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An overview of Automation, Robotics, and Sensor-based Approaches in Weed Detection and Control

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Abstract: Limiting factors of general weed control methods create the situation for the design-development of new approaches based on robotics, automation, and sensor techniques. Several studies have documented the yield loss associated with weed competition and weed discrimination, identification, and control mechanisms. The automatic distinction between crop and weed has importance in weed control applications. Sensor-based approaches, machine vision systems, RTK GPS-based systems, and some other techniques are effective in weed control and help in improving crop yield. Robotic technology could provide a means to reduce the current dependency of agriculture on chemical herbicides by minimizing environmental impacts. The new technologies promise the future improvement of agriculture's few remaining unmechanized and drudgery tasks. So, here we tried to give an overview of these improved technologies in weed control applications.

Keywords: Machine vision, RTK (Real-time-kinematics), GPS (Global positioning system)

Agriculture and weed control or weeding both is old practices. Since the beginning of agriculture, farmers have struggled continuously in their farmland to control weeds. Weed can be considered a pivot issue in farm management practices and is responsible for losses in farm produce of about 45% (Rao et al 2020). Crop yield and quality loss are due to many factors, including crop-weed competition, weed and crop plant density, weed emergence time relative to crop, length of weed existence (roughly one-third of the cycle of a beneficial crop), and weed proximity with the crop plants. Knowledge about biology and the nature of weeds is most important in selecting successful weed control techniques. Weed control tasks with manual, biological, chemical, cultural, mechanical, and thermal methods are more expensive, laborious, tedious, and time-consuming. Manual weeding is the most efficient method of weed control but is a labor and time-consuming process, with more chances of physical injuries associated with this method. (Maurya et al 2020). Mechanical weeding operations are not suitable for all crops and not sufficient for intra-row weeds (Upadhyay et al 2012). Presently weed control methods (in row crops) follow a combination of tillage (mechanical cultivation) with pre-emergence or post-emergence application of chemical herbicides and hand hoeing (Utstumo et al 2018). Consequently, chemical-based weeding can be an effective biological method and economically efficient irrespective of environmental impacts in many circumstances. Increasing regulations on pesticide use on consumer concerns and growing interest in organically produced foods in certain regions limit the chemical-herbicide application's long-term acceptability. Meanwhile, selective post-emergence herbicides are unavailable or ineffective, requiring the hoeing of “in-row” weeds. Thermal weed controlling uses an electric discharge, laser, and flame. Among all rapidly growing weed control techniques, site-specific weed management (SSWM) is taking the top position. It refers to machinery/equipment embedded with technologies that detect weeds growing in a crop and successfully control them without disturbing the beneficial crop. Integrating site-specific weed distribution data, the composition of weed species, size, and impact on crop field is essential to effective site-specific weed management (Chauhan et al 2017). Many advanced research studies are going on weed detection. Some of them are (1). Row guidance system: vision-based automatic row guidance system and RTK-GPS-based row guidance system, (2). Sensor-based and Machine vision recognition of plant species, and (3). GPS mapping systems: automatic RTK-GPS crop seed mapping and automatic GPS and machine vision weed mapping. Among all weed control methods, automatic crop-weed discrimination takes an important role (Abbas et al 2018).

New approaches based on the combination of sensors with different properties and microcontroller processors need to develop that can be used for effective weed control. Since the availability of sensors is not easy for farmers and knowledge of handling them requires some additional effort. Hence, suitable sensor-based systems are not yet widely adopted for practical purposes. The combination of automatic weed detection and mechanical or chemical control is one of the emerging areas in the sustainable crop production field. Therefore, automated or sensor-based weed control is one of the new approaches for non-chemical or low chemical weed control or controlled mechanical weed removal (Chauhan et al 2017).

MATERIAL AND METHODS

Basic weed detection and control system architecture: The selection of weed identification and discrimination method isa high priority for real-time weed detection and control. Sensor-based weed detection and control systems work based on the above strategy. An agricultural robot consists of three key components:

1. a sensing system: measures significant biological and physical properties;
2. a data-processing system: processes the sensor data to know how to manipulate the subsequent system, and
3. a mechanical weeding or chemical spraying unit: actuators manipulated to do the functions accordingly."

