Robotics-automation and sensor-based approaches in weed detection and control: A review

Asha KR, Aman Mahore, Pankaj Malkani and Akshay Kumar Singh

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Abstract
Undesirable and unwanted plants grow autonomously, nonuniformly in farmland and compete with the beneficial crop called a weed. It strives with the crop for nutrients, sunlight, water, space and grows at a faster rate. This results in a decreased growth rate of crop seedlings, make them susceptible to pests and diseases, eventually responsible for crop yield reduction and pertains to the poor economic condition of farmers as well as the nation. Hence, weed control is very crucial in crop production. Several studies have documented the yield loss associated with weed competition. Limiting factors of general weed control methods create the situation for design-development of new approaches based on robotics, automation and sensor techniques. Many research studies documented various weed discrimination, identification and control mechanisms in the fields. The automatic distinction between crop-weed has its own importance in weed control applications. Sensor-based approaches, machine vision systems, RTK GPS based systems, etc. are found better to achieve effective weed control and helps in improving crop yield. Robotic technology could provide a means to reduce current dependency of agriculture on chemical herbicides, strengthening its sustainability, and minimizing environmental impacts. These new technologies hold promise towards the improvement of agriculture’s few remaining unmechanized and drudging tasks. This paper reviews the robotics-automation and sensor-based approaches in the detection of weeds and their control strategies.

Keywords: Weed detection, automation, robotics, sensor, machine vision, RTK (Real-time-kinematics), Weed control etc.

Introduction
Agriculture and weed control or weeding both are old practices. Since the beginning of agriculture, farmers have struggle continuously in their farmland to control weeds. Weed can be considered a key problem in farm management practices and responsible for major losses (Fig.01) in farm produce of about 45%.

Weeding is the process of preventing or eradicating weed infestations to achieve profitable crop growth and it depends on resource availability and economic status of farmers. The magnitude of crop yield and quality loss affected by various factors including crop-weed

Fig 1: Annual loss in agriculture produce (%)
competitiveness, weed and crop plant density, emergence time of weed relative to crop, duration of weed presence (about 1/3rd period of a beneficial crop), and weed’s proximity to beneficial crop plants. Knowledge about biology and the nature of weed is important in the selection of successful weed control techniques. Tasks of weed control with manual, biological, chemical, cultural, mechanical and thermal methods are more expensive, laborious, tedious and time-consuming. Effective and efficient use of agricultural land is necessary to meet the increasing requirements of a growing population.

Manual weeding is the most efficient method of weeds control. It includes operations like hoeing, plucking and uprooting performed using long and short-handled weeder, wheel hoes, cono-weeders, and other hand tools. It is a labor and time-consuming process, more chances of physical injuries associated with this method. Different cropping practices and mulching comes under cultural weeding whereas biological weeding follows the use of microorganisms (Parasites and predators) and genetic engineering.

Mechanical weeding operations are performed by animal-drawn or engine-driven harrows, cultivators, weeder. It is not suitable for all crops and not sufficient for intra-row weeds while chemical weeding measures use chemicals like herbicides which have several adverse effects on human beings, plants, and animals as well as on the environment. Presently weed control methods (in row crops) following a combination of tillage (mechanical cultivation) with pre-emergence and/or post-emergence application of chemical herbicides and hand hoeing (Utstumo et al., 2018) [47]. While chemical-based weeding can be an effective biologically method and economical efficient irrespective of environmental impacts in many circumstances. Increasing regulations on pesticide use consumer concerns and growing interest in organically produced foods in certain regions limit the chemical-herbicide application’s long-term acceptability. When selective postemergence herbicides are unavailable or ineffective, hoeing of “in-row” weeds are required. In thermal weed control electric discharge, laser and flame are used. Among all rapidly growing weed control techniques, site-specific weed management (SSWM) is taking the top position. It refers to a machinery/equipment embedded with technologies that detect weeds growing in a crop and successfully controlling them without disturbing the beneficial crop. Integrating site-specific weed distribution data, composition weed species, size, and impact on crop field are essential to effective site-specific weed management (Chauhan et al., 2017) [11].

Many advanced research studies conducted on weeds 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 a major role.

New approaches based on the combination of sensors with different properties and microcontroller processors need to be developed and that can be used for effective weed control. Since the availability of sensors is not easy for farmers and knowledge of handling them needs some additional efforts. Hence, suitable sensor-based systems are not yet widely adopted for a practical purpose.

The combination of automatic weed detection and mechanical or chemical control is one of the emerging areas in the field of sustainable crop production. Therefore, automated or sensor-based weed control is one of the new approaches for non-chemical or low chemical weed control and/or controlled mechanical weed removal.

