Computers and Electronics in Agriculture 214 (2023) 108270

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

A mixed-autonomous robotic platform for intra-row and inter-row weed removal for precision agriculture

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ARTICLE INFO

Keywords:
Automatic weed removal
Artificial intelligence
Robotics
Mixed-autonomous rovers

ABSTRACT

The presence of weeds poses a common and persistent problem in crop cultivation, affecting both yield and overall agricultural productivity. Common solutions to the problem typically include chemical pesticides, mulching, or mechanical weeding performed by agricultural implements or humans. Even if effective, those techniques have several drawbacks, including soil and water pollution, high cost-effectiveness ratio or stress for operators. In recent years, novel robotic solutions have been proposed to overcome current limitations and to move towards more sustainable approaches to weeding. This work presents a mixed-autonomous, robotic, weeding system based on a fully integrated three-axis platform and a vision system mounted on a mobile rover. The rover's motion is remotely controlled by a human operator, while weeds identification and removal is performed autonomously by the robotic system. Once in position, an RGB-D camera captures the portion of field to be treated. The acquired spatial, color and depth information is used to classify soil, the main crop, and the weeds to be removed using a pre-trained Deep Neural Network. Each target is then analyzed by a second RGB-D camera (mounted on the gripper) to confirm the correct classification before its removal. With the proposed approach, weeds are all the plants not classified as the main crop known a priori. The performance of the integrated robotic system has been tested in laboratory as well as in open field and in greenhouse conditions. The system was also tested under different light and shadowing conditions to evaluate the performance of the Deep Neural Network. Results show that the identification of the plants (both crop and weeds) is above 95%, increasing to 98% when additional information, such as the intra-row spacing, is provided. Nevertheless, the correct identification of the weeds remains above 97% ensuring an effective removal of weeds (up to 85%) with negligible crop damage (less than 5%).

1. Introduction

Thanks to recent technological advancements, the development of autonomous robots in agriculture has increased in the last years. Such technologies have become more advanced and affordable, enabling the automation of a wide range of tasks including planting, watering, and harvesting crops (Oliveira et al., 2021). One of the key advantages of using autonomous robots in agriculture is their precision, accuracy, and ability to work non-stop with minimal or no downtime. This allows farmers to increase their productivity and efficiency, as the robots can work continuously to perform its tasks. In addition, autonomous robots are able to operate in harsh and dangerous environments, such as fields with steep slopes or areas that are contaminated with pesticides or other chemicals. This makes them an ideal solution for tasks that would be difficult or impossible for humans to perform. However, there is also a number of challenges that need to be overcome to fully realize the potential of autonomous robots in agriculture.

While tasks such as planting, watering, and harvesting crops in most of cases require high precision but minimal intelligence to be performed by agricultural machinery, selective weeding requires a high precision complex system able to identify and effectively remove the different infesting species. Indeed, these unwanted plants compete with crops for water, light, and nutrient. Thus, it is fundamental to eradicate them or to control their growth. In many agricultural areas, mulching in combination with manual weeding is still the most effective way for weeds prevention and management, as they allow for minimal growing space for weeds and less damage to surrounding plants and

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https://doi.org/10.1016/j.compag.2023.108270
Received 1 March 2023; Received in revised form 28 August 2023; Accepted 21 September 2023
Available online 4 October 2023

soil. However, it poses economic and environmental concerns (Anane et al., 2020), and requires additional manual work that can impact on workers who are exposed to several musculoskeletal disorders, mainly due to the harsh postures and severe climate conditions (Ramahi and Fathallah, 2006).

Alternatives can be found in using pesticides, which are effective but suffer from several drawbacks. Firstly, there is an issue with pesticide selection: different weed species, with different growth timings and cycles are sensitive to different chemicals, and often multiple interventions are needed. Secondly, chemicals might pose risks for humans and negatively impact on environment. Finally, the crop itself might suffer from quality and yield losses due to phytotoxicity reactions. Mechanical solutions such as cultivators are a valuable alternative since they can be pulled behind a tractor and used to remove weeds laying in crops inter-rows with negligible damages to the cultivation (Sozzi et al., 2021). Some advanced solutions also allow intra-row weeding: however these manned implements are extremely slow and are effective only when weeds are clearly separated and from the crop.

1.1. Weed identification

When it comes to correctly separate crops from weeds, it is needed to rely on camera-based systems. Common approaches mainly include traditional image processing and deep learning. When weed detection is conducted with traditional image-processing technology, extracting features (such as color, texture, and shape, of the image) and combining them with traditional machine learning methods (such as random forest or Support Vector Machine, SVM, algorithm) (Wu et al., 2021; Li et al., 2022) or deep learning techniques (Rai et al., 2023) are necessary. These methods need to manually define the features to be used and have a high dependence on the image acquisition method. Chang and Lin (2018), developed a weed identification systembased on thresholding the HSV (Hue, Saturation, and Value) color model. Since the approach is dependent on the light source, the system has been tested at different time during the day. During the daytime, crops (*Lactuca sativa*) and weeds were correctly identified, on average, in 80% of the cases. Color is not the only discriminant for plant classification: texture and shape features are also important. The most common texture feature descriptors are based on statistical analysis or image transformation (Bharati et al., 2004). Using a combination of band-pass filters, multi-resolution images transformations, and gradient extractions, Bakhshipour et al. (2017) extracted a series of 52 texture features enabling the correct identification of crops and weeds. Geometric parameters – such as perimeter, area, diameter, and similar – are the most intuitive features that are easy to implement and unaffected by the light. These shape features have been successfully applied in the species recognition task of plant leaf images (Mansheng and Dongjian, 2007; Agrawal et al., 2012; Deng et al., 2014). However, such features cannot reliably and accurately perform classification in complex natural scenarios, such as high weed density, overlapping, or shadowed weeds and crops. With the increase of the computational power and the increase in data volume, deep learning algorithms can extract multiscale and multidimensional spatial semantic feature information of weeds through Convolutional Neural Networks (CNNs) due to their enhanced data expression capabilities for images, avoiding the disadvantages of traditional extraction methods. Wu et al. (2019) proposed a CNN-based weed control system that uses a non-overlapping, multi-camera system to track and detect weeds using template matching. Dang et al. (2023) extended the YOLO detectors with a new dataset (CottoWeedDet12) of weeds important to cotton production in the southern United States. The system can be used in real-time and thus allows for a continuous weeding. In a different context, Bac et al. (2013) used Classification and Regression Trees (CART) classifier trained with 46 pixel-based features to classify vegetation to construct an obstacle map to plan collision-free motion for a harvesting manipulator.

1.2. Robotic weeding systems

Weed identification is just the initial step for its removal: once the position is known, a robotic system must be used to pick and remove it. In recent years, there is an increased interest in moving from passive machinery attached to tractors to semi- and fully-autonomous machines able to handle different tasks with minimal human supervision. One of the major distinctions among these robots is the method of weeding they employ. Some utilize tine and hoes, similar to traditional cultivators, while others have interchangeable tools for more precise handling. One of the first works is the one presented by Blasco et al. (2002), consisting of a 6 degrees of freedom (DOF) manipulator mounted on a cart. The cart advances on a straight line (a crop row), taking advantage of two cameras to do visual servoing; detection is achieved through a Bayesian discriminant analysis. Once detected, the robot positions an electrode on the weed which can discharge 15 kV at 30 mA for 200 ms ensuring the removal of the weed. A similar robot has been presented by Michaels et al. in Michaels et al. (2015). A delta robot is used to pick a single turf of weed while the robot is moving along the crop. The robot could remove 1.75 weeds per second at a speed of 37 mm/s.

