
The use of agricultural robots in crop spraying/fertilizer applications

Ron Berenstein, University of California-Berkeley, USA

- 1 Introduction
- 2 Challenges in current robotic sprayers
- 3 Case study: robotic sprayers in vineyards
- 4 Conclusion
- 5 Future trends
- 6 Where to look for further information
- 7 References

1 Introduction

Application of nutrients, fungicides and pesticides is one of the most important processes in agricultural production and can have a significant impact on crop yield, quality and ultimately profitability (Singh et al., 2005). It is estimated that approximately 30–35% of crop losses can be prevented when harmful insects and diseases are eliminated by applying pesticides (Cho and Ki, 1999). Although pesticides are needed in modern agriculture, they are poisonous and dangerous for humans (Dasgupta et al., 2007; Rogan and Chen, 2005) and the environment (Pimentel and Lehman, 1993; Reus et al., 2002).

The current common approach for pesticide application is mechanized non-selective spraying in which a human drives a tractor connected with a mechanized sprayer that sprays the crops continuously. The sprayer can be mounted (Fig. 1a) or towed by the tractor (Fig. 1b). Another method of pesticide application includes a human operator selectively spraying targets using a backpack sprayer. However, this type of spraying is rarely in use due to the long operational times, the exposure of the human to the hazardous pesticide material and human fatigue. Despite the use of pesticide protection equipment (e.g. central filtration system and personal head mask for the mechanized and manual spraying methods, respectively) the human is still exposed to hazardous pesticides that can cause negative health issues (Swan et al., 2003).



Figure 1 Tractor sprayers. (a) The sprayer is mounted directly on the tractor (also known as three-point sprayer), (b) trailed sprayer where the sprayer is being towed by the tractor.

Agricultural robots have been developed for many operations, such as field cultivation, planting, spraying, pruning and selective harvesting (Edan et al., 2009; Nishiwaki et al., 2004; Oberti et al., 2016). Robotic spraying technology can benefit from these latest developments in agri-related robots.

Robotic technology can provide a way to reduce the quantity of pesticide applied, improve its sustainability and reduce its environmental impact (Slaughter et al., 2008). A target-specific robotic sprayer can reduce the amount of pesticides applied in modern agriculture and potentially remove or minimize the human presence during the pesticide spraying process (Lee et al., 1999). Studies show that up to 60% of pesticide use can be reduced when fruit and vegetables are sprayed specifically (Elkabetz et al., 1998; Gil et al., 2007; Goudy et al., 2001).

A review on autonomous robotic weed control systems (Slaughter et al., 2008) describes the current status of the four core technologies (guidance, detection and identification, precision in-row weed control and mapping) required for the successful development of a general-purpose robotic system for weed control and sprayer robot. Although several complete robotic weed control systems have demonstrated the potential of technology in the field, additional research and development are needed to fully realize this potential. The two core tasks for an agricultural spraying robot are sensing - for target detection - and 'robotics' - for the spray execution (Song et al., 2015).

Automation in the weed control process has received increased attention from the scientific community and is already in use in the agricultural industry (Slaughter et al., 2008). Since mechanical removal is a difficult process, the plantations use herbicides to remove unwanted plants (Lameski et al., 2018). Slaughter et al. (2008) presented a review describing the current status of the four core technologies (guidance, detection and identification, precision in-row weed control and mapping) required for the successful development

of a general-purpose robotic system for weed control. Since then, several publications showed advances in robotic weeding (Vuong et al., 2017; McCool et al., 2018; Pérez-Ruíz et al., 2014). A commercially available automated weeder has become available for the farm (BlueRiver¹).

2 Challenges in current robotic sprayers

There are four core technologies required for developing a general-purpose robotic sprayer (Slaughter et al., 2008): guidance, detection and identification, precision in-row weed control and mapping. The developments must deal with the three sources of variation in a crop environment: objects, environment and crops (Bac et al., 2014).

2.1 Guidance and mapping

Accurately travelling along crop rows is a crucial proficiency agricultural robots must have. While the most common solution to guide vehicles along pre-planned routes is to use global navigation satellite systems (GNSS), the high cost of using high-precision GNSS and the lack of availability in all agricultural environments (Vázquez-Arellano et al., 2016) has led to investigations on how to guide the robot using computer vision (English et al., 2014). In the last few decades, vision-based guidance systems and algorithms were investigated in depth (Li et al., 2009; Reid et al., 2000). Research and development included guidance using RGB images, point cloud (depth images) and the use of multispectral sensors (Table 1).

