A novel autonomous weedicide spraying machine for row based crops for agricultural applications using embedded linux

Maheswaran Shanmugam
Kongu Engineering College
Sathesh Shanmugam
Kongu Engineering College
Gomathi R.Duraisamy
Kongu Engineering College
Dhanalakshmi Samiappan
SRM Institute of Science and Technology
Ashok Kumar Loganathan
PSG College of Technology
Suresh Muthusamy (infostosuresh@gmail.com)
Kongu Engineering College
Hitesh Panchal
Government Engineering College
Ravita Lamba
MNIT: Malaviya National Institute of Technology

Research Article

Keywords: Weedicide, Autonomous Robotic Sprayer, Octave, Linux, Microcontroller, Embedded System

Posted Date: July 28th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1864358/v1

Abstract

An innovative approach to control the weeds by spraying the weedicide using ARM processor based single board credit card sized computer called Raspberry Pi with a selective spraying to reduce the wastage of chemicals was developed. The system was developed for precision spraying of weedicide using quantified information of the weeds from the image processing in Octave. This unit consists of a camera to capture the input image, Octave installed in a Raspberry Pi board and an autonomous robotic sprayer. The captured image was converted into gray scale then area thresholding was done to separate the crops and the weeds. The position of weed obtained from Octave was transferred to the microcontroller to control the sprayer movement by serial communication. Thus, the developed autonomous weeding system saves an amount of 48% of weedicide and provides an efficiency of 89%.

1. Introduction

The source of life for all mankind undoubtedly lies in the agricultural land. But now-a -days the usage of various kinds of chemicals and modern innovative approach in this field has ruined the soil fertility and productivity. The usage of chemicals is mainly to eliminate the presence of unwanted weeds which grow beside the crops. Weeds are potentially harmful plants growing in the unwanted areas which impair the quality of farm outcome (Hu, Thomasson, and Bagavathiannan 2021; Yiming et al. 2007). In addition to all the above problems, the nutrition available in the soil is shared among the crops and also the weeds present in the field which demands a greater need to eliminate the weeds (Shanmugam and Ramasamy 2014). When focusing narrowly over one particular crop turmeric, the presence of weed has led to a reduction in yield or diminutive growth of crops. The presence of weed in turmeric fields is of major concern. Presently, it is found that India produces 82% of turmeric and plays a predominant role in the world market. Next to India, China has 8% of turmeric production, Myanmar produces 4%, and both Nigeria and Bangladesh have only 3% of turmeric production. The process used to eliminate the weeds in case of conventional agriculture is direct spraying of weedicide over field (Machleb et al. 2020). However the major drawback of such direct method is spraying of chemicals in untargeted regions. In order to decrease the wastage of chemicals and to protect the environment, a method called precision agriculture can be used (Pawlowski et al. 2009).With the help of modern technology, the precision farming is very useful for site specific inputs in order to get more yields (Paudel et al. 2021; Subahi and Bouazza 2020). In (Ricciardi et al. 2021) projected a weed identification technique using image processing method and it was simulated using chemicals and high voltage. This system uses simulation and unsuitable for field implementation. In (Muppala and Guruviah 2020; Rehman et al. 2019) proposed a vision system which was able to categorize the patch of the weed and the row of the crop in real-time. It identifies only the weed and it is not implemented in the hardware. As an initiative method in corn, a microcontroller based manual three row roller contact type herbicide sprayer was designed to control weed population (Tewari et al. 2014). As this method involves computers, the cost gets increased and also does not support the autonomous system.

2. Methods And Materials

Precision agriculture in the field of weed management is a quite strenuous task as it involves the process of separating the crop from different types of weeds and demands various approaches to collect the data (Osorio et al. 2020). All the existing ways of machine vision approach incorporate 1) Foreground and background segmentation and 2) Detection of weeds. Segmentation of weed and crop under varying environment is an intricate task (Hernández-Rabadán, Guerrero, and Ramos-Quintana 2012; You, Liu, and Lee 2020). However, weed detection is a difficult task in case of later stages of development and hence it requires area based threshold information. Deciding the position of weed is difficult (John et al. 2020).

Thus, to prevent all the damages due to the weed, a method is developed which is capable of locating the position of weed (Chinnasamy 2012). In this project, the pioneering automated electromechanical weeder was designed using Octave and single camera based position estimation to destroy the weeds. This proposed system is highly efficient enough to accurately locate the weeds. Three main stages involved in this process were 1) Image acquisition and colour transformation, 2) Segmentation of foreground from background, 3) Classification of plant and weed. To separate weed, area based thresholding of the converted gray scale and segmented image was performed (Shanmugam and Asokan 2015).

2.1 Precision Spraying

The identified weed locations from the Octave algorithm were given as input to the microcontroller based robotic sprayer control. This input values was used to activate the sprayer and to fix the location of the weeds. Once the sprayer gets activated and position gets adjusted, it starts spraying over the weeds. This reduces the wastage of weedicide and also provides protection to crops. The autonomous electromechanical vehicle moves in the field using the information gained from the processed image to spray the weedicide precisely on desired locations alone in the turmeric field.

2.2 Overall Block Diagram

The general system processing is illustrated in the Fig. 1as a functional diagram. The block diagram described the complete weeding process from capturing of input image to the tail end (spraying of weedicide on weed).