Methods like machine vision or image processing, GPS, variable-rate applications, and robotics could provide technological tools to enable robotic weeding.

Working Principles of weed detection and control methods: Andujar et al (2012) designed a weed recognition and control system using the ultrasonic sensor. The system consists of an ultrasonic sensor connected to a power source (12V battery), a data acquisition system (Labjack U12) connected to a laptop through the USB connector, and a robotic operating system (ROS) with a harrowing unit (Fig. 1). Ultrasonic devices works based on the measurement of reflected sound waves. The estimation of the distance is based on the physical principle of time of flight, producing a short burst of sound in a unique direction. After the impact of an object, the wave returns to the receiver.

$$\text{Distance} = \frac{\text{Speed} \times \text{Time}}{2} \quad \text{...... (1)}$$

The device measures the acoustic signal's travel time and transforms it into a voltage signal also possible to convert the output voltage to distance units. The ultrasonic sensor measures the distance between weed mixtures and crop plants. Monitoring weed infestations as a measure of harrowing intensity and these changes were employing previous weed density and tine angle measurements. Weed density classes are defined using fuzzy logic and correlated with ultrasonic measurements. The distance between the sensor and the plants was calculated using Equation (1). A fuzzy set was developed by Rueda-Ayala et al (2015) based on the correlation data of ultrasonic readings (height) with weed densities for laboratory measurements (Table 1).

The intensity classes, controlling the electrical actuator, and harrow tines movement were related to individual ultrasonic measurements. The harrowing intensity uses the angle made by tine with the horizontal and converted to the percentage of maximum angle (90°).Ruiz et al*.* (2014) modeled and built up an intra-row weed detection and control system. The four technologies are driven by the general-purpose autonomous weed control system**:** RTKGPS or machine vision, weed recognition (hyperspectral imaging, machine vision, RTKGPS), precise in-row weeding (micro-spray, cutting, thermal, electrocution), and mapping (GPS & machine vision). RTK-GPS can utilize for auto-guidance in seedbed preparation, with automatic on-the-fly, and geo-positioned mapping during transplanting. This map was used to give input about the location of crop plants to the RTK GPS during the weeding operation. The program was set in the control unit of weeding hoe blades such that except for the crop plant location, it assumes any other plant as a weed. As the intra-row hoes (Fig. 2) pass the plant and reach the exact location, the pneumatic cylinders reposition the hoes to follow the grey dashed lines until they meet in the center of the row. This process was repeated for each plant.

Machine vision-based weed detection and control: The machine vision system is employed to identify the weeds and crops and destroy the weeds by locating them with help of a control unit based on different discrimination factors and the accuracy of some machine vision techniques given in Table2 (Guzman et al 2019). The combined system of automatic weed detection by machine vision and weed control by electrical discharges consists of two machine vision systems and an end effect or for weed identification, location, and control.

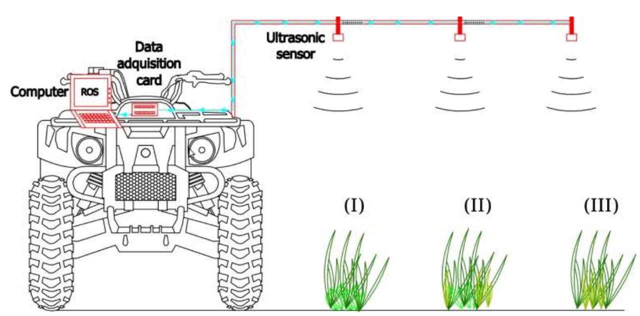

Fig. 1. Ground-based ultrasonic system for weed detection (Andujar et al 2012)

Primary machine vision system: This was designed to detect the individual weeds with the mission to locate weeds on a real-time basis with the forward movement of the robot. The system consists of a color camera connected to a digitizing board inserted into a Pentium-based computer. The vision system needs to process each image captured to the desired pixel quality based on real-time data acquisition and transmission specifications. The developed software was divided into three major tasks: image acquisition, image processing, and transmission of the location of the weeds to the supervisory system and the secondary machine vision system. The information transferred to these systems has to position each weed in the image, the digital signatures of each of the weeds, and a time reference (Blasco et al 2002).