Global positioning systems (GPS) are the key tool used for positioning and maintaining maps for precision agricultural tasks and are used for yield mapping and variable chemical applications. Real-time kinematics (RTK) GPS which has improved accuracy can be used for automated vehicle guidance (Slaughter et al., 2008). Bak and Jakobsen (2004) developed a robotic platform for mapping of weed populations in the field. Their work included the development of the robotic platform, the platform controller and experiments of the platform manoeuvring in the field. Peteinatos et al. (2014) developed ground-based sensors carried by a robot in the field to detect weed and weed infestation level.

2.2 Target detection

One of the main barriers to pesticide reduction using robotic sprayers is the target detection process. Despite R&D performed along the past decade

¹ <http://www.bluerivertechnology.com>.

Table 1 Agricultural robotic guidance

| Application | Sensor | Reference |
|--|--|--------------------------------|
| Robot guidance along crops rows - open field | RGB | English et al. (2014) |
| Driving along row crops - open field | RGB | Xue and Xu (2010) |
| Row navigation - open field | RGB | Chang and Song (2017) |
| Autonomous speed sprayer guidance using vision and fuzzy logic | RGB | Cho and Ki (1999) |
| Crop rows detection for agricultural robots navigation | RGB | Jiang et al. (2010) |
| 3D imaging systems for agricultural applications | 3D | Vázquez-Arellano et al. (2016) |
| Path planning and obstacle avoidance - row crops | Stereo vision | Rovira-Más et al. (2006) |
| Autonomous navigation - maize field | LIDAR | Hiremath et al. (2014) |
| Robot navigation and plant detection | Ultrasonic | Harper and McKerrow (2001) |
| Mapping and navigation - open field | Sonar | Toda et al. (1999) |
| Vegetation detection for mobile robot navigation | Multispectral | Bradley et al. (2004) |
| Vehicle steering control using overhead guide | N/A | Gat et al. (2016) |
| High-precision straight-line navigation - greenhouse | Six axis compass | Chang et al. (2016) |
| Robot navigation in greenhouses | Ultrasonic (low and mid-range), digital compass, radar | González et al. (2009) |

Table 2 Detection and identification

| Application | Sensor | Reference |
|--|-----------------|-----------------------------|
| Real-time apple detection - apples | RGB | Bulanon et al. (2004) |
| Grape clusters and foliage detection | RGB | Berenstein et al. (2010) |
| Precision weed control - cotton | RGB | Lamm et al. (2002) |
| Human-robot collaboration for target detection - vineyards | RGB | Berenstein and Edan (2012a) |
| Fusion of visible and thermal images for fruit detection | Thermal and RGB | Bulanon et al. (2009) |
| Adaptive thresholding for pepper detection | RGBD | Vitzrabin and Edan (2016) |
| Orange fruit detection algorithms | RGB | Hannan et al. (2010) |
| Fruit detection system using deep neural networks | RGB and NIR | Sa et al. (2016) |
| Weed detection (<i>Avena sterilis</i>) | RGB | Tellaache et al. (2008) |

(Table 2) detection rates are low with a maximum of a 90% hit rate. The reasons for these low rates are because of the complicated field conditions caused by the changes in illumination (due to changes in the sun direction, clouds),

shading, the highly variable plant characteristics (size, colour, texture, shape, location) and the occlusion of targets (caused by leaves, branches). Berenstein et al. (2010) showed a 90% hit rate for grape clusters (green type) detection while using a colour CCD sensor and applying morphological manipulation on the RGB channels. Work by Diago et al. (2012) showed 95% hit rate for detecting grape clusters (red type) but since the background was an artificial white screen (to avoid confounding effects from the background vegetation) the actual hit rate performance in real-world conditions will probably decrease. A recent review of this topic is Luo et al. (2016).