Pérez-Ruíz et al. in Pérez-Ruíz et al. (2014) presented a fully mechanical solution to remove the intra-row weeds using movable hoes. The system autonomously moves the hoes, having a pre-programmed knowledge of the crop planting pattern and real-time odometry data as the control inputs for the hoes accurate positioning. Xiong et al. (2017), instead, presented a mobile robot built from a quad bike, mounting a laser tool for weed removal. The weed recognition is performed first by HSV thresholding to discriminate ground from plants. Then, multiple morphological operations are applied to separate items in the image. The final discrimination is then performed using a mixture of information of those items such as area, elongation, and compactness. The weeding procedure was tested both in static (i.e., robot stops and each weed is lit up with laser before moving to the next area), and dynamic condition (i.e., robot keeps moving while weeding).

McCool et al. (2018) developed the AgBot II, an autonomous robot that uses a set of different tools to treat different weed infestations. It comprises a camera which is used to discriminate the crops from the infestations using different color spaces and ensure consistent results; the robot also employs a lighting module to maintain the same level of illumination during the detection process. The mechanical weeding system works autonomously and can utilize either a tine or an arrow hoe, both designed to have minimal impact on the soil. Florance Mary and Yogaraman (2021) developed a lightweight mobile robot that uses a Convolutional Neural Network (CNN) to distinguish between main crops and weeds. After detecting all the weeds in an area, it uses a 3 DOF robotic arm to reach the targets and drill them into the ground, then it moves to the next target. After all the weeds are drilled, it moves forward to the next area. Even though it is large enough to be comparable with other weeding robots, it only weighs 8 kg. A key aspect in weeding is also the time needed to remove the infestants from the field. Quan et al. (2022) proposed an intra-row, mechanical system that uses a rotating, vertical disk knife to remove the weed from a maize crop. A CNN classifies the plants in three classes (one for the maize and two for the weeds) and then activates the mechanical system once the weeds are detected.

Finally, chemicals are used in the robot developed by Underwood et al. (2015). It is a fully electrical vehicle mounting an UR5 robot (Universal Robots, Denmark) which has a steerable nozzle as end-effector. The autonomy is provided by two lidars placed on the front and on the back of the vehicle, and by a spherical camera used to identify obstacles. Crop sensing is made possible by the use of multi-spectral cameras and stereo vision. Utstumo et al. (2018) used a camera and a support vector machine classifier to separates carrots from other plants, then identify the location of the weeds to selectively drop a precise amount of pesticide on each of the detected leaves. A similar solution is proposed by Jin et al. (2023), where the sprayer is placed in a fixed, grid position and activated when the CNN identifies the presence of a weed.

Fig. 1. An overview of the technologies integrated in the mixed-autonomous rover. (A) The full rover setup in a greenhouse. There are no tracks for the wheels of the cart, so the alignment with crop rows is manually made through a remote controller. (B) The top camera provides a bird-eye-view of the portion of the field to be treated and identifies the crops and the weeds. (C) The gripper and the gripper camera used, respectively, to pick the weeds and to refine the position of the targeted weeds before their picking.

1.3. Outline

Building on the current state of the art, this paper presents a mixed-autonomous, robotic, weeding system designed to identify the weeds using computer vision and artificial intelligence methods, and to accurately remove the weeds without damaging the surrounding crops. We evaluated the performance of the system both in a laboratory scenario and in real scenarios (open field and greenhouse). The paper is structured as follows: in Section 2 we will present in details the structure of the robot and the approach used to identify and remove the weeds. Then, in Section 3 we will introduce the experimental setup used to validate the robot in a field application followed by the results and their discussion in Section 4. We conclude the paper with Section 5 where we summarize the findings and propose future improvements of the system.

2. Materials and methods

2.1. Overview

As shown in Fig. 1, the robotic system includes a gantry robot, a gripper, and a vision system mounted on a mobile cart. The cart (by Leozann Ecogreen s.r.l., Renazzo, Italy) is a light weight, fully electric vehicle that can be remotely controlled by an operator. The two active wheels and two passive ones enable a complete mobility of the whole system. The system is controlled at high level by a computer running the Robot Operating System (ROS 2) (Macenski et al., 2022), and at low level by a PLC/CNC controller.

2.2. Robotic system

The main robot is an XYZ gantry robot (drylin E 3 axes, Igus inc., USA) which can move up to 0.5 m/s. It is oriented having the z axis perpendicular to the ground and at its end it mounts a gripper (EGP 40-N-S-B, Schunk, Germany) with a 3D-printed claws made of PLA (Polylactic Acid) embedding two soft pads (Fig. 1C). Despite the stroke per jaw of only 6 mm and its compact size, the gripper can apply forces up to 30 N sufficient to eradicate most of common weeds.

The gantry robot has a workspace of $800 \times 800 \times 500\ \mathrm{mm}^3$, which is compatible with the standard dimension of cultivation in greenhouses and open field. Compared to other solutions, such as classic 6 DOF manipulators mounted upside-down or delta robots, the gantry robot has several advantages. In fact, manipulators are prone to singularities, making it hard to remove vertically every weed while delta robots have a semi-spherical workspace which limit the reachability of every point on the planar ground. On the contrary, the developed gantry robot is designed to have sufficient room to allow vertical movements needed for weeds removal down to the roots.

2.3. Vision system

The vision system is composed by two RealSense RGB-D cameras. Such devices are promising sensors and widely used in fruit detection and localization since they provide depth information and infrared information in addition to RGB information (Fu et al., 2020). A first camera (Intel Realsense D345i, Intel, USA) is mounted above the gantry robot (Fig. 1B) at about 1 m from the ground. It has a large depth range (0.3–3 m) and a wide field of view (RGB: $87° \times 58°$, depth: $69° \times 42°$) that make it possible to cover the entire workspace and detect the position of all weeds in advance before the weeding operation starts. The second camera (Intel Realsense 405, Intel, USA) is mounted aside the gripper (Fig. 1C). It has a similar field of view as the previous one (RGB and depth: $87° \times 58°$) but has a reduced depth range (7–50 cm). Nevertheless, the camera has a higher resolution, and it is used to correct the position and the classification of the weed the robot is about to reach.

2.4. Robot controller

The robots are controlled at low level by a PLC/CNC system (SIAX A100, Sipro, Italy) which converts the internal variables into commands for the motors using the EtherCAT protocol. The trajectory is computed by an external control system (see Section 2.7) and all the points are passed to the PLC/CNC which takes care to apply the control laws for each motor. The maximum speed of the motors has been tuned to reduce the energy consumption, avoid oscillations of the system, and achieve the maximum torque when needed. For instance, the RPM of the motor on the z-axis was reduced in order to maximize the torque to lift the gripper (weight 0.78 kg) while allowing for extra forces to eradicate the weeds from the soil. On the other hand, other axes do not have specific torque requirements, so priority was given to the maximum speed (up to 0.5 m/s). Once in position, the gripper is closed to grab the plant, which is then released in one of the drop locations positioned at the back of the workspace (Fig. 1A).