2.3 Hardware Development

In this machine vision based electromechanical weeding process, the primary and the essential condition was the capture of image using a digital camera. A series of pictures was taken using the digital camera under the sunlight and was used to trigger the process of segmentation and weed detection. Separation was done followed by which detection was done. The processing was done in Octave software installed in ARM cortex embedded raspberry pi board.

2.4 Software Development

The process of image segmentation along with weed detection and microcontroller programming is described in Fig. 2.

The raw input images that were taken using digital camera under controlled conditions were given as an input to the image processing algorithm in Octave. The first and the foremost step in this process involved the usage of algorithm for foreground and background separation. As mentioned in the flowchart, the common materials which form the base for the development of this process were Raspberry Pi board and Octave software(Marot and Bourennane 2017).

2.5 Raspberry Pi Board

Table 1

Raspberry Pi Board Specifications

Sl.No	Component Name	Specifications
1.	Processor	Broadcom BCM2836 ARM cortex A7 quad core Processor Speed: 900 MHz
		GPU : Dual core Video core IV Multimedia co-Processor
3.	Voltage and power draw	650mA @5V
4.	RAM Memory	1GB SDRAM @400MHz
5.	SD card storage	Micro SD card (Bottom of the Board)
6.	GPIO	40
7.	USB 2.0	4
8.	Ethernet	10/100Mb Ethernet RJ45 Jack
9.	Audio & Video	Composite Video and Audio 3.5mm Jack
10.	Camera Interface	-
11.	HDMI Interface	-
12.	Display Interface	-

The raspberry Pi board consists of a default Raspbian OS and besides, there are some other OS like Noobs and many other OS which are linux based. Raspbian OS is similar to that of linux which is open source and all the commands used are also a replica of linux. In many of its kind, the Fig. 3 represents the brief explanation of components present in raspberry pi board and Table 1 provides the specifications of raspberry pi board. It is the one which provides the possibility of graphical user interface (GUI). It has a lot of peripherals to support different operations.

2.6 Octave Software

The Octave software programming is a tool similar to C language which aids most of the C library files/functions. It is a type of interpreted programming tool which supports the structured programming concepts. The functions and the system calls from the UNIX environment are also supported to certain extend. It is unsupported for passing arguments by reference. Octave and Matlab are mostly used by researchers, and engineers, in both industry and academic institutions to perform numerical computations and testing mathematical algorithms. For example, NASA used it to develop spacecraft docking systems; Jaguar Racing used it to display and analyze data transmitted from their Formula 1 cars; Sheffield University used it to develop software to recognize cancerous cells. Most of the functions of Matlab are present in Octave and are easily accessible with the package called Octave forge. At the same time, some of the functions of Matlab are not present in Octave.

2.7 Process Flow

The process of weed separation and location involves the following steps:

1) Image acquisition

2) Background separation

3) Classification of weeds and crops

4) Position of weeds

A raspberry pi camera was used to capture the image and the size of the image was initially configured into1024 x 768 pixels. The Octave software took longer time to process the images. Later the pixel size was reduced to 640 x 480 which offered the same result within a minimum time. The 640 x 480 pixel size was used during the entire process. The various implemented algorithms for background separation process were

a. OTSU Thresholding
b. Excess Green method
c. Intensity based Thresholding

a) OTSU Thresholding

Otsu's method, named after Nobuyuki Otsu was applied to perform grouping-based image threshold or the reduction to binary image from the gray level. A bi-modal histogram approach is followed in this algorithm containing two pixels namely foreground and background pixels, it then finds the optimum threshold separating the two classes and assume one for foreground pixels and zero for background pixels. Depending upon the threshold, some plant pixels will be classified as foreground and background. The Otsu's method of threshold needs extensive analysis for fitting the threshold value (Hague, Marchant, and Tillett 2000; Khambampati et al. 2018). So the method used was the ExG-ExR (Excess Green – Excess Red) as described in (Bassine, Errami, and Khaldoun 2019; Meyer and Neto 2008; Sivaranjani et al. 2019).

b) Excess Green Method

The technique applied for the classification was ExG minus ExR which has a constant index of zero threshold values. So it is not needed to have OTSU or any other threshold value. The ExG-ExR technique acts well on the growth (middle stage) of turmeric crops. ExG minus ExR technique is explained in the following:

Due to the changes present in the light intensity, the fundamental components of the color such as R (Red), G (Green) and B (Blue) get changed. Misclassification happens when the soil gets more green component in the high illumination and the plants gets less green component in the shade region. To minimize the effect of illumination, the ratios mentioned below are calculated for the given image, explaining the component of the colour in neglecting the intensity of light.

$r = R/(R + G + B)$ $g = G/(R + G + B)$ $b = B/(R + G + B)$ (1)

where R(red) ,G(green) and B(blue) has a range of values between zero and one as standardized coordinates of RGB and found out using the following steps.

$R = R/R_{max}$, $G = G/G_{max}$, $B = B/B_{max}$ (2)

Where $R_{max}=G_{max}=B_{max}=255$ for our 24-bit color images.

