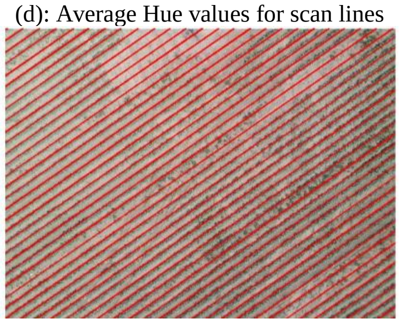
(b): Hue image



(c): Detected crop row orientation



(d): Average Hue values for scan lines



(e): Detected crop rows final output

Figure 10. A sample for the achieved results at each step of the methodology.

Furthermore, the methodology succeeded to detect the crop rows at different growth stages. As shown in table (1), the imagery data acquisition was performed at two different dates for the same agriculture field. The first imagery data was collected in June 24th 2018, while the second imagery data was collected in July 4th, 2018. The 10 days difference between these two dates caused a change in the crop growth stage, as can be noticed in the RGB images of the cases (2 & 3) in figure (9). The challenge to detect the crop rows at early growth stages is related to the feasibility to detect the crop plants. At early growth stages, as can be seen in the images acquired in June 24th, the plants are small, the crop rows have small width, and the density of vegetation objects within the crop rows are too small. Such properties make the ability of the imagery system to detect crop rows, or the vegetation objects, is very challenging especially from high altitudes using low-cost imagery sensors. Such imagery sensors are not capable to provide images with high spatial resolution. Although these challenges, the proposed methodology was able to detect the crop rows with acceptable accuracy even at high altitudes, as can be noticed in cases # (8, 9, and 10), in figure (9) for the images acquired at 80, 100, and 120 meters altitudes. Also, with the comparison of the detected crop rows in the images acquired at the same altitudes on these two dates of imagery acquisition, as in cases # (2 & 3), the proposed methodology was able to detect the crop rows with similar accuracy even with the change of rows width, or the growth stage.

Moreover, as can be noticed in figure (10), the proposed methodology is providing the ability to detect the crop rows that has problems or limitation with the planted crop rows through comparing the average of Hue values of each scanned line. It can be noticed that the rows where the crop width or density of crop is less compared to other rows can be easily detected as the Hue value of these row, as shown in figure (10-d) are lower compared to other crop rows average Hue values. Such ability allows this methodology to be developed and used for crop planting assessment to evaluate and detect problems with the crop planting process. Finally, as shown in figure (9), especially in figure (c) of case # (1), the weed plants can be noticed easily after the crop row detection process. Therefore, the proposed methodology can be developed to be used as weed detection process.

The main limitation in the proposed methodology is related to the process time. Because of the need to evaluate each section at different angles, the process time is too high to use the proposed methodology for real time application. Also, the detection of the suitable step angle to be 1^0 or less need to be more automated not based on the author trials.

5. CONCLUSIONS

This paper introduced a new crop row detection methodology which can be used as an initial step for different applications as weed detection and crop growth assessment. The proposed crop row detection methodology enhances the potential to develop the use of low-cost UAV imagery systems which are equipped with low-cost RGB imagery sensors. In general, the proposed methodology was able to detect the crop rows from RGB images acquired at different altitudes without the need to perform a vegetation segmentation process usually used for different crop rows detection methodologies.

Generally, the proposed methodology composed of three main steps. First, the acquired RGB images are converted into Hue images through changing the images color space into HSV. The use of Hue space enhances the ability to work on the color of the different components of the images without any illumination effects. Then, the proposed methodology detects the crop rows orientation. Through creating different sections in the Hue images at different orientation angles, the correct crop rows orientation can be detected as the one that provides the smallest PC2 using PCA of the Hu values within each section. Finally, the crop rows are detected using a line scanner process. A line scanner with the same detected orientation goes through the Hue image, where the average Hue value for each scan line is plotted is a separate graph. The peaks and the values of the created graphs represents the crop rows and the soil rows. To differentiate between the crop and soil rows, the Hue values of the peaks and valleys are compared with the Hue value of green color.

To evaluate the proposed methodology, different RGB images were acquired for a Canola agriculture field at different flight heights and different dates. The achieved results approved the ability of the proposed methodology to detect the crop rows from the imagery data without the need to perform a vegetation segmentation. Furthermore, the results showed the ability of the system to detect the crop rows in the images acquired at high altitudes as 100 and 120 meters. Also, the proposed methodology was able to detect the crop rows in the images acquired at early stages where the crop rows width was small.

Finally, based on the achieved results, it is recommended for future work to use the proposed methodology as a main step for weed detection approach. Moreover, the average Hue for each scan line can be used for crop row growth assessment applications.

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