2.5. Plant identification

One of the critical aspects of this application is the ability to correctly detect weeds and make sure to distinguish them from the main crop (Fig. 2A). As in previous works, the initial processing was based on a color space conversion. The images from both the cameras are converted to the HSV color space, and then an adaptive thresholding method is employed to create the binary image using all the available channels (Fig. 2B). The crops and the weeds are defined as the target, which can be easily segmented thanks to the high contrast between the objects in the scene, namely the plants and the soil. In fact, plants often appear homogeneously green due to the presence of chlorophyll, which absorbs blue and red light and reflects green light. In contrast,

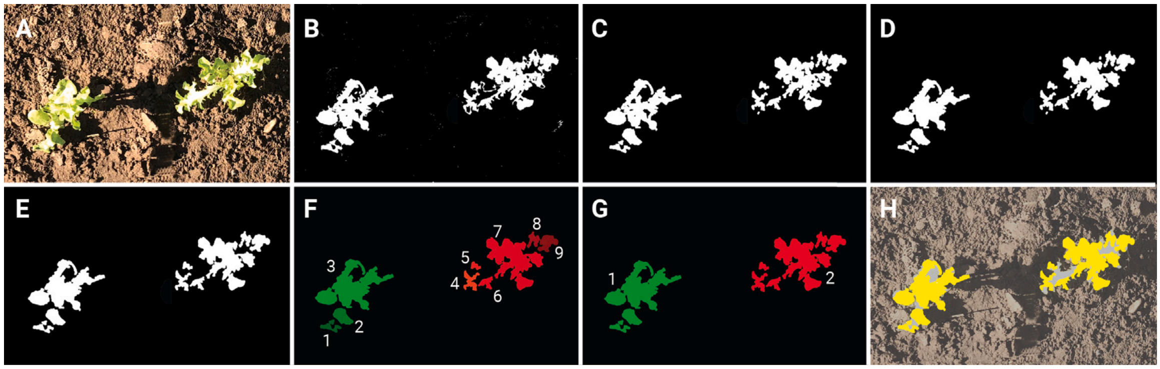

Fig. 2. Image processing. (A) Original image. (B) HSV thresholding. Here it is possible to see some noise due to reflection in the soil. (C) Morphological opening to remove small objects. (D) Morphological closing to fill the holes in the images. (E) Adaptive thresholding based on the area to remove small, unconnected components. (F) Connected components to identify each of the single cluster extracted from the image, 9 in this example (G) Adaptive merging using distance and area as discriminants. Differently, the colors indicate the merging clusters. (H) Final mask overlaid on the original image.

the ground can have a wide range of colors, depending on factors such as the type of soil, moisture, presence of vegetation and the light conditions.

A simple thresholding does not guarantee a perfect segmentation of the plants since its value would be affected on various factors such as crop variety, soil condition, lighting and shadows. Indeed, the initial mask can be noisy as green elements can be detected sparsely in the soil and the plants themselves could have holes as some of their pixels may lay below the threshold. In order to improve the segmentation and thus obtain better defined clusters of pixels –i.e., regions of interest where only a plant or a weed is visible– a set of morphological operations have to be applied on the mask (Serra and Soille, 2012). A first opening operation is used to remove small sparse points (Fig. 2C), that may be due to noise, while keeping larger objects. This operation erodes all the elements in the image using a pre-define structure. In our case, we used a disk structuring element having dimension 3 × 3 pixels. To merge the remaining elements into a larger cluster, we applied a closure operation using a disk structuring element having dimension 10 × 10 pixels (Fig. 2D and E). This removes small holes and gaps by filling them with pixels that are adjacent to holes. In the last step, we perform an adaptive merging of the non-connected clusters using the relative distance and the area as discriminates. For each cluster we compute the nearest neighbor and merge the smaller into the larger if within a certain distance (Fig. 2F and G). This makes the object appear more solid and connected, especially when not all the portions of the plant are selected by the mask, as shown in Fig. 2H.

Once the process is completed, for all non-masked areas (i.e., the plants) we compute a bounding box which is used to crop the original image to obtain a picture for each plant. The fact that not all the plant is selected does not pose a real issue, since the bounding box contains all the clusters having the same group. However, it may happen that the merging does not contain all the correct clusters, so the bounding box does not actually cover the entire plant. This is one of the edge cases that should be considered in future work.

Each of these new images is then fed to a pre-trained neural network which returns the name of the plant within a set of 3000 available plant species. The network is part of PlantNet (Garcin et al., 2021), an open-source identification system that helps identifying plants through images. In this work we selected the model based on ResNet18, a residual, convolutional neural network (CNN) that is 18 layers deep designed for fast learning. This is possible thanks to the peculiar arrangement of the convolutional layers and the filters used independently for each channel of the input image, which reduces the number of parameters in the model and allows it to be more efficient (Ramzan et al., 2019).

Knowing of the plant or the set of plants to be considered as the main crop, we use the output of the Softmax function to classify all the plants. Differently from other approaches, instead of focusing on the weeds, we identify the main crop within a subset of possible plants, then all the remaining are considered weeds. This approach is effective because it generalizes the concept of weed to any plant that is not the current crop, even previous cultivation that was not properly removed from the field. In addition, the system automatically excludes the weeds that are in a non-reachable position due to mechanical constraints. Fig. 3 shows an example of the classification.

2.6. Weed removal

Once all the weeds have been identified and localized, the system computes the optimal picking path by using the information provided by the RGB-D cameras. First, the thresholding mask is used to compute a set of geometric parameters such as the plant center of mass, W_c^i, and its minimum diameter W_d^i (Fig. 3B). With such information, a circular region centered in W_c^i and having diameter half of W_d^i is applied over the depth image. The values along the z-axis of the points within the region are averaged to obtain an estimation of the height of the plant. Similarly, the height of the soil is computed by inverting the mask. The two values are then averaged together to compute the picking position for each weed. This allows to adapt the picking of the weeds regardless the uneven terrain and the height of the plant.

After the initial classification, the three-dimensional position (centroid) of each weed is transformed in the world reference and added to a list with all the target locations. Then, the robot moves above each element, where the second camera acquires the image of the current target. When the plant is in the field of view of the wrist-mounted camera, the system performs another segmentation (using the same parameters) and classification of the detected plants. This information is used to refine the positioning of the gripper during the pick-and-place or to exclude a plant that was already removed or wrongly classified.

As the secondary camera is closer to the ground, its FOV is reduced; it may happen that in the scene only part of some crops is visible, leading to wrong recognition of that plant as weed. To overcome this problem, in addition to the information of the weeds, we store in a different list the three-dimensional position (centroid) and volume (computed as the product between the bounding box and the maximum height in the region) of each crop. The volumes are used by the second camera to exclude the area from the workspace. In this way, the wrongly detected weed will not be considered as a target.