Indices computation: They are computed as follows:

Excess Green = $ExG = 2g - r-b$ (3)

Excess Red-$ExR = 1.4r-g$ (4)

Excess green minus excess red = $ExGR = ExG-ExR$ (5)

The removed gray image was converted to binary by conditional assignment. In the ExG-ExR method, the final image value above zero is defined as the plants and below zero is defined as background (Komarkova and Sedlak 2018; Meyer and Neto 2008; Tian et al. 2019). The various steps were calculated using Eq. (1) to Eq. (5). By means of the conditional assignment, zero was set to the background and 1 was set to the plant images, this defines it as a whole binary image. Though this method was better compared to Otsu method, there were some errors in this case because of the change in illumination during the entire daytime.

c) Intensity based threshold

After capturing the image, the input RGB image was converted into HSV. The following formulae help in identifying the mathematical procedure to do foreground and background separation using intensity based threshold.

$R^{'}=R/256$, $G^{'}=G/256$, $B^{'}=B/256$ (6)

$C_{max}=Max(R^{'},G',B^{'})$ $C_{min}=Min(R^{'},G',B^{'})$ $C = C_{max} - C_{min}$ (7)

$H = 0^{o}$ if $C = 0$

60^{o} $((G'-B^{'})/C)mod\ 6$ if $C_{max}=R^{'}$

60^{o} $(((B'-R^{'})/C) + 2)$ if $C_{max}=G^{'}$

60^{o} $(((R'-G^{'})/C) + 4)$ if $C_{max}=G^{'}$ (8)

$S = 0^{o}$ if $C_{max}=0$

C/C_{max} if $C_{max}\neq 0$ (9)

$V = C_{max}$ (10)

After converting the image into HSV, the threshold value for green colour was applied in the algorithm to discriminate the background. The values for hue image were greater than 0.19 and less than 0.45. For the saturation image, the threshold was in between 0.2 and 1 and for value it was less than 1. All the above thresholds were used and finally the foreground and background separation was obtained using Eq. (6) to Eq. (10).

2.7.1 Differentiating Crop from Weeds

In this electromechanical spraying process, it is very important to locate the position of weeds in order to precisely spray the weedicide only in that location avoiding the wastage of weedicide. To do so at the earliest, separating of weeds and crops in the input image is essential. There are many procedures available to separate the weeds and the plants (Lin 2009; Trong et al. 2020). Often, shape- based classification was done for discriminating the weeds from the crops (Leopardi-Verde et al. 2021; Watchareeruetai et al. 2007). If the shape based classification is adopted, the learning type processing should be done. It is a long process as the shape of the leaf will not be the same at all the time. The wind makes the leaf to oscillate which makes a lot of leaf shape pattern to be taken and trained, unless it will be a misprocessed output. And also the over brightness may cause the process to lose some of the shape information of the leaf unless an efficient coding is written to overcome this effect.

A simple and efficient methodology after inferring to lot of methods known as the area based classification was adopted (Cantarino et al. 2019; Nyman 2008). In this simple methodology of processing, the area (size) of the plant was considered as the important factor for processing. The process involves a random trial and error method to fix the required threshold range to separate the crop from the weed. Based on the analysis done from various input images provided to the Octave coding it was finally estimated that the area value of 4000 pixels was fixed as a threshold.

$$I(x,y) = \begin{cases} C, & Area >= T \\ W, & Area < T \end{cases} \quad (11)$$

W, Area < T

Where, C is the Crop

W is the Weed

I(x,y) is the Input Image

Area is the detected area of each component in the image

T is the threshold value which is set by analysis

The Eq. (11) clearly explains the classification technique using area threshold algorithm. If the detected area of filtered object is less than the threshold value, it was considered as weed else it was considered as crop. Threshold value will differ for various crop fields and can be set by area analysis of particular crop in the image.

2.7.2 Position of Weeds

Exactly locating the position of a particular object in an image that captured using a single camera was a difficult task. Hence a procedure for calculating the centroid of an object in the image was followed. The centroid of the objects which were located at some respective distance was calculated. The centroid provides the approximate position of the weeds stem because the crops were separated using an area based threshold algorithm. But for this the camera was fixed in a location above the ground at a particular angle with respect to the optical centre of it. As the input image captured was not a top view image, the centroid obtained will not focus the exact stem location of weeds. The Euclidean distance calculated using Eq. 12 can rectify this error.

Centroid = square root $((x1-x2)^2 + (y1-y2)^2)$ (12)

Finally, the centroid values obtained from the Octave coding was provided as input to the microcontroller by passing on them through serial communication. Controller acts as a link between the Octave software and robotic sprayer. The input obtained was used to help the microcontroller to decide the position of the solenoid valve and also activate the valve present in that location alone. The solenoid valve was adjusted to X and Y value of centroid obtained. The Fig. 4.completely describes the process carried out to detect the weeds using the algorithm.

3. Autonomous Robot

After the separation of weeds, their positions were obtained using the processing steps and the next step was to spray the weedicide on the weed. For the satisfactory functioning of the robotic arm, three axes were required for positioning. But in this method, the Z position of the sprayer was fixed as the weeds were in the fixed ground plane. The weed positions of X and Y was found by the algorithm and was used to spray the weedicide using the solenoid valve. The vehicle's forward movement must be between the rows in turmeric field. The row detection method produces the line of tracking for the machine's forward movement. The software program in the controller was written in such a way that, the data indicate the position of the weed and should thus be used to control the electronic valves. The vehicle shown in Fig. 5, consists of various components which are tabulated in Table 2. Microcontroller was programmed to control the movement of the vehicle by controlling the DC gear motors based on the signal obtained from the accelerometer, the proximity and the ultrasonic sensors.