During real-time operation, images were scanned, and each pixel was automatically assigned to a plant or soil class, depending on its RGB (Red, Green & Blue) coordinates. The image is converted from RGB to HSV (Hue-Saturation value) in image pre-processing. The equation below represents the HSV color space and the pixels hue value Ph (i, j), saturation value Ps (i, j), and value Pv (i, j) in the color space and their conversion relationship with the RGB color model (Equation: 2, 3 and 4.)

$$P_h(i,j) = \cos^{-1}\left\{\frac{0.5\left[\left(P_r(i,j)-P_g(i,j)\right)+\left(P_r(i,j)-P_b(i,j)\right)\right]}{\sqrt{\left(\left(P_r(i,j)-P_g(i,j)\right)^2-\left(P_r(i,j)-P_b(i,j)\right)\left(P_g(i,j)-P_b(i,j)\right)\right)}}\right\} \quad \dots (1)$$

$$P_s(i,j) = \frac{\max\left(P_r(i,j),P_g(i,j),P_b(i,j)\right)-\min\left(P_r(i,j),P_g(i,j),P_b(i,j)\right)}{\max\left(P_r(i,j),P_g(i,j),P_b(i,j)\right)} \quad \dots (2)$$

$$P_v(i,j) = \frac{\max\left(P_r(i,j),P_g(i,j),P_b(i,j)\right)}{255} \quad \dots (3)$$

In a second step, the area, the perimeter, and the centroid of each weed are calculated. Objects smaller than the pre-set threshold are considered noise and filtered. Objects larger than another pre-set threshold were considered a crop. The remaining objects were considered weeds (Fig. 3), and t and c ordinates of their centroid were sent to the supervisor and the second vision system. The values of the two above-mentioned thresholds were established during the offline training operation. For each detected weed, a digital signature based on its luminance distribution was also sent to the second vision system.

Secondary vision system (Blasco et al 2002): The objective is to locate the previous weeds, one at a time, provide their actual position, and correct the trajectory of the weeding tool, thus compensating for positioning errors generated by the lack of accuracy of the inertial unit. The module consisted of a monochromatic camera coupled to a specific processing system. The camera is firmly attached to the manipulator and was initially focused on weeds by the primary vision system. At the request of the supervisor, the second vision system grabs an image located on the same weed under its field of view, comparing its signature with that of the primary camera system. Finally transmits the actual coordinates of the weed to the supervisor, and directed the end effector to this position. The end-effector is an electrode that produces electrical discharges of 15 kV and 30mA during 200 ms approximately. The machine was powered by a set of four 24V batteries that provide nearly 40 A. The six degrees of freedom of the robot are implemented by six electrical motors

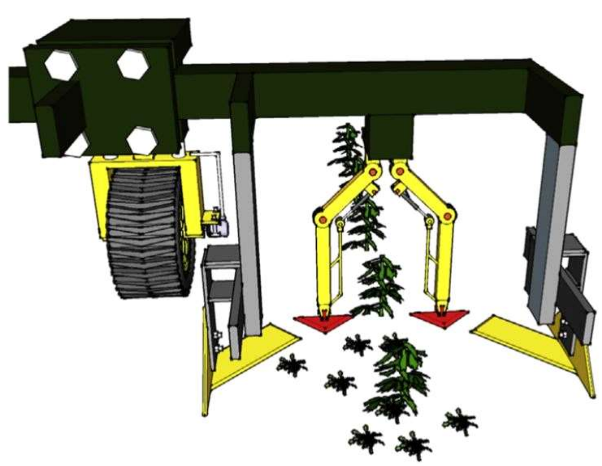

Fig. 2. A miniature co-robotic weeding unit with a pair of intra-row hoes (red triangles) and an odometry sensor (Ruiz et al 2014)

Table 1. Plant height ranges to control harrowing intensity correspond to five discrete classes in Decision Support System (Rueda-Ayala et al 2015)

Class	Min height (cm)	Max height (cm)	Plant density (plants m^{-1})	Harrowing intensity
0	0	10	0-15	None
1	10	15	16-30	Lightest
2	15	20	28-47	Light
3	20	25	45-63	Strong
4	25	77	>60	Strongest

(100W each). At last, the end-effector moves in the trajectory decided by the primary and secondary vision system information (Fig. 4).