According to the classification output from the two cameras, the system performs one of the following actions. When the same plant is detected by both cameras, the system performs the picking. If the top camera fails (by identifying the plant as weed) but the gripper camera correctly identifies it as crop, then the scheduler moves to the next target. If the plant is correctly identified by the top camera, but the

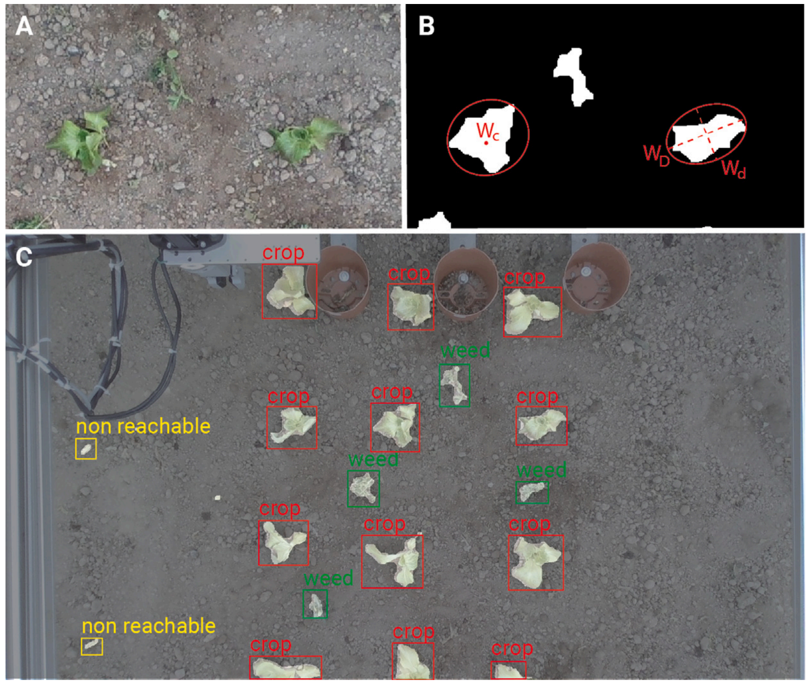

Fig. 3. Plant classification. (A) A portion of the original image from the top camera. (B) Result of the segmentation. White areas are the portions of the image containing the detected plants; black areas represent the soil or objects in the field of view of the camera. Overlaid are the cluster parameters such as the center of mass, W_c, and the minimum and maximum diameter of the ellipsoid, W_d and W_D respectively. (C) The original image overlaid by the processed segmentation mask with highlighted all the plants in the scene. Each bounding box containing a plant (squares in the picture) is then used as an input for a pre-trained ResNet18 network, which classifies the plants in two classes: crops (red boxes) and weeds (green boxes). To avoid errors in removing the weeds, the system automatically excludes the weeds that are in a non-reachable position (yellow boxes).

gripper camera fails, the bounding boxes intersect leading, again, to skip the target and move to the next one. Finally, the failure point is when both cameras were not able to recognize the plant as the main crop, which may be due to light conditions or imperfections of the plant.

After each picking, the robot moves the gripper to the disposable area (positioned at the back of the workspace) minimizing travel time between the current position and the next one. The weeding cycle continues until the list is emptied, then the user is informed that can move forward the cart to another region until the whole field is treated.

Table 1
A summary of the parameters considered in the different experimental scenarios.

	Laboratory	Open field	Greenhouse
Field size (width, length)	0.8×0.8 m^2	2.5×1.5 m^2	0.7×10 m^2
Number of plants (per test)	20	52	200
Number of species (per test)	2	8	5
Plant height (range)	20–150 mm	50–350 mm	20–100 mm
Plant diameter (range)	50–100 mm	30–100 mm	30–70 mm
Distance between plants	–	250 mm	250 mm
Time period	Nov–Jan	Jul–Aug	Jan–Feb
Total hours	150 h	60 h	100 h

2.7. System integration

At the current stage of the project, the cart is still remotely controlled by an operator, while the weeding operation is fully autonomous. Despite this, it is actually possible to estimate the velocity of the cart using visual odometry but the trajectory planning for autonomous driving is not implemented yet, so weeding occurs in static conditions, i.e., when the cart is not moving, leaving this improvement for future work.

The whole system is controlled at high level by a computer running ROS 2 which: (i) acquires and processes the data from the cameras, (ii) controls the motion of the gantry robot, and (iii) operates the claw. ROS allows for a modular structure which can be extended and modified when needed. Communication with the motors is done via a ROS node, which implements a custom protocol to communicate with the PLC/CNC system. A finite-state machine (FSM) handles the weeding operation one target at a time. Python classes were created to implement the FSM, the states and the transitions between them.

For each component, we implemented a dedicated ROS node that is tightly interconnected with the others, providing a direct communication among the vision system, the deep learning module, and the robot to guarantee a precise localization of the weeds to be removed. Additional nodes have been created to perform specific calculation such as image thresholding and to run the pick execution scheduler. Fig. 4 depicts a schematic representation of the modules of the system and their connections.

3. Experimental setups

In order to verify the efficiency of the robotic system, we performed a campaign of tests both in laboratory and outdoor scenarios, considering different natural illumination conditions. The system has been tested and evaluated in a time span of three months for a total of more than 300 h. A first portion of the evaluation was carried out in laboratory scenario where both the vision and the robotic system have been thoroughly tested. A second series of evaluations was carried out in the open field to understand the impact of light on the performance of the image processing and of the classification algorithms. A last series of tests was carried out in a greenhouse, where the integrated system was evaluated on the field. Table 1 summarizes the parameters for each experimental setups, while Table 2 summarizes the plants used in each scenario.

The initial tests have been performed without the semi-autonomous cart and with no direct control of the light and soil conditions. A variable number of target plants from two different species (height ranging

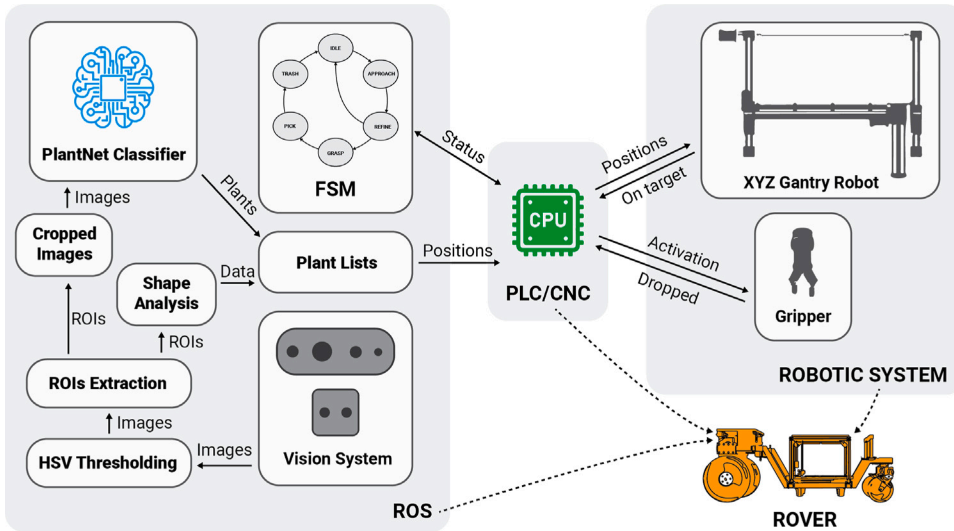

Fig. 4. A schematic overview of the interconnection between the different modules of the system.

Table 2
The lists of plants used in all the experiments presented in the paper.

English name	Latin name	Laboratory	Open field	Greenhouse
Lettuce	*Lactuca sativa*	×	×	×
Savory	*Satureja*	×		
Escarole	*Cichorium endivia*		×	
Red Chard	*Beta vulgaris*		×	
Fennel	*Foeniculum vulgare*		×	
Italian chicory (Treviso)	*Cichorium intybus*		×	
Italian chicory (Chioggia)	*Cichorium intybus*		×	
Cucumber	*Cucumis sativus*		×	
Curly Blonde Lettuce	*Lactuca sativa*		×	
Couch grass	*Elymus repens*			×
Dandelion	*Taraxacum*			×
Common purslane	*Portulaca oleracea*			×
Baconweed	*Chenopodium album*			×

from 20 to 150 mm) have been placed in the soil at a known location within the workspace. Then, the positions of each plant have been computed using the proposed identification method and the results were compared with the ground-truth values. To prove the consistency in the detection, the experiment was performed 10 times before varying either the location of the plants or the light conditions (i.e., at different time during the day).