2.3 Control

The use of spraying nozzles in modern industry is widespread for different applications such as cleaning (Canny, 1986), coating (Sharifi et al., 2002) and painting (Breiman et al., 1984). Manufacturers offer a wide range of nozzles with manually adjustable spraying angles and even automatic spraying systems that can control the flow rate (e.g. Spraying Systems Co, PulsaJet, AutoJet). Due to the nature of products and applications in the industrial domain, the nozzle spraying angle is preset manually according to the designated target, which is well defined. In the agricultural domain, the targets have inherent high variability in size (e.g. watermelon, lettuce) and shape (e.g. grape clusters, cherry tomatoes, eggplant, kiwi, strawberry) (Kapach et al., 2012) that requires adjusting the spraying coverage to the specific target.

Extensive research has been performed over the past two decades on spraying robots, mainly for the automotive industry (Berenstein et al., 2015), with focus on path planning of the robotic arm and achieving uniform paint thickness layers (Diao et al., 2009; Sahir Arıkan and Balkan, 2000; From et al., 2011; Conner et al., 2005). Agricultural spraying robots (Table 3) have been developed mostly for weed control and plant protection applications (Pergher and Petris, 2008; Singh et al., 2005; Slaughter et al., 2008; Steward et al., 2002; Mandow et al., 1996; Zhao et al., 2016; Gazquez et al., 2016; Guan et al., 2015). One of the main goals of the agriculture engineering research, and in particular the precision agriculture community, is to reduce the use of pesticides while preventing crop losses due to pests (Pérez-Ruiz et al., 2015).

3 Case study: robotic sprayers in vineyards

In the following case study, we discuss the design and implementation of a smart spraying framework that includes a fully functional mobile robot positioned in the field equipped with a smart sprayer and a remote human supervisor assisting the robot with the target detection task. The case study deals with the smart implementation of pesticides towards grape clusters aiming to direct spray towards only the grape clusters.

Table 3 Weed and spray methods

| Application | Control method | Reference |
|--|------------------------------|-----------------------------|
| Site-specific weed management | Direct-injection sprayer | Goudy et al. (2001) |
| Non-chemical weed control | Electrical discharge | Blasco et al. (2002) |
| Weed vision-based perception | Mechanical weed control | Strand and Baerveldt (2002) |
| Plant protection with a variable rate application | Spraying, ultrasonic sensors | Gil et al. (2007) |
| Spraying robot - grape production | Chemical spraying | Ogawa et al. (2006) |
| Individual weed treatment using a robotic arm | Chemical spraying | Jeon et al. (2005) |
| Unmanned aerial vehicle for spray application | Chemical spraying | Huang et al. (2008) |
| Pesticide dose adjustment in vineyard spraying | Chemical spraying | Pergher and Petris (2008) |
| Precision spraying methods | Coloured water spraying | Berenstein and Edan (2012c) |
| Human-robot collaboration for vineyard spraying | Coloured water spraying | Berenstein and Edan (2017) |
| Teleoperated robotic sprayer | Water spraying | Adamides et al. (2017) |
| Automatic adjustable device for precision spraying | Coloured water spraying | Berenstein and Edan (2018) |
| Specification development of a robotic system for pesticide spraying in greenhouse | Chemical spraying | Komasilovs et al. (2013) |
| Information from spraying, harvesting and grading operation robot | Chemical spraying | Arima et al. (2003) |

The potential reduction of pesticide use is inversely proportional to the per cent of grape clusters in the image. An analysis of the relation between the per cent of grape clusters in real field images to the saving potential is shown in Fig. 2. The saving potential increases with a smaller number of grape clusters in the image. Fewer grape clusters are common early in the season and can be caused by a gap between the grapevines.

The human and robot work collaboratively to detect targets in a sequential mode. The framework places the human at a remote location equipped with a target-marking device (e.g. a stationary computer, laptop, tablet, PDA or smartphone) and uses the human's excellent perception skills to mark targets on images captured by the robot in the field.