**Basic weed detection and control system architecture**

Plants can be described in terms of their geometrical, mechanical and optical properties. Also, the spectral signature of every plant and background is different in certain bands. So, the selection of weed identification and discrimination method is important 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 basic 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**

\[
\text{Distance} = \frac{\text{Speed} \times \text{Time}}{2} \quad \ldots (1)
\]

Andujar et al., (2012) [2] 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.2). Ultrasonic devices are 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.
The device measures the acoustic signal's travel time and transforms it into a signal of voltage. It is possible to convert the output voltage to a distance. The ultrasonic sensor measures the distance between weed mixtures and crop plants. The harrowing intensity change was based on measurements of weed density and tine angles that are previously tested to effectively monitor weed infestations. Weed density classes defined using fuzzy logic and are correlated with ultrasonic measurements. The distance between sensor and plants were calculated using equation (1). The developed fuzzy set for weed density after correlating data of ultrasonic readings (height) with weed densities measured in the laboratory was given in Table 1 (Rueda et al., 2015)

The intensity classes, controlling of electrical actuator and harrow tines movement were related to individual ultrasonic measurements. The harrowing intensity was taken as the angle made by tine with the horizontal and converted to the percentage of maximum angle (90°).

Rueda et al., (2014) modeled and built up an intra-row weed detection and control system. Four key technologies were 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 be utilized for auto-guidance in seedbed preparation, and with automatic on-the-fly, 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. A program was set in the control unit of weeding hoe blades such that except the location of the plant, it assumes any plant as a weed. As the intra-row hoes (Fig.3) 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 is repeated for each plant.

Table 1: Measured plant height ranges to control harrowing intensity corresponds to five discrete classes in Decision Support System (Rueda-Ayala et al., 2015)

| Class | Min Height (cm) | Max Height (cm) | Plant Density (plants m⁻²) | 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          |

Machine vision based weed detection and control

The machine vision system is used for the identification of weed and crop and locating the weed plants that are to be destroyed by the weed control system (Guzman et al., 2019). Machine vision-based weed detection can be achieved by different factors for discrimination. Here is the list of the accuracy of different techniques given below (Table 2).

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

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

Here a combine system of automatic weed detection by machine vision and weed control by electrical discharges. In this method two machine vision system and an end effector is used for identification, location and control of weeds.

Primary machine vision system: This was designed to detect the individual weeds with the mission to locate weeds on a
real-time basis while the robot is moving forward. The system comprised of a color camera connected to a digitizing board that is inserted on a Pentium based computer. The vision system has 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. The information transferred to these systems has to position each system and the secondary machine vision system. The transmission of the location of the weeds to the supervisory system has to process each image captured to the desired pixel accuracy of the inertial unit. This module consisted of a monochromatic camera coupled to a specific processing system. The camera is firmly attached to the manipulator and that was initially focused on weeds that the primary vision system detects. On the request of the supervisor, the secondary vision system grabs an image and located on the same weed under its field of view, comparing its signature with that of the primary camera system. Finally, it transmits the actual coordinates of the weed to the supervisor, which 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 is powered by a set of four 24V batteries that provides approximately 40 A. The six degrees of freedom of the robot are implemented by six electrical motors (100W each). Finally, the end effector moves in the trajectory decided by the primary and secondary vision system information (Fig.5).

\[ P_h(i, j) = \cos^{-1}\left(\frac{\sqrt{(r(i,j)-r_h(i,j))^2+(s(i,j)-s_h(i,j))^2}}{(r(i,j)-r_h(i,j))^2+(s(i,j)-s_h(i,j))^2+1}\right) \] … (1)

\[ P_g(i, j) = \frac{\max(P_g(i,j), P_h(i,j)) - \min(P_g(i,j), P_h(i,j))}{\max(P_g(i,j), P_h(i,j))} \] … (2)

\[ P_b(i, j) = \frac{\max(P_b(i,j), P_g(i,j), P_h(i,j))}{255} \] … (3)

In a second step, the area, the perimeter and the centroid of each weed are calculated. Objects smaller than a preset threshold consider as noise and filtered. Objects larger than another preset threshold were considered as a crop. Remaining objects were considered as weeds (Fig.4) and the coordinates of their centroid were sent to the supervisor and the secondary 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 secondary vision system.