The cart setup was then assembled at Oliver Agro S.R.L. (Engazzà di Salizzole, Verona, Italy) where custom components were designed to mount the robotic system on the cart and to fine tune the position of the different elements. To collect the eradicated weeds, a trashing system has been added to the cart. It consists of three plastic buckets placed in the back side of the structure. This design choice requires that at every pick, the robot has to move both x and y axes to move to the closest drop zone. The solution is not optimized since it requires more energy consumption compared to having a trashing area at each side of the vehicle. However, it allows having more available workspace, as only one of the four sides of the robot's workspace is reduced.

The system was then transported to the test area (Brà Ortofrutta società agricola semplice s.s., Engazzà di Salizzole, Verona, Italy) where a portion of an open field was made available to evaluate the performance of the vision system with different natural light conditions. We planted seven different species of plants in a 2.5×1.5 m^2 space, keeping the intra-plant distance of 250 mm. The vision system was then placed above the cultivated field and programmed to capture a set of four images at every hour of the day from 7:00 AM to 9:00 PM for a total of two weeks. Together with the images, the relative luminosity of the day and the temperature were measured with an external sensor (MT-912 LightMeter, Urceri, China) and stored for optimizing the thresholding parameters according to the external illumination. Fig. 5 shows the experimental setups for the laboratory and open field scenarios.

In the same location, a greenhouse was prepared for the field test (Fig. 6). From the original 20×4 m^2 field, we only used about 70 cm in width and 10 m in length. We acquired from a local nursery about of 200 plants of lettuce (*Lattuca sativa*) having a diameter ranging from 30 mm to 70 mm. Then, we planted them in 3 rows keeping both the inter-row and intra-row spacing about 25 cm resulting in 12 crops inside the workspace of the robot. As tests were performed in winter, and due to plowing of the field, no plants were present on the field, so by the time we planted the lettuce, weeds did not have the time to grow. For this reason, we also had to manually introduce some weeds in between the crops, trying to reach a variability in numbers and shapes. The soil was leveled, not compacted and watered, a favorable condition to ease the pick of the weeds without risking to break the stem. After aligning the trash bins of the cart with the crop inter-row spacing, we repeated a series of 20 consecutive weeding operations for a total of 100 h over a span of a month, leveraging the natural illumination of the soil. For each test we checked the amount of correctly recognized plants, the amount of picked weeds, the amount of damaged crops, and the execution time.

4. Results and discussion

Initial tests were carried out with all the available deep neural networks and the one providing the more reliable results was selected. The selected network (ResNet18) comes already pre-trained using more than 300,000 plant images of different species and can correctly identify a target plant (genus) with an accuracy of 97.3% by using as input just a picture of its leaf (Garcin et al., 2021).

It is worth saying that in all the experimental scenarios we had a peculiar and simple situation: the soil is more or less leveled, so all the operations were performed with the robot and the camera perfectly parallel to the ground. It may happen that the situation will not always be such structured and the cart itself could be tilted if one wheel encounter a hill or a hole. Considering the 3D information provided by the RGB-D cameras this is not an issue in terms of plant localization, but in the computation of the pick location could lead to some issues.

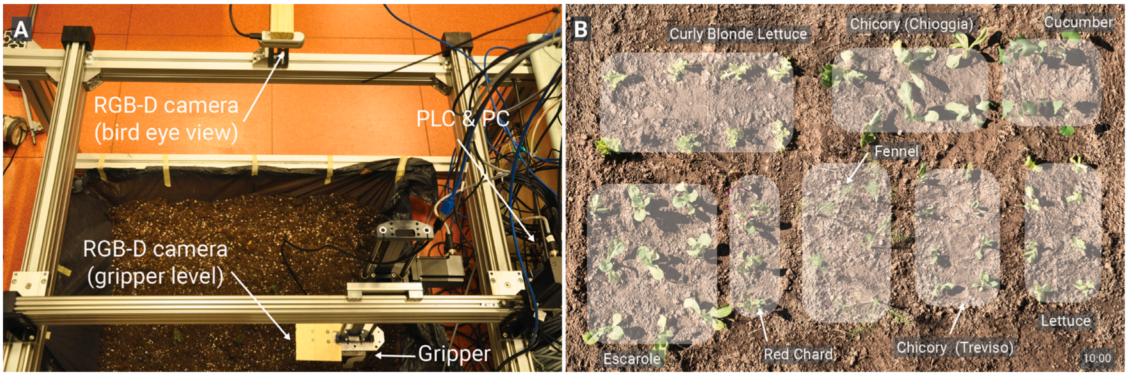

Fig. 5. Experimental setups for the laboratory and open field experiments. (A) The laboratory setup consists of the gantry robot and the vision system only. Plants have been placed in the artificial soil (depth 240 mm) within the robot workspace. (B) The open field setup and the displacement of the plants used. Plants are grouped by species and placed in a non-organized manner to not provide additional spatial information during the tests.

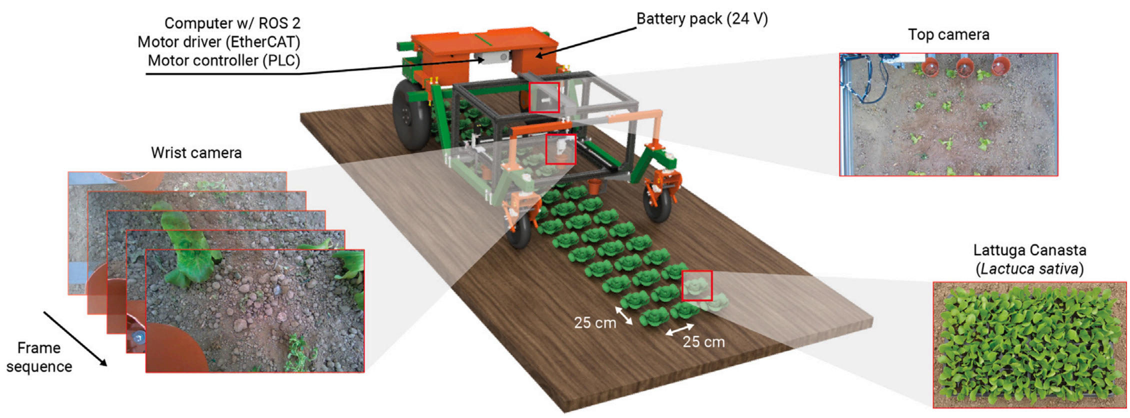

Fig. 6. Experimental setup for field validation. The XYZ gantry robot has been mounted on the semi-autonomous cart and then tested in the field. The two cameras have been used to, respectively, analyze the initial crop configuration (top camera) and to track the targeted weed while approaching, removing, and dispose of it (wrist-camera). In the tests, we used a particular variety of *Lattuca sativa* (Red leaf lettuce) which was manually planted in a pre-plowed field.

4.1. Laboratory scenario

For the initial tests, we select two plant species, lettuce and savory, to be considered, respectively, as the main crop and the weeds. Savory was selected since the plant has a thin stem covered by many tiny leaves, which created a peculiar situation that is also found in the field. Nevertheless, any other plant would have been a good option for testing since the system is trained to identify the main crop, and then it automatically classifies all the remaining plants as weeds.