3.1 Automatic adjustable spraying device

An adjustable spraying device (ASD) was designed and built as an experimental tool in order to implement the one target-one shoot (OTOS) spraying method

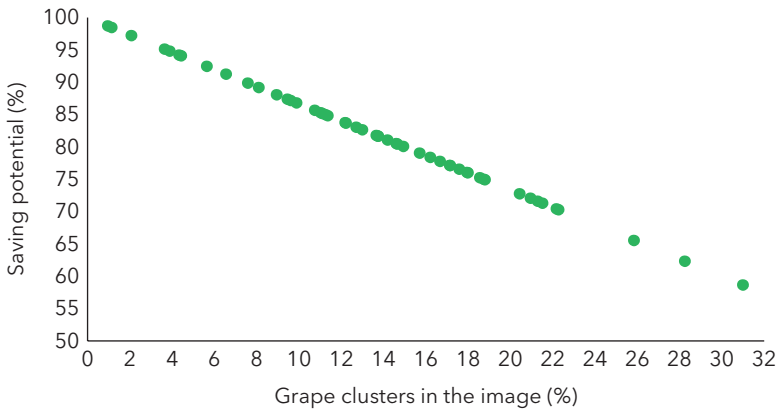


Figure 2 Evaluation results of the relation between saving potential and grape clusters in the image. Source: adapted from Berenstein et al. (2010).

(Berenstein and Edan, 2012c), applying single spray for each target by adjusting the spraying diameter according to the target. Two other alternatives were evaluated, fixed nozzle spacing and optimal spray spacing, both with fixed spray diameter (i.e. several sprays to completely cover the target). Analysis of the spraying costs (Fig. 3) reveals the advantage of selecting the OTOS spraying method.

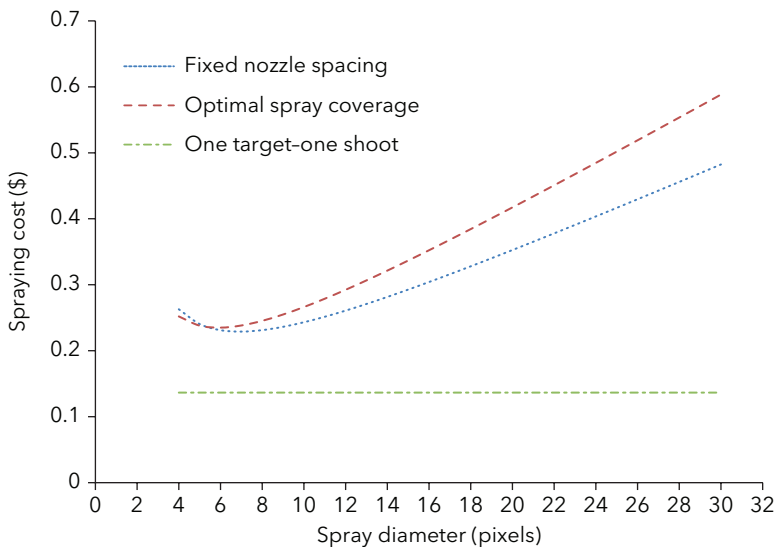


Figure 3 Economic function results.

The device is mounted on to a mobile robotic sprayer that supplies pressurized pesticide. The operational concept of the ASD is as follows:

- 1 Direct the nozzle to face the crop (perpendicular to the crop).
- 2 Capture an image using the ASD camera.
- 3 Find the targets positions and diameters.
- 4 For each target perform the following routine:
 - a Direct the ASD towards the target centre,
 - b Adjust the nozzle diameter to equal the closing circle diameter of the target, and
 - c Open the sprayer electric valve for a specific pre-defined time.

3.1.1 ASD design and characteristics evaluation

The ASD is presented in Fig. 4. The ASD base is constructed from three aluminium parts, two pressure plates that mount the spraying nozzle and the two line beam lasers, and a shoulder. The shoulder is connected to the pressure plate with four screws and its height can be adjusted.

The ASD was based on a commercial spraying nozzle (AYHSS 16) using the recommended spraying pressure of 20 (bar). The spraying nozzle is constructed from two parts, the nozzle base and the nozzle cup. The nozzle base is mounted on to the pressure plates. The pressurized pesticide hose is connected to the nozzle base and the flow is controlled using an electric valve (on/off). The spraying diameter can be controlled by rotating the nozzle cap over the nozzle base. This nozzle was chosen since it is in common use among farmers that adjust the spraying diameter prior to the spraying task.