The vehicle was supposed to travel in a straight line. If it takes the wrong direction, it can be controlled based on the information received from the accelerometer. A single image covers an area of 40 cm x 30 cm (aspect ratio). The data received from the Octave gave the XY value to reach the position of the weed. If the target weed position was above 25 cm from the vehicle's horizontal position, then 10 RPM motor was activated to move the sprayer's nozzle upwardly to target the weed. The nozzle setup was positioned for two angles by the 10 RPM motor. Proximity sensor was attached in the chase nearby the wheel to find out the distance travelled by the vehicle.

Table 2
Components used in the Robot with Specifications

Sl.No	Parts Name	Qty	Specifications
1.	Adjustable spraying nozzle	4	Manually adjustable boom
2.	Digital Camera	1	Raspberry Pi camera 5 MP
3.	Weedicide control solenoid Valve	4	12 V DC Solenoid valve/ NC type
4.	Coverage area control motor	1	Driven by 10 rpm, 12V DC gear motor
5.	Wheel	4	Driven by 30 rpm, 12V DC gear motor
6.	Ultrasonic distance sensor	3	HCSR04, range – 2 cm to 4m
7.	Weedicide Pump	1	FLO-2203, cut off 70 psi, 2.6lpm, 2.1A, 12 V, motor with auto overload /under load protection
8.	Raspberry Pi SBC	1	Pi 2 Model B
9.	Weedicide Tank	1	1 L Water Tank
10.	Robot Control Microcontroller with proximity sensor ,battery, drivers and accelerometer, buzzer etc.,	-	(Inside the casing)PIC18F458/ Proximity/ 12V / 7Ah/ Lead Acid/ADXL 335

Three ultrasonic sensors were used to detect the row end, the ridges and the furrows. Four normally open solenoids were activated by relays based on the information (position) received from the Octave image processing algorithm. Four nozzles were used to spray on the targeted with an adjustable boom. The entire image was divided into four parts and the weeds positions were grouped accordingly. The amount of the weedicide depends up on the density of the weed on that particular area. Solenoid activation period was adjusted depends on the weed density which were covered under the corresponding nozzle. Out of four nozzles, two nozzles point out the ridges and other two point out the furrows. Weedicide was sprayed out from a pump which has the over load protected auto cut off feature. The buzzer gets activated if the weedicide tank goes empty. Once the weed list (particular to an image) got exhausted, the trigger was given to take the next image for processing. All the communication between the raspberry pi and the microcontroller was a serial communication. The system included a projection to provide a shadow for the area exposed to avoid direct sunlight. Figure 6. shows the robot in the field testing.

3.7 Tracking Algorithm

A furrow tracking was an essential part for the automation of weed control which is shown in Fig. 7. To track the furrows, the robot uses three ultrasonic sensors (straight, left, right) which are not affected by sunlight. These sensors were fixed in the robot which unselects the small ups and downs in the field. With the help of these sensors, left and right turnings were calculated. For that, an efficient algorithm (shown as flowchart, Fig. 10) was developed for tracking the furrows and weedicide spraying in turmeric field.

The initial step in the algorithm was the pattern calculation for left and right turnings based on the number of furrows (The no. of furrows should be even number). For example, if the number of furrows was six then the pattern for turning was LT-RT-RT-RT-LT-LT-RT-RT-LT-LT-RT-RT-RT-LT (RT- right turn, LT-left turn). For an efficient spraying process, the calculation procedure was divided into two cases.

In the first case, as shown in Fig. 8, the value of the variable temp (as per flowchart) was calculated. The value is an even value based on the formula (total furrows − 1)/2. After the pattern calculation process, turn the robot to left or right direction. Here, it is considered as left turn and the spraying process starts. If it detects an empty space from the right sensor, the spraying process would be stopped to avoid overlapping when the robot follows the same path while returning. If again an empty space is detected, the robot starts its spraying process.

The right sensor should be continuously monitored and the spraying process should be controlled until the front sensor signal is detected. After the front sensor signal is detected, robot should be turned right and should continue the spraying process. This process is continued based on the initially calculated pattern. Meanwhile, total turnings are counted. Once the turning count is equal to furrows + 3, it is required to monitor the left sensor to avoid overlapping as it is done at the starting stage and then monitoring of turning counts are to be repeated for the remaining half of the field.

In the second case as shown in the Fig. 9, the temp value is an odd value based on the formula (total furrows-1)/2. The only difference between these two cases is that, the weedicide spraying process at the entering point of the field. In the second case, the spraying process is stopped at the starting point. Then the weedicide spraying process is controlled with the help of the right sensor. When the robot returns to the starting point of the field, the right sensor should be monitored to avoid overlapping. After detecting the starting point, the spraying process should be stopped and then the steps should be followed as in the first case. Likewise the spraying process is controlled for the remaining half of the field.

4. Results And Discussions

The developed autonomous electromechanical weeder was tested in a 1 hectare area. The complete area was divided into number of field and was prepared for easier movement of vehicle. Before this the manual spraying is carried out in different field areas and the amount of weedicide required is calculated. It is found that a total of 321 liters per hectare of weedicide mixed water (24.7 number of tank X 13 liter capacity tank). The developed system was tested in different fields with varied weed density and the field area was approximated to $20m^2$. A comparison between manual and proposed autonomous spraying is done as shown in Table 3.