A different number of targets (at first only of the same species, then together) were placed in the soil at known locations within the workspace. The position of each plant was obtained using the proposed identification method, then the results were compared with the ground-truth value (Fig. 7A). In all the cases, the system was able to correctly identify the weed with an accuracy of 97.8% and then extract their locations. Depending on the plant size and its position in the workspace, the error in measuring the plant location is within 10 to 100 mm. Larger errors occur for larger plants or groups of plants that partially overlay each other. In addition, there were cases where the algorithm splits the plant into two (o more) different entities, altering the accuracy in the computation of the plant location (Fig. 7B). These inaccuracies are due to the resolution of the camera, which is positioned at 1 m above the ground to view the whole workspace without interfering with the motion of the gantry robot. To improve the accuracy and thus improve the picking, the data acquired from the second RGB-D camera was then used.

After the initial estimation and correct classification of the target plants, the robot moves towards the target, and, once over it optimizes its position by performing a second classification of the underling plant using the second camera. By doing so, the search area for the weed was reduced on average by 57% (which corresponds to a movement of 30 mm) and up to 95% for cases where the plant was small and compact. This refinement ensured a reaching rate to the target of up to 95%.

Similarly, the position of the weed along the z-axis is improved. During the initial measurements, some depth data from the ground is used to compute the picking height of the plant. With a camera closer to the target, it is possible to reduce the portion of incorrect data selection. The initial estimation has an average value of 700 mm with respect to the origin of the system (placed at the top left intersection of the x and y axes, at a height of 800 mm from the ground). During the refinement, the z-value of the picking point has been corrected by shifting its value upwards, thus ensuring a better picking and avoiding collision with the ground when performing the task.

With the updated picking height, the accuracy in weed removal is slightly higher than 92%. Failed removal occurred with plants that had a high bending of the stem (due to a wrong approach angle) and for plants with a total height lower than 50 mm (due to limitation on the z-axis). Fig. 7C shows a complete sequence of removal and dropping of a weed placed in the workspace of the robotic system, together with a lettuce plant that has not been removed or touched.

4.2. Open field scenario

We then evaluated the performance of the vision system in detecting different species of plants under different light conditions (Fig. 8A).

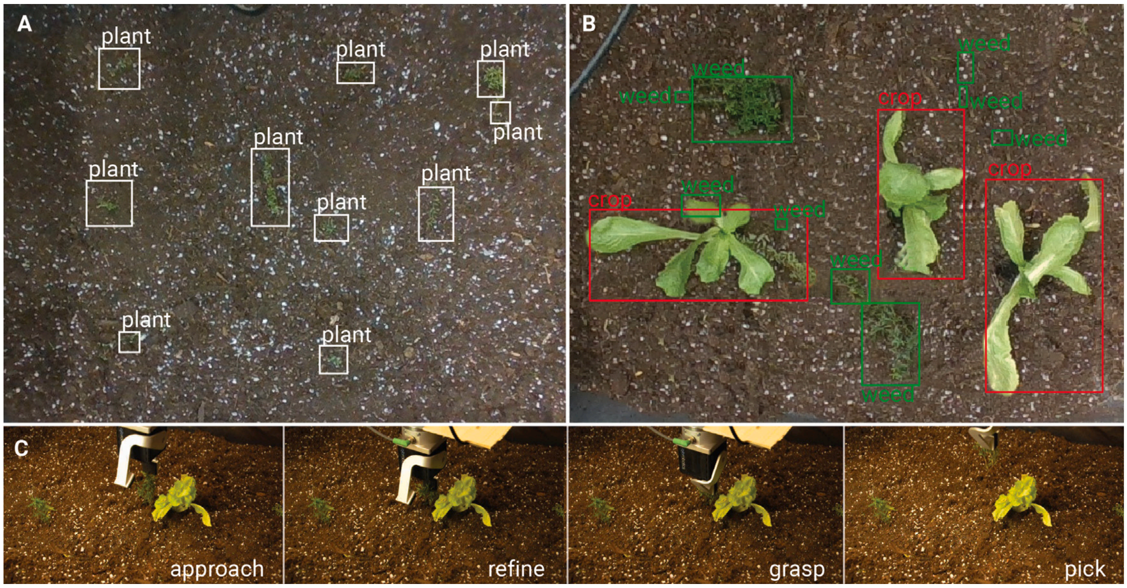

Fig. 7. (A) Identification of target plants (Savory). (B) Autonomous localization of weed. Red boxes contain crop plants that must be untouched during the weed removal process. Green boxes, instead, indicate the location of the weeds. (C) An example of complex weed removal (close to the main crop).

Since the adopted approach's goal is to identify the main crop, we selected a series of plants and grew them in the open field.

This series of experiments had three main objectives: (i) the selection of the optimal thresholding parameters as a function of illumination intensity (no extra light was used in the experiments); (ii) the empirical evaluation of the proposed segmentation protocol using both a fixed set of values for all the considered cases, and an adaptive thresholding (obtained at the previous stage); (iii) evaluation of the accuracy in the classification using the region of interest (ROI) defined by one of the thresholding methods.

We acquired a set of 840 images collected in the time span of two weeks (14 days) at regular intervals (15 min) from 7:00 AM to 9:00 PM. For each of the acquired images, we manually defined a ground-truth image where the plants were selected. We ran a grid search optimization algorithm where the six parameters (min/max Hue, min/max Value, and min/max Saturation) were dynamically changed to obtain the optimal set of values for each of the considered sets. Together with the images, we collected the illuminance of the environment, which values were averaged per hour-set. Results show that the threshold value for the Hue component remains almost constant during the day (standard deviation, 0.0085) both for its maximum and minimum values. Regarding the Value and Saturation components, we fixed the maximum value to 1.0 since values above 0.67 and 0.82 did not produce any valuable change in the results, and lower values remove large portion of the plants. Their minimum values, instead, were the ones that show a visible change during the day with a standard deviation of 0.0581 and 0.1247, respectively. To obtain an illuminance-dependent thresholding, we fit a third-degree polynomial for the minimum values of Saturation and Value while keeping the others constant. Fig. 8B shows the results of the optimization.

To prove the effectiveness of having an illuminance-depending thresholding with respect to having a fixed set of values, we compared the results in terms of number of clusters extracted from each of the approaches. To select the fixed thresholding, we averaged the ones obtained in the previous experiment. As shown in Fig. 8C, the fixed thresholding has in general better performance, providing 6% fewer clusters than the adaptive one. After the merging of the clusters, the two approaches provide similar results, with the adaptive thresholding performing 2% better than the fixed one. This means that the adaptive thresholding generates a higher number of clusters close to each other, which can be easier merged. The high number of clusters obtained in these experiments is due to the fennel that has a widespread leaf' system (Fig. 5B) which generates numerous clusters which tend not to aggregate. In addition, we evaluated the coverage of the clusters using the same ground-truth images presented before. Thanks to the high number of clusters (i.e., high number of pixels in the mask), the adaptive thresholding can detect up to 95% of the pixels belonging to the plants (mean coverage: 87%). Similarly, the fixed thresholding achieved a similar mean coverage, 84%, but maximum coverage of 91.5%.

The last series of tests was about the classification performance of the extracted ROIs. Fig. 5D shows that the model chosen for the task is robust enough to provide an average accuracy of 88.9% and 88.3% for the fixed and adaptive thresholding, respectively. The class that reduces the performance is the fennel, which was classified 30% of the cases as a carrot (*Daucus carota L.*) due to the similarity of the leaves. However, its classification accuracy improved when the illuminance is low because it helps to aggregate larger clusters and thus to have a more informative ROI. Excluding the fennel class from the computation of the average accuracy, it increases up to 90.66% and $91,25\%$ for the fixed and adaptive thresholding, respectively.