RESULTS AND DISCUSSION

The ultrasonic sensor system is used to detect the density of weed infestation in the field. The height data obtained from the ultrasonic sensor was correlated with total biomass and the weed density that were obtained by manual harvesting of weed after the detection process. Weed presence was correctly predicted in more than 92% of the cases. The use of ultrasonic sensor readings proved useful to discriminate grasses (up to 81.1% of success) and broadleaf weeds (up to 98.5% of success). The correlation coefficient was 0.99 for weed height assessed by the ultrasonic sensor and weeding intensity adjusted by the system. Using this method of weed detection Rueda-Ayala et al (2015) developed and system to automatically control the weed. As per the density of weed, the intensity of the tillage was changing. This pre-decides in the system algorithm using fuzzy logic. The harrowing intensity sent by the control unit to the tines to change their angle thus adjusting the harrowing intensity– corresponded well to the change in weed infestation level along the field. The system performed well at high driving speeds needed for harrowing operations (e.g., 12 km/h).

Table 2. Accuracy of different machine vision techniques (Raj and Kavitha 2018)

Method	Accuracy (%)
Spectral reflectance property	85-87
Colour property	50-96
Topology property	83-91
Texture features	30-78
Wavelength transformation	86-94
Pattern matching algorithm	91-97

RTK GPS-based weed detection method was used in association with the intra-row weed control system. The crop (tomato) plants were visually evaluated immediately after the co-robot operation of each row to determine the number of crop plants harmed by the hoes. Field Trials were conducted at 1.2, 1.6, and 2.4 km/h. At the 0.8 and 1.2 km/h travel speeds, no flag contact or damage to the crop plants, respectively, were observed. At the 1.6 km/h speed, flag contact or major damage to the crop plants occurred about 0.5% and 1% of the time, respectively, and increased to 5% in the 4 km/h flag trial and 3% in the 2.4 km/h crop trial. Based on these results, a co-robot travel speed of 1.2 km/h was selected for further study. An 8 h long operational trial was then conducted in the commercial crop field at a travel speed of 1.2 km/h. During this 8 h trial, 0.5% of the crop plants were accidentally killed or received major root damage by the co-robot hoes. The findings showed the feasibility of using RTK-GPS in controlling the path of weeding knives automatically, which is operating between the intra-row region of crop plants in sustainable cropping. This system could save about 57.5%

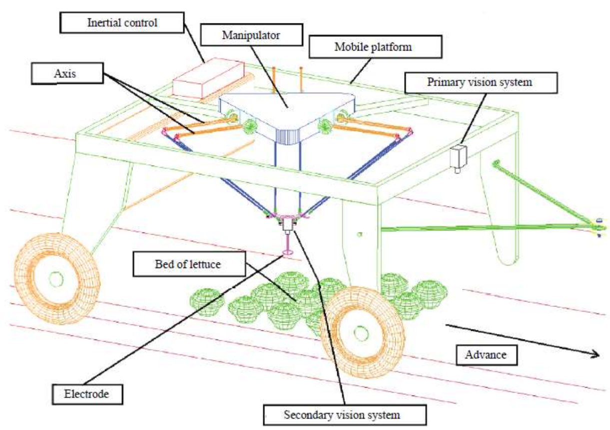

Fig. 4. Electrical control weeding using machine vision system (Blasco et al 2002)