**Secondary vision system:** The objective is to locate the previous weeds, one at a time, and to provide their actual position, to correct the trajectory of the weeding tool, thus compensating for positioning errors generated by the lack of accuracy of the inertial unit. This module consisted of a monochromatic camera coupled to a specific processing system. The camera is firmly attached to the manipulator and that was initially focused on weeds that the primary vision system detects. On the request of the supervisor, the secondary vision system grabs an image and located on the same weed under its field of view, comparing its signature with that of the primary camera system. Finally, it transmits the actual coordinates of the weed to the supervisor, which 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 is powered by a set of four 24V batteries that provides approximately 40 A. The six degrees of freedom of the robot are implemented by six electrical motors (100W each). Finally, the end effector moves in the trajectory decided by the primary and secondary vision system information (Fig.5).

**Detected weeds (Blasco et al., 2002)**

During real-time operation, the 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) during image pre-processing. Equation below represents the HSV color space and the pixels hue value \( P_h(i, j) \), saturation value \( P_s(i, j) \), and value \( P_v(i, j) \) in the color space and their conversion relationship with the RGB color model.

\[ P_h(i, j) = \cos^{-1}\left(\frac{\sqrt{(r(i,j)-r_h(i,j))^2+(s(i,j)-s_h(i,j))^2}}{(r(i,j)-r_h(i,j))^2+(s(i,j)-s_h(i,j))^2+1}\right) \] … (1)

\[ P_s(i, j) = \frac{\max(P_g(i,j), P_h(i,j)) - \min(P_g(i,j), P_h(i,j))}{\max(P_g(i,j), P_h(i,j))} \] … (2)

\[ P_v(i, j) = \frac{\max(P_b(i,j), P_g(i,j), P_h(i,j))}{255} \] … (3)

In a second step, the area, the perimeter and the centroid of each weed are calculated. Objects smaller than a preset threshold considered as noise and filtered. Objects larger than another preset threshold were considered as a crop. Remaining objects were considered as weeds (Fig.4) and the coordinates of their centroid were sent to the supervisor and the secondary 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 secondary vision system.

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**Detected weeds (Blasco et al., 2002)**
**Table 3: Weed Detection and Control studies**

| S. N | Researcher Name | Source | Research topic | Research approach | Researcher details | Journal name |
|------|-----------------|--------|----------------|-------------------|--------------------|--------------|
| 1    | 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 |
| 2    | 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 |
| 3    | D.C. Slaughter   | Slaughter *et al.*, (2008) | Autonomous robotic weed control systems: A review | --- | University of California, Biological and Agricultural Engineering, Davis, CA 95616, United States | Computers and electronics in agriculture |
| 4    | J. Blasco        | Blasco *et al.*, (2002) | AE—Automation and emerging technologies: robotic weed control using machine vision | Robotics and Machine-vision system assisted mechanical weeding | emolto@ivia.es | Biosystems Engineering |
| 5    | 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 |
| 6    | 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 |

**Fig 5:** Electrical control weeding using machine vision system (Blasco *et al.*, 2002) [6]
| No. | Author(s) | Reference | Title | Institution(s) | Field of Study |
|-----|-----------|-----------|-------|-----------------|----------------|
| 7   | N. D. Tillett | Tillett et al, (2008) | Mechanical within-row weed control for transplanted crops using computer vision | Department of Biological and Agricultural Engineering, Gembloux Agricultural University, Gembloux, Belgium | Biosystems Engineering |
| 8   | Zoltan Gobor | Zoltan Gobor, (2013) | Mechatronic system for mechanical weed control of the Intra-row Area in Row Crops | Bavarian State Research Center for Agriculture, Institute for Agricultural Engineering and Animal Husbandry, Germany | KI-Künstliche Intelligenz |
| 9   | W. Bond and A. C. Grundy | Bond and Grundy, (2001) | Non-chemical weed management in organic farming systems | Horticulture Research International, Wellesbourne, Warwick, UK | Weed research |
| 10  | Cointault Frédéric | Frederic et al, (2012) | Texture, color and frequentional proxy-detection image processing for crop characterization in a context of precision agriculture | Agro-Sup Dijon, France | Agricultural science |
| 11  | 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 | Department of Bio mechatronics Engineering, National Pingtung University of Science and Technology, Pingtung 91201, Taiwan | Robotics |
| 12  | Bjorn Astrand And Albert-Jan Baerveldt | Astrand and Baerveldt (2002) | An agricultural mobile robot with vision-based perception for mechanical weed control | Halmstad University, Halmstad, Sweden | Autonomous robots |
| 13  | A. Piron | Piron et al, (2011) | Weed detection in 3D images | Environmental Science and Technology Department, Gembloux Agricultural University, Gembloux, Belgium | Precision agriculture |
| 14  | Yun Zhang | Zhang et al, (2012) | Robust hyperspectral vision-based classification for multi-season weed 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 |
| 15  | F. Lopez-Granados | Lopez-Granados, F., (2011) | Weed detection for site-specific weed management: mapping and real-time approaches | Institute for Sustainable Agriculture/CSIC, P.O. Box 4084, 14080-Córdoba, Spain. Email: fgranados@ias.csic.es | Weed research |
| 16  | Gerassimos G. Poteinatou | Poteinatou et al, (2014) | Potential use of ground-based sensor technologies for weed detection | Department of Weed Science, University of Hohenheim, Otto-Sunder-Str. 5, 70599 Stuttgart, Germany. Email: G.Poteinatou@Uni-Hohenheim.de | Pest management science |
| 17  | Amir H. Kargar B. and Ali M. Shirzadifar | Shirzadifar, A. M., (2013) | Automatic weed detection system and smart herbicide sprayer robot for corn fields | Department of Electrical Engineering, Shiraz University, Iran | First RSI/ISM International Conference on Robotics and Mechatronics (ICRoM) |
| 18  | Uri Shapira | Shapira et al, (2013) | Field spectroscopy for weed detection in wheat and chickpea fields | The Remote Sensing Laboratory, Jacob Blaustein Institutes for Desert Research, Ben-Gurion University of the Negev, Beer Sheba, Israel | International journal of remote sensing |
| 19  | Daniela Stroppiana | Stroppiana et al, (2018) | Early season weed mapping in rice crops using multi-spectral UAV data | Institute for Electromagnetic Sensing of the Environment (IREA), Consiglio Nazionale delle Ricerche, Milano, Italy | International journal of remote sensing |
| 20  | Christian Frasconi | Frasconi et al, (2014) | Design and full realization of physical weed control (PWC) automated machine within the RHEA project | Luisa Martelloni, Centro di Ricerche Agro-Ambientali “Enrico Avanz”, 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) |
Results
The ultrasonic sensor system was used to detect the density of weed infestation in the field. The height data obtained from the ultrasonic sensor was correlated with the 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 weed density 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⁻¹).