Table 3

Amount of Weedicide Usage

Sl.No.	Usage of weedicide (litre/hectare)		Reduction in weedicide use (%)	Relative Deviation RD (%)
	Proposed Spraying	Manual Spraying		
1.	174	321	45.79	47.53
2.	178	321	44.54	
3.	169	321	47.35	
4.	145	321	54.82	
5.	176	321	45.17	

Relative deviation (RD) was calculated using Eq. (13) (Kumar and Pandey 2012; Man et al. 2017).

$$\mathrm{Relative Deviation} = \mathrm{RD} = 1/n\left(?_{a=1}^{n}\frac{\left(H_m - H_a\right)}{H_m}\right)100$$

13

Where

n = Number of Samples

H_m = Weedicide consumption from Manual spraying

H_a = Weedicide consumption from Autonomous spraying

Glycophospate is the chemical that was mixed with water in the ratio of 1:1000 and used for weed control. On an average 145 litres to 178 litres per hectare is used based on weed density and the percentage reduction varies between 44.54 and 54.82.The developed machine weeding effectiveness was tested using Eq. (14)(Zeng et al. 2021).

$$W_e = \frac{W_b\text{-}W_a}{W_b}$$

14

Where W_e= Weeding Efficiency

W_b= Number of weeds before Weedicide application

W_b= Number of weeds after Weedicide application

The area selected for the calculation is 1.2 m^2 from each selected field (10 number of image inputs each has 40 cm x 30 cm size).

Table 4
Weeding Efficiency

Field No.	Number of weeds before weeding	Number of weeds after weeding	Weeding Efficiency
1.	48	42	87.5
2.	35	31	88.57
3.	34	30	88.24
4.	21	19	90.48
5.	37	33	89.19
Average			**88.8**

Thus, an Octave controlled single camera positioning system took image from the field and intensity based thresholding followed by area thresholding proved to provide a clear discrimination between weed and plant. The proposed system provides 89% of weeding using the centroid position obtained. Table 4 gives the percentage of efficiency of the proposed weeding process.

5. Conclusion

The projected system successfully provides the separation of weeds and crop using intensity based segregation of background from foreground followed by area threshold. The estimated weed position, pixel position information obtained from Octave was given to the vehicle to realise the position of weeds and made spraying of weedicide over field possible. It proves to be a feasible alternative for the available weeding methods because it removes the weed with an efficiency of 89%. In addition to the above, it also reduces the usage of weedicide at about 48% eventually protecting the crops and also the soil from turning into an infertile one. The tuning of autonomous tracking system can be done to improve the percentage efficiency of weeding. Ultimately, it proves to control the weed and increases the yield of turmeric field with small chemical usage and high quality of crops.

Declarations

Conflict of interest

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data Availability:

The data used to support the findings of this study are available from the corresponding author upon request

Funding information

There was no financial support received from any organization for carrying out this work

Ethical Approval

This material is the authors' own original work, which has not been previously published elsewhere. The paper is not currently being considered for publication elsewhere. The paper reflects the authors' own research and analysis in a truthful and complete manner.

Consent to Participate

I have been informed of the risks and benefits involved, and all my questions have been answered to my satisfaction. Furthermore, I have been assured that any future questions I may have will also be answered by a member of the research team. I voluntarily agree to take part in this study

Consent to Publish

Individuals may consent to participate in a study, but object to having their data published in a journal article

Competing Interests

To the best of my knowledge and belief any actual, perceived or potential conflicts between my duties as an employee and my private and/or business interests have been fully disclosed in this form in accordance with the requirements of the journal

Author contribution

Maheswaran Shanmugam, Sathesh Shanmugam- Drafting the manuscript

Gomathi R.Duraisamy, Dhanalakshmi Samiappan- Supervision

Ashok Kumar Loganathan, Suresh Muthusamy - Assisting in drafting the manuscript

Hitesh Panchal, Ravita Lamba - project administration

References

1. Bassine, F. Z., Errami, A., and Khaldoun, M. 2019. Vegetation Recognition Based on UAV Image Color Index. *2019 IEEE International Conference on Environment and Electrical Engineering and 2019 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)* (pp. 1-4): IEEE.