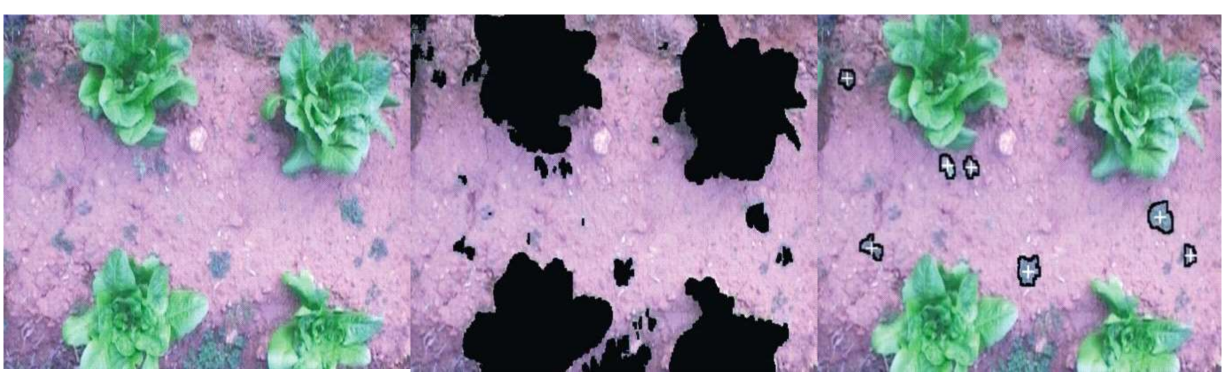

Fig. 3. Weed detection by machine vision system (a) Original field image showing weeds and crop (b) Plant and soil segmentation (c) Detected weeds (Blasco et al 2002)

Table 3. Weed detection and control studies

Researcher name	Source	Research topic	Research approach	Researcher details	Journal name
M. Norremark	Norremark et al (2012)	Evaluation of an autonomous GPS-based system for intra-row weed control by assessing the tilled area	RTK-GPS navigation guided system	Department of Biosystems Engineering, Faculty of Agricultural Sciences, Aarhus University, Denmark e-mail: Michael.Norremark@djf.au.dk	Precision Agriculture: An International Journal on Advances in Precision Agriculture
H.W. Griepentrog	Griepentrog et al (2007)	Autonomous inter-row hoeing using GPS-based side-shift control	RTK-GPS navigation guided system with hoeing attachment	Copenhagen University, Faculty of Life Sciences, Dept. of Agricultural Sciences, Denmark. E-mail: hwg@life.ku.dk	Agricultural Engineering International: the CIGR Journal
D.C. Slaughter	Slaughter et al (2008)	Autonomous robotic weed control systems: A review	---	The University of California, Biological and Agricultural Engineering, Davis, CA 95616, United States	Computers and electronics in agriculture
J. Blasco	Blasco et al (2002)	AE—Automation and emerging technologies: robotic weed control using machine vision	Robotics and Machine-vision systems assisted mechanical weeding	emolto@ivia.es	Biosystems Engineering
R Y VAN DER WEIDE	Van Der Weide et al (2008)	Innovation in mechanical weed control in crop rows	Mechanical weeding: Pneumatic blowing, Torsion weeders, Finger weeders	Applied Plant Research, Wageningen University, and Research Centre, Lelystad, the Netherlands	Weed research
J. Bontsema	Bontsema et al (1998)	Intra-row weed control: a mechatronics approach	Digital signal processor (DSP) with mechanical weed control system	Wageningen, The Netherlands	IFAC Proceedings Volumes
N. D. Tillett	Tillett et al (2008)	Mechanical within-row weed control for transplanted crops using computer vision	Computer-based machine vision guidance along and mechanical weeding attachment	Tillett & Hague Technology Ltd., Greenfield, Bedfordshire, UK	Biosystems Engineering
Zoltan Gabor	Zoltan Gabor (2013)	Mechatronic system for mechanical weed control of the Intra-row Area in Row Crops	Detection system composed of RGB sensor and laser sensor with mechanical weeding tool (hoe, electric driven)	Bavarian State Research Center for Agriculture, Institute for Agricultural Engineering and Animal Husbandry, Germany e-mail: zoltan.gobor@lfl.bayern.de	KI-Künstliche Intelligenz
W. Bond and A. C. Grundy	Bond and Grundy (2001)	Non-chemical weed management in organic farming systems	Selective weed control operations (cultural, mechanical, thermal, and biological methods)	Horticulture Research International, Wellesbourne, Warwick, UK E-mail: andrea.grundy@hri.ac.uk	Weed research
Cointault Frédéric	Frederic et al (2012)	Texture, color, and frequential proxy-detection image processing for crop characterization in a context of precision agriculture	Remote sensing and sensor-based image detection using Proxy-Detection Image Processing	Agro-Sup Dijon, France	Agricultural science
Chung-Liang Chang and Kuan-Ming Lin	Chang and Lin (2018)	Smart agricultural machine with a computer vision-based weeding and variable-rate irrigation scheme	Computer-based machine vision system with multitasking unit	Department of Bio Mechatronics Engineering, National Pingtung University of Science and Technology, Pingtung 91201, Taiwan Email: chungliang@mail.npust.edu.tw	Robotics