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 co-robot operation each row to determine the number of crop plants harmed by the hoes. Field Trials were conducted at 1.2 km h⁻¹, 1.6 km h⁻¹, and 2.4 km h⁻¹. At the 0.8 km h⁻¹ and 1.2 km h⁻¹, travel speeds, no flag contact or damage to the crop plants, respectively, were observed. At the 1.6 km h⁻¹ 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⁻¹ flag trial and 3% in the 2.4 km h⁻¹ crop trial. Based on these results, a co-robot travel speed of 1.2 km h⁻¹ 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⁻¹. 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, that is operating between the intra-row region of crop plants in sustainable cropping. This system could save about 57.5% of 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.

Table 4: Comparison among 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 on sowing map | Image processing |
| Recognition effectiveness| Only predicts density of weed  | Only separates crop from others on basis of map | More effectively recognizes crop and weed with distinct properties |
| Accuracy in recognition  | Weed presence predicted with 92.8% of success | Correlation coefficient is 0.95 | Weed discrimination is 84% |
| Processing time          | 195ms                          | 16.7ms               | 482ms                       |
| Weed Control Method      | Mechanical online harrow with automatic adjustable time angle | A pair of intra-row hoes with variable area overlap | 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 system and complex mechanical components | Less recognition percentage and high-power requirement |

The comparison of ultrasonic, RTK-GPS and machine-vision-based weed detection and control systems are compared and details are given in 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 material and methods. The electrical discharges induced by the electrode located on the end-effector produced cell plasmolysis on the plants, which could be observed several hours after the treatment. The confirmation of the complete destruction of the affected tissue was observed after several (3–4) 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.

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

| Particular                  | Time, MS | Time % |
|-----------------------------|----------|--------|
| Image acquisition           | 71        | 14.7   |
| Segmentation soil/plant     | 86        | 17.9   |
| Filtering                   | 73        | 15.1   |
| Weed detection              | 252       | 52.3   |
| Total                       | 482       | 100    |

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.
Conclusion
Weed detection using the ultrasonic sensor was based on the height and density of foliage coverage. This method is used only for the inter-row weed control in terms of intensity of weed based on the angle of the hoe blade. Whereas, the machine vision system can identify the weed and crop in between the rows and can 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 problems in the use of RTK GPS is that one has to use a mapping system during planting operation and the high cost, as well as the effect of cloud on GPS accuracy, are the limiting factor for this technology. RTK GPS alone cannot work for weed detection and control as it requires either an optical sensor or digital camera for getting the geo positioned coordinates of crop plants. The whole study confirms automatic weed detection and control system as a promising technology for sustainable development and crop production. It helps to reduce the chemical applied in the form of herbicides thus reducing 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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