4.3. Greenhouse scenario

In this series of experiments, we tested the integrated system in a real scenario where a set of plants were grown in a green house and the task was to remove the weeds from the field (see Fig. 9 for an example of a complete pickng sequence). Since the two thresholding methods are comparable in results, we first evaluate their performance, then we opted to use the fixed threshold approach since the robotic system is not equipped with an illuminance sensor which is left for future integration.

The plastic film of which the greenhouse is made, affects the sunlight that passes through it; in particular, the selection of the material allows different intensity of light (Kittas et al., 1999), while the color of the film can reduce the color spectrum that passes through. The greenhouse covering plastic was white and even though it allows the plants to absorb the sunlight, it reduces the color spectrum. With the use of the fixed and the adaptable thresholdings, the plant detection remained unchanged and could extract the position of the plants with an accuracy of 98%. However, the classification of the crops dropped to 70% for the fixed case, while it remain almost unchanged (96.2%) for the adaptable one.

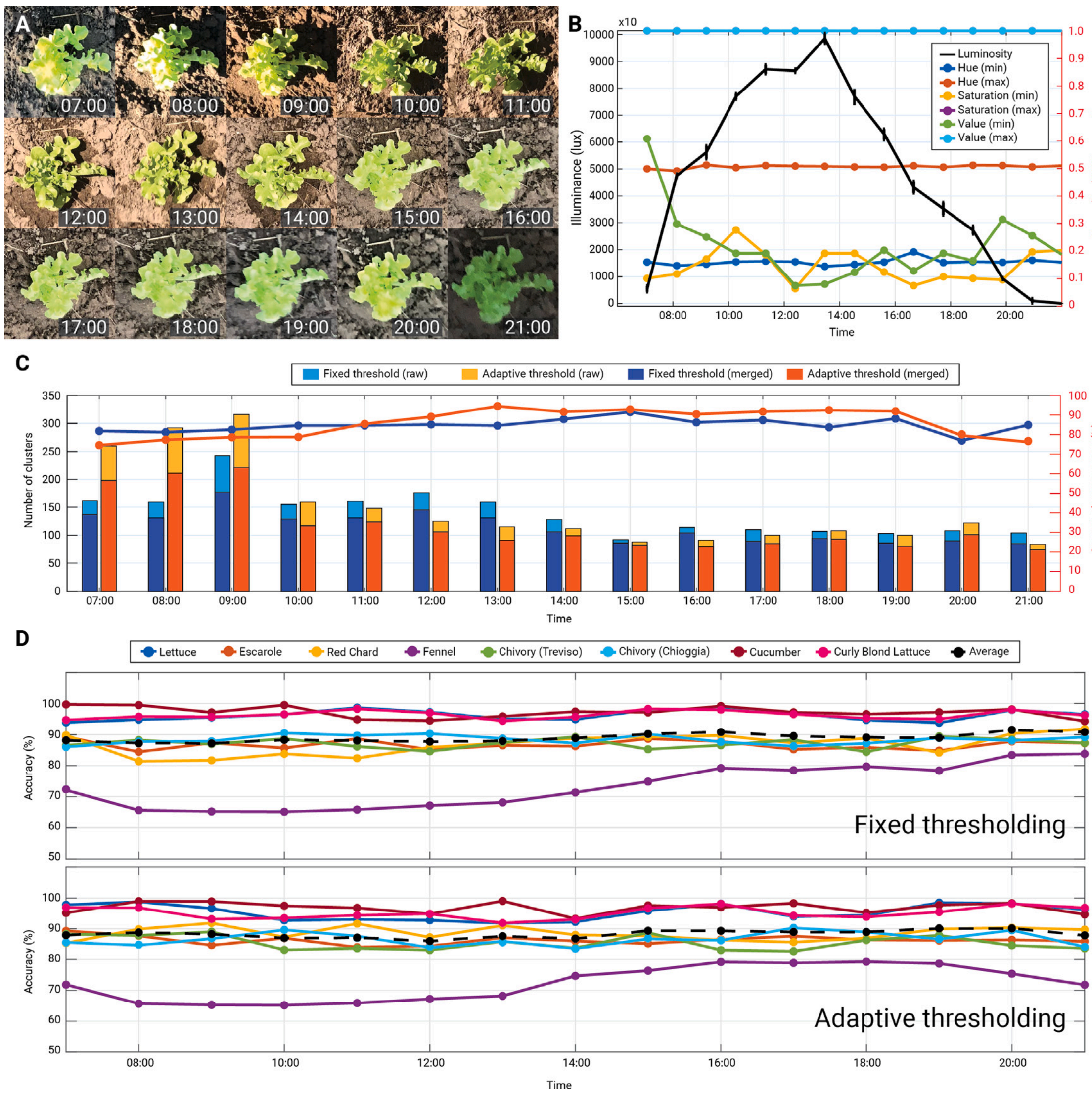

Fig. 8. Results of the open field scenario. (A) Example of the change in the illuminance during the day. The plant in the picture is a Curly Blonde Lettuce belonging to the set of plants chosen for the experiment. (B) HSV thresholding parameters (right axis) plotted against the environmental illuminance (left axis). (C) Number of clusters obtained by using a fixed thresholding and an illuminance-dependent one. The two methods are comparable and provide a correct mask with an accuracy of 95%. (D) Classification results of the selected plants using the region of interest provided by the two thresholding methods.

The change in the light condition, in addition to the change of the perceived colors, caused additional shadow projection which not only affected the fixed thresholding, but also the feature extraction of the neural network. We tried to overcome the issue by using a uniform lightning source; however, the classification accuracy improved only slightly (78.3%). For comparison, Gai et al. (2020), which implemented an algorithm using fusion of color and depth images to distinguish between crop plants and weeds, obtained segmentation success rate of 92.4% on lettuce. Chandel et al. (2021) obtained similar results to ours with their integrated inter- and intra-row weeding system, which resulted in a 92.8% weed mortality in maize field and 84.1% in pigeon pea crops.

To avoid erroneous classification, we opted for an approach used also in commercial products, which consists in adding a priori knowledge to the system. The common approach is to integrate several parameters to fully describe the operation environment. These vary according to the application domain, but in general comprise the crop dimension, distance between each plant, and number of crop rows. Here, we only need to integrate the intra-row spacing to cross-check the extracted ROIs against a known scheme (i.e., their expected location given a pre-defined starting point).

With this addition, we could reach a detection accuracy of 98%. However, it turned out that in several cases we have an overestimation of the location of the plants, i.e., the same plant is detected multiple times. In particular, the system detected 268 lettuce plants against the 256 real ones, meaning an 5% overestimation, while it detected 144 weeds against the 76 real ones, raising the overestimation to 89%. This result is due to the complexity of the shape of the weeds in the fields, which is not properly captured by the top camera. In fact, some selected weeds are made of tiny leaves (e.g., the couch grass or the common purslane), which makes it hard to merge the pixels in a single cluster. As a result, this cause unwanted picking of dirt, stones, and the erroneous computation of the picking point.