2. Cantarino, I., Carrion, M. A., Goerlich, F., and Ibañez, V. M. 2019. A ROC analysis-based classification method for landslide susceptibility maps. *Landslides, 16*(2): 265-282.
3. Chinnasamy, G., Palaniswamy, M, Pavithra, M, Periasamy, A & Muruganand, S. 2012. Identification of weeds in turmeric (Curcuma Longa) plants using unsupervised SKPCA algorithm with Image Processing. *International Journal of Science and Nature, 3*(1): 121-124.
4. Hague, T., Marchant, J., and Tillett, N. 2000. Ground based sensing systems for autonomous agricultural vehicles. *Computers and Electronics in Agriculture, 25*(1): 11-28.
5. Hernández-Rabadán, D. L., Guerrero, J., and Ramos-Quintana, F. 2012. Method for Segmenting Tomato Plants in Uncontrolled Environments.
6. Hu, C., Thomasson, J. A., and Bagavathiannan, M. V. 2021. A powerful image synthesis and semi-supervised learning pipeline for site-specific weed detection. *Computers and Electronics in Agriculture, 190*: 106423.
7. John, K. N., Valentin, V., Abdullah, B., Bayat, M., Kargar, M. H., and Zargar, M. 2020. Weed mapping technologies in discerning and managing weed infestation levels of farming systems. *Research on Crops, 21*(1): 93-98.
8. Khambampati, A., Liu, D., Konki, S., and Kim, K. 2018. An automatic detection of the ROI using Otsu thresholding in nonlinear difference EIT imaging. *IEEE Sensors Journal, 18*(12): 5133-5142.
9. Komarkova, J., and Sedlak, P. 2018. UAV Spectral Image Mapping of Shoreline Vegetation. *GIM International, volume 32, issue: 6*.
10. Kumar, and Pandey. 2012. A device to measure dynamic front wheel reaction to safeguard rearward overturning of agricultural tractors. *Computers and electronics in agriculture, 87*: 152-158.
11. Leopardi-Verde, C. L., Guzmán-González, S., Carnevali, G., de Stefano, R. D., and Tapia-Muñoz, J. L. 2021. Weeds of commercial crops in Colima, Mexico. *Revista Mexicana de Biodiversidad, 92*: 923622.
12. Lin, C. 2009. A support vector machine embedded weed identification system. University of Illinois at Urbana-Champaign.
13. Machleb, J., Peteinatos, G. G., Kollenda, B. L., Andújar, D., and Gerhards, R. 2020. Sensor-based mechanical weed control: Present state and prospects. *Computers and Electronics in Agriculture, 176*: 105638.
14. Man, S., Ter Haar, C. C., de Jongh, M. C., Maan, A. C., Schalij, M. J., and Swenne, C. A. 2017. Position of ST-deviation measurements relative to the J-point: Impact for ischemia detection. *Journal of electrocardiology, 50*(1): 82-89.
15. Marot, J., and Bourennane, S. 2017. Raspberry Pi for image processing education. *2017 25th European Signal Processing Conference (EUSIPCO)* (pp. 2364-2366): IEEE.
16. Meyer, G. E., and Neto, J. C. 2008. Verification of color vegetation indices for automated crop imaging applications. *Computers and Electronics in Agriculture, 63*(2): 282-293.

17. Muppala, C., and Guruviah, V. 2020. Machine vision detection of pests, diseases and weeds: A review. *J. Phytol., 12*: 9-19.
18. Nyman, M. 2008. Image analysis and morphological operations as tools for weed and crop detection.
19. Osorio, K., Puerto, A., Pedraza, C., Jamaica, D., and Rodríguez, L. 2020. A deep learning approach for weed detection in lettuce crops using multispectral images. *AgriEngineering, 2*(3): 471-488.
20. Paudel, K. P., Mishra, A. K., Pandit, M., and Segarra, E. 2021. Event dependence and heterogeneity in the adoption of precision farming technologies: A case of US cotton production. *Computers and Electronics in Agriculture, 181*: 105979.
21. Pawlowski, Guzman, Rodríguez, Berenguel, Sánchez, and Dormido. 2009. Simulation of greenhouse climate monitoring and control with wireless sensor network and event-based control. *Sensors, 9*(1): 232-252.
22. Rehman, T. U., Zaman, Q. U., Chang, Y. K., Schumann, A. W., and Corscadden, K. W. 2019. Development and field evaluation of a machine vision based in-season weed detection system for wild blueberry. *Computers and Electronics in Agriculture, 162*: 1-13.
23. Ricciardi, V., Mehrabi, Z., Wittman, H., James, D., and Ramankutty, N. 2021. Higher yields and more biodiversity on smaller farms. *Nature Sustainability*: 1-7.
24. Shanmugam, M., and Asokan, R. 2015. A Machine-Vision-Based Real-Time Sensor System to Control Weeds in Agricultural Fields. *Sensor Letters, 13*(6): 489-495.
25. Shanmugam, M., and Ramasamy, A. 2014. Sensor-Based Turmeric Finger Growth Characteristics Monitoring Using Embedded System under Soil. *International Journal of Distributed Sensor Networks, 2014*.
26. Sivaranjani, C., Kalinathan, L., Amutha, R., Kathavarayan, R. S., and Kumar, K. J. 2019. Real-Time Identification of Medicinal Plants using Machine Learning Techniques. *2019 International Conference on Computational Intelligence in Data Science (ICCIDS)* (pp. 1-4): IEEE.
27. Subahi, A. F., and Bouazza, K. E. 2020. An intelligent IoT-based system design for controlling and monitoring greenhouse temperature. *IEEE Access, 8*: 125488-125500.
28. Tewari, V., Kumar, A. A., Nare, B., Prakash, S., and Tyagi, A. 2014. Microcontroller based roller contact type herbicide applicator for weed control under row crops. *Computers and Electronics in Agriculture, 104*: 40-45.
29. Tian, K., Li, J., Zeng, J., Evans, A., and Zhang, L. 2019. Segmentation of tomato leaf images based on adaptive clustering number of K-means algorithm. *Computers and Electronics in Agriculture, 165*: 104962.
30. Trong, V. H., Gwang-hyun, Y., Vu, D. T., and Jin-young, K. 2020. Late fusion of multimodal deep neural networks for weeds classification. *Computers and Electronics in Agriculture, 175*: 105506.
31. Watchareeruetai, U., Takeuchi, Y., Matsumoto, T., Kudo, H., and Ohnishi, N. 2007. A Lawn Weed Detection in Winter Season Based on Color Information. *MVA* (pp. 524-527).