Cont...

Table 3. Weed detection and control studies

Researcher name	Source	Research topic	Research approach	Researcher details	Journal name
Bjorn Astrand And Albert-Jan Baerveldt	Astrand and Baerveldt (2002)	An agricultural mobile robot with vision-based perception for mechanical weed control	Machine vision and robotics	Halmstad University, Halmstad, Sweden Bjorn. Astrand@ide.hh.se	Autonomous robots
A. Piron	Piron et al (2011)	Weed detection in 3D images	Machine vision system with video recording	Environmental Science and Technology Department, Gembloux Agricultural University, Gembloux, Belgium e-mail: piron.a@fsagx.ac.be	Precision agriculture
Yun Zhang	Zhang et al (2012)	Robust hyperspectral vision-based classification for multi-season weed mapping	Hyperspectral image-based plant recognition, Machine vision system with a CCD camera and line-imaging spectrograph for close-range weed sensing and mapping.	Department of Biological and Agricultural Engineering, University of California, Davis, One Shields Avenue, Davis, CA 95616, United States	ISPRS Journal of Photogrammetry and Remote Sensing
F. Lopez- Granados	Lopez-Granados, F (2011)	Weed detection for site-specific weed management: mapping and real-time approaches	Remote sensing based on multispectral aerial imagery, unmanned aerial vehicles (UAV), and robotic weeding systems	Institute for Sustainable Agriculture/CSIC, P.O. Box 4084, 14080-Córdoba, Spain. E-mail: flgranados@ias.csic.es	Weed research
Gerassimos G. Peteinatos	Peteinatos et al (2014)	Potential use of ground-based sensor technologies for weed detection	Ground-based sensors for weed detection (cameras, distance sensors, spectrometers, fluorometers)	Department of Weed Science, University of Hohenheim, Otto-Sander-Str. 5, 70599 Stuttgart, Germany. E-mail: G.Peteinatos@Uni-Hohenheim.de	Pest management science
Shirzadifar, A. M	Shirzadifar (2013)	Automatic weed detection system and smart herbicide sprayer robot for cornfields	Machine vision algorithm and robotic weeding	Department of Electrical Engineering, Shiraz University, Iran	First RSI/ISM International Conference on Robotics and Mechatronics (ICRoM)
Uri Shapira	Shapira et al (2013)	Field spectroscopy for weed detection in wheat and chickpea fields	Remote sensing-based spectroscopy for weed detection	The Remote Sensing Laboratory, Jacob Blaustein Institutes for Desert Research, Ben-Gurion University of the Negev, Beersheba, Israel	International journal of remote sensing
Daniela Stroppiana	Stroppiana et al (2018)	Early-season weed mapping in rice crops using multi-spectral UAV data	UAV imagery for weed mapping with help of a Parrot Sequoia sensor mounted on a quadcopter	Institute for Electromagnetic Sensing of the Environment (IREA), Consiglio Nazionale Delle Ricerche, Milano, Italy	International journal of remote sensing
Christian Frasconi	Frasconi et al (2014)	Design and full realization of physical weed control (PWC) automated machine within the RHEA project	Machine vision-based detection with a micro-sprayer system	Luisa Martelloni, Centro di Ricerche Agro-Ambientali "Enrico Avanzi", University of Pisa, via vecchia di Marina 6, 56122, San Piero a Grado, Pisa, Italy	In Proc. 2nd Int. Conf. on Robotics and associated High-technologies and Equipment for Agriculture and forestry (RHEA-2014)

of the work required for weeding in intra-row. The model had a determination coefficient (R2) of 0.95 and RMSE (weeds/m2) of 42.3, showing that the method is appropriate for autonomous weed recognition and control.