The picking accuracy reached the 85% of the cases, which is slightly lower compared to the indoor experiments (92%); the overestimation of detected plants is the main reason of this result. In most of the cases, the gripper reached one of the outer leaves of the weed that was wrongly detected as a separate plant, which were too small or too low (close to the ground) to be correctly picked up. The overestimation error resulted in the increase of the total execution time of each weeding operation.

Despite the high picking accuracy, some crops were wrongly classified as weed and removed from the soil. The damaged crops were

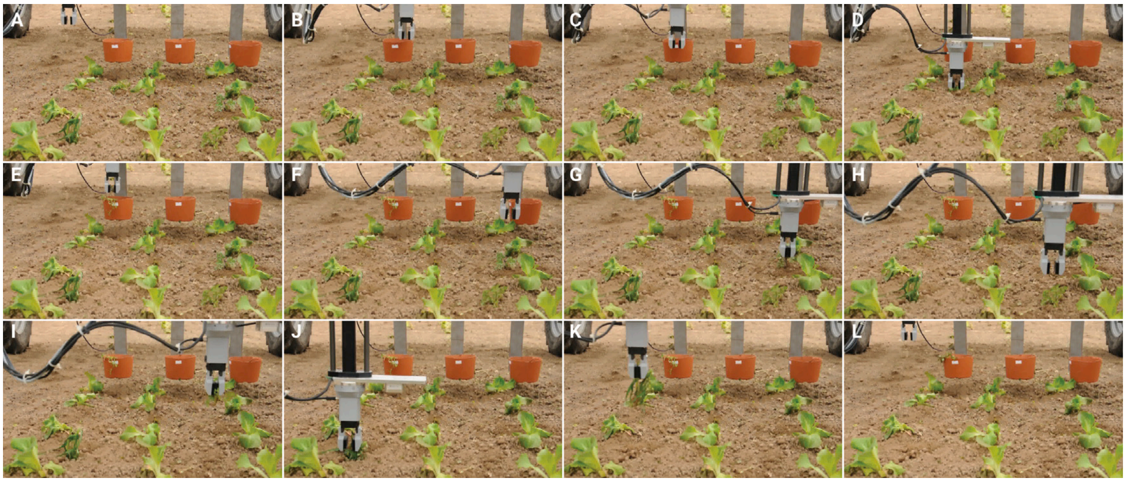

Fig. 9. An example of a picking sequence for weed removal. (a) The initial setup: 12 plants of lettuce and 4 weeds placed randomly withing the workspace. (b) The approaching phase, where the robot moves towards the coordinates computed from the top camera. (c) The refinements of the picking point due to the corrections computed by the second camera. (d) Picking of the weed. (e) Disposal of the weed into the closest trash bin. (f–g) The removal of the second weed places intra-row between two lettuce plants. (h–i) The removal of the third weed. (j–k) The removal of the last weed. (l) The cleaned field with the robot at home position.

Table 3
Table showing the comparison of performance of the system under different conditions: the setup in the laboratory, the field setup where only the HSV fixed thresholding has been tuned, and the field setup when a priori knowledge has been added.

	Laboratory	Greenhouse	
	Threshold only	Threshold only	A priori knowledge
Detection accuracy	95%	98%	98%
Crop overestimation	5%	5%	5%
Weed overestimation	87%	89%	89%
Correctly identified crops	98%	70%	98%
Correctly identified weeds	97.8%	98%	98%
Refinement error	10–100 mm	–	10–20 mm
Correctly picked	92%	–	85%
Average weeds/minute	10	–	6
Damaged crops	0.5%	–	4%

less than 4% of the total plants, which was an acceptable result also considering the picking accuracy. This was possible thanks to the second camera (wrist-camera), which corrects the estimation obtained by the top camera. Moreover, the use of the second camera leads to a refinement in the picking location for most of the weeds, with a correction ranging from 10 to 20 mm, which allowed a more precise grasping. A comparison of the performance of the robot in the three scenarios is summarized in Table 3.

The execution time of each weeding operation was also recorded. In the laboratory settings, the average weed removal was 10 weeds/min, while in the field experiments it dropped to an average of 6 weeds/min or a weed every 10 s. One of the reasons, together with the overestimation of the weeds, could be the different positioning of the trash bin that were moved from the side of the workspace to its back, increasing the travel distance. Time performance can be reduced by moving the location, leading to a minimum amount of movement to drop each weed. For comparison, Michaels et al. (2015) could perform 10 times faster than our solution, but their weeding tool was a stamp used to push weed into the ground instead of removing it, simplifying the complexity of the task. Similarly, laser weeding (Kaierle et al., 2013; Andreasen et al., 2022) can provide a fast method for removing weeds in the early stage of the plant (Andreasen et al., 2022). The proposed mechanical solution, instead, can reach every weed on the ground at a different growth stage, reducing the energy consumption and keeping the cost contained. In fact, lasers require several kW to be operated, reducing the system's autonomy which is a key factor in their adoption together with the high cost (Tran et al., 2023).

5. Conclusions

Weeds removal is a critical issue in agricultural management. Common solutions to treat weed infestation in crops either consist in mulching the soil, using chemical pesticides, or mechanical weeding performed by machines or humans. Robotic solutions are entering the picture, however, there is a need for further research and development in order to improve their capabilities and make them more effective at performing agricultural tasks. In this optic, in this paper, we presented a mixed-autonomous robotic system design to remove weeds from crops.

The presented robotic system comprises a remote-controlled rover and a fully-autonomous robotic system for weed detection and removal. This consists of a gantry robot, a gripper, and a set of RGB-D cameras. By leveraging computer vision and artificial intelligence, we demonstrated the capability of the system to accurately identify and remove weeds in a crop. The robot is still in a prototype phase and can be improved in several ways such as improving the control system, adding autonomous navigation capabilities, and refining the recognition system. On top of that a GPS RTK, a lidar, a sonar, and other sensors can be added so that autonomy can be implemented also in cart movement. These improvements could lead to a fully autonomous solution that is efficient, eco-friendly, and safe for farmers. From the software point of view, the main improvements are in the recognition system. At the moment the initial segmentation is tuned to highlight only green vegetables, however, crops might have different combination of colors. To solve the color issues, one way could be to change the approach and build and train a neural network capable to not only recognize, but also to localize different plants in a single image, skipping the feature extraction step we performed using computer vision.

This work demonstrates the feasibility of a robotic weeding system that can identify and eliminate individual weeds with precision, removing them from the field instead of leaving them behind. This successful prototype lays the groundwork for further research and development aimed at enhancing the efficiency, safety, and profitability of agricultural operations. This technology has the potential to promote sustainable agriculture and underscores the significance of innovation in this area.

CRediT authorship contribution statement

Francesco Visentin: Conceptualization, Methodology, Validation, Investigation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Simone Cremasco:** Software, Validation, Investigation, Data curation. **Marco Sozzi:** Writing – review & editing, Supervision. **Luca Signorini:** Resources. **Moira Signorini:** Resources. **Francesco Marinello:** Writing – review & editing, Supervision. **Riccardo Muradore:** Writing – review & editing, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request

Acknowledgments

The authors would like to thank "Brà Ortofrutta società agricola semplice s.s." for having made available a portion of their greenhouse and the plants used in the field experiments. The authors would also thank Leozann Ecogreen for providing the electric cart and Sipro for their supervision during the development of the PLC-based controlling system.

Fundings

This work has been partly funded by the POR FESR 2014–2020 Regione del Veneto project: "L'agricoltura del futuro e gli alimenti funzionali: una sfida per la ricerca e il rilancio del territorio", CUP: B76B20001010009.

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