32. Yiming, Z., Xianglong, Y., Xishan, G., Mingang, Z., and Liren, W. 2007. A design of greenhouse monitoring & control system based on ZigBee wireless sensor network. *Wireless Communications, Networking and Mobile Computing, 2007. WiCom 2007. International Conference on* (pp. 2563-2567): IEEE.
33. You, J., Liu, W., and Lee, J. 2020. A DNN-based semantic segmentation for detecting weed and crop. *Computers and Electronics in Agriculture, 178*: 105750.
34. Zeng, Z., Martin, A., Chen, Y., and Ma, X. 2021. Weeding performance of a spring-tine harrow as affected by timing and operational parameters. *Weed Science, 69*(2): 247-256.

Figures

Figure 1

General Block Diagram

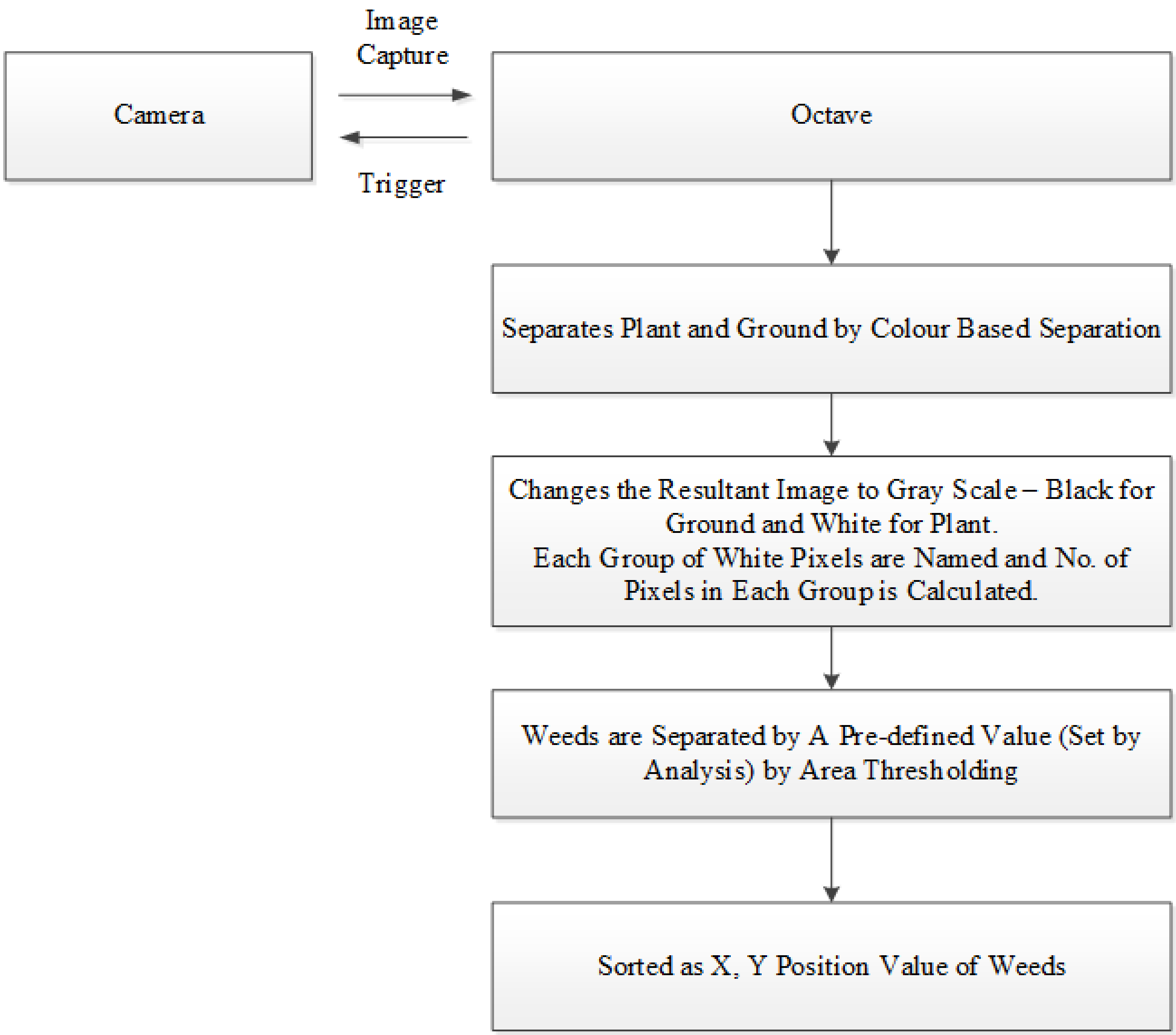

Figure 2

Flowchart Describing Image Segmentation and Weed Detection

Figure 3

Parts of Raspberry pi SBC

Figure 4

Simulation Results

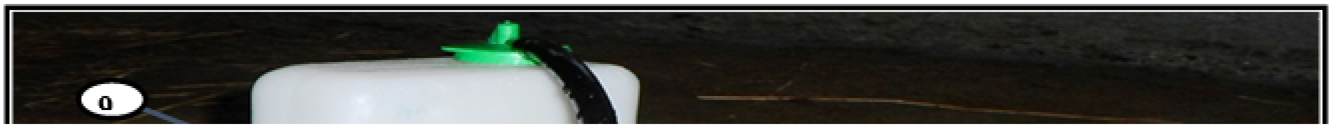

Figure 5

Autonomous Robot with Parts

Figure 6

Autonomous Robot in the test field

Figure 7

Field Diagram for Tracking

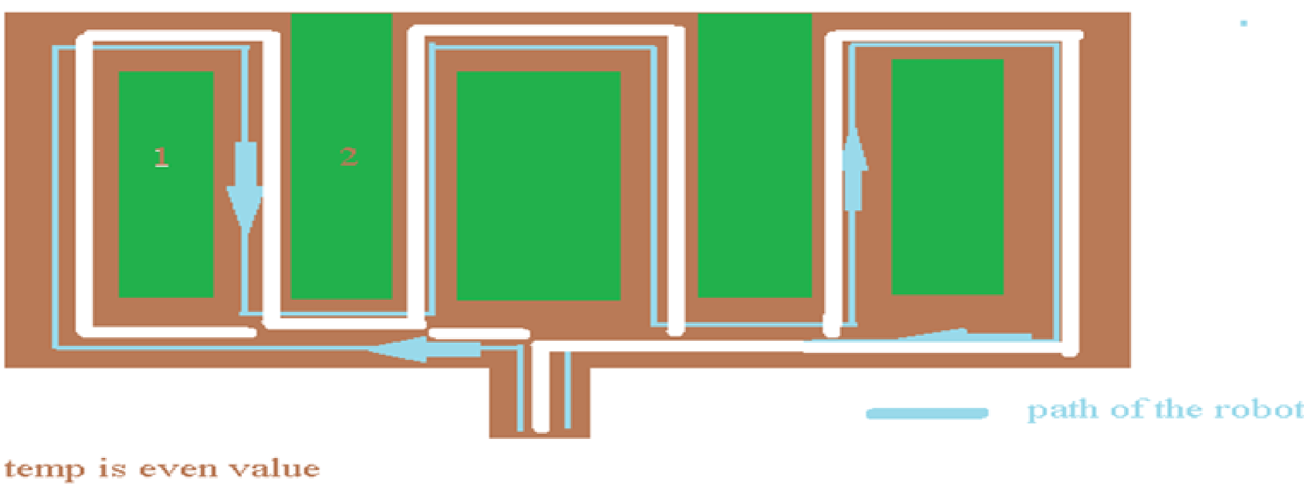

Figure 8

Proposed Spraying Strategy for First Case-Temp is Even

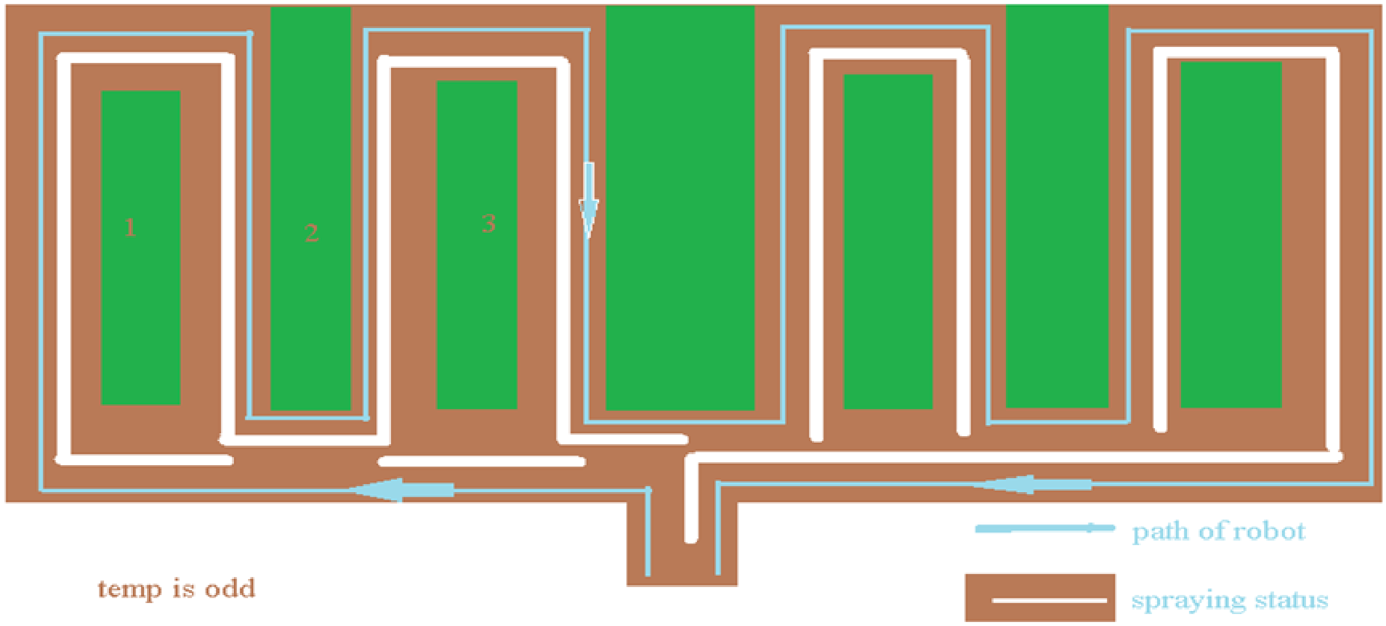

Figure 9

Proposed Spraying Strategy for Second Case-Temp is Odd

Figure 10

Flowchart of Autonomous Robot for Tracking

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- WPCbiography.docx