The comparison of ultrasonic, RTK-GPS, and machine vision-based weed detection and control systems are compared (Table 4). The machine-vision system for recognition of the weed and locating system can be controlled by the electrical discharge method as discussed in the material and methods. The electrical discharges induced

Table 4. Comparison of the technologies discussed

Properties	Ultrasonic sensor-based method	RTK-GPS based method	Machine-vision based method
Sensors used	Ultrasonic sensor	Optical sensor	Camera
Recognition mechanism	Height of plants	Location of plant-based of sowing map	Image processing
Recognition effectiveness	Only predicts density of weed	Only separates crop from others on basis of the map	More effectively recognizes crops and weeds with distinct properties
Accuracy in recognition	Weed presence predicted with 92.8% of success	The correlation coefficient is 0.95	Weed discrimination is 84%
Processing time	195ms	16.7ms	482ms
Weed Control Method	Mechanical online harrow with automatically adjustable tine angle	A pair of intra-row hoes with variable area overage	Electrical discharge type robotic end effector
Advantage	Low-cost system	High accuracy	Medium accuracy but 100 control of recognized weeds
Disadvantage	Low accuracy and no provision for intra-row weed management	High cost of RTK GPS and complex mechanical components	Less recognition percentage and high-power requirement

Table 5. Segmentation process results

Particulars	Classified as soil, %	Classified as plant, %
Real soil pixels	95	5
Real plant pixels	3	97

Table 6. Discrimination capability in lettuce cultures

Particulars	Classified as weeds, %	Classified as lettuces, %
Real weed	84	16
Real lettuces	1	99

Table 7. Average results per image

Process	Time, ms	Time, %
Image acquisition	71	14.7
Segmentation of soil/plant	86	17.9
Filtering	73	15.1
Weed detection	252	52.3
Total	482	100

by the electrode located on the end-effector produced cell plasmolysis in the plants, which could be observed several hours after the treatment. The confirmation of the destruction of the affected tissue was observed after several (3 to 4) days. Different results (Table 7) including soil and plant segmentation process (Table 5), discrimination capabilities between crop and weed (Table 6) of machine vision system are given below.

The machine-vision system can successfully recognize 84% of weeds and 99% of the beneficial crop (lettuce) with an average recognition time of 482ms without causing damage to the beneficial crop. This system can able to eliminate 100% of weeds having less than five leaves or weeds of height less than 20cm (Utstumo et al 2018).

CONCLUSION

Weed detection using the ultrasonic sensor works based on the height and density of foliage coverage. This method is used only for inter-row weed control in terms of the intensity of weed based on the angle of the hoe blade. But the machine vision system could identify the weed and crop between the rows and be used for the intra-row weed control mechanism. While RTK GPS-based weed detection and control system is much more effective and accurate than the above two methods. The problem with using RTK GPS is that one has to use a mapping system during planting operation, and the high cost and the effect of the cloud on GPS accuracy stand as the limiting factor. RTK GPS alone cannot work for weed detection and control as it requires either an optical sensor or a digital camera to get the geo-positioned coordinates of crop plants. The whole study confirms automatic weed detection and control system is a promising technology for sustainable development and crop production. It helps to reduce the chemical applied in the form of herbicides and reduces environmental degradation. These systems demonstrate the promise of robotic weed control technology for reducing the hand labor or pesticide application requirements of existing weed control methods. Additional research is needed to fully optimize the technology for the wide range of conditions found in commercial agriculture worldwide.

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