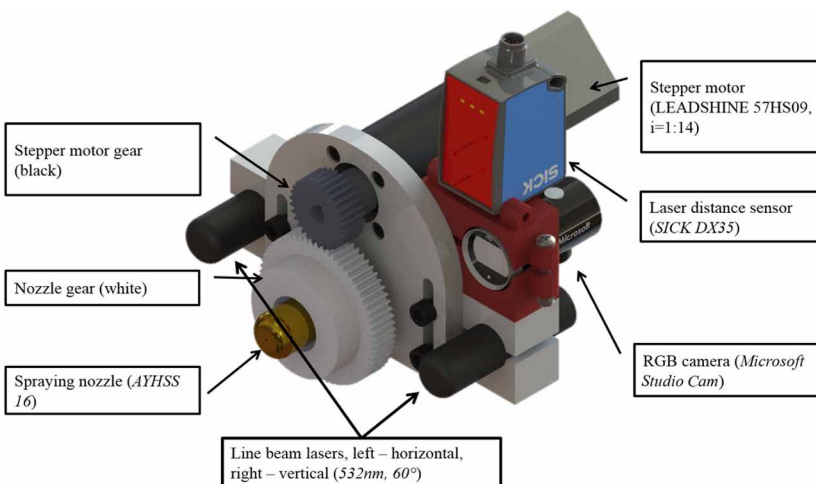


Figure 4 Spraying device. (a) Isometric view - CAD, (b) front view, (c) side view.

A stepper motor, mounted on the shoulder, is used to control the spraying diameter. The stepper motor is connected to the nozzle cap using two tangent gears, one connected to the stepper motor and the other connected to the spraying nozzle cap (Fig. 4). Rotational feedback of the stepper motor is acquired using a rotational potentiometer (ten rounds, 1 K Ω) connected to the stepper motor gear. An Arduino (uno) board closes the stepper motor position loop using feedback from the potentiometer and the desired circular position.

Other peripheral sensors are mounted on to the ASD; a laser distance sensor (SICK DX35) for measuring the distance between the device and the target, a colour camera (Microsoft LifeCam Studio) for capturing images from the field and later used for automatic target detection and two line beam marking lasers (532 nm, 50 mW, 60°) positioned horizontally and vertically for marking a cross (+) over the target. The entire device is mounted on a Pan Tilt Unit (PTU) (FLIR D46-17) able to rotate horizontally $\pm 180^\circ$ and vertically $+31^\circ$ up to -80° .

A PC is connected to an Arduino board, laser distance sensor, colour camera, PTU and the electric valve controlling the pesticide flow. The main software for managing the ASD was based on Microsoft Visual Studio (C#). The software collects data from the ASD sensors and controls the ASD orientation by adjusting the PTU, the ASD nozzle by rotating the stepper motor and the electric valve opening/closure, according to the collected data.

The spray diameter was evaluated in order to find the spray diameter (spray cone) for varying nozzle apertures. Using this relation between the nozzle aperture and the spray diameter, the spray diameter can be adjusted according to the target size.

The experimental setup (Fig. 5a and b) included the ASD facing the target base with a target attached. The target base was constructed from steel net and was mounted vertically on a manually controlled conveyor in front of the ASD (Fig. 5b). The target used for evaluation was a white paper sheet, 0.5 m wide, which was stretched top to bottom and fixed to the target base (Fig. 5b shows

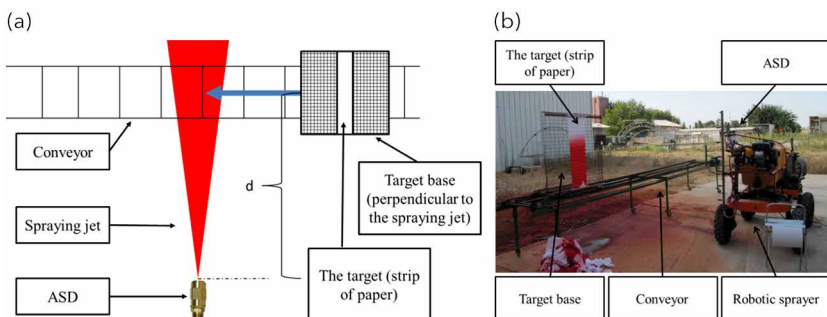


Figure 5 The configuration of an experiment for spray diameter evaluation. (a) Experiment scheme, (b) field view of the experiment.

the target fixed to the target base after spraying). In order to view the spray deposition and post-analyse the position of the spray, a red water-soluble food dye (Florma red 696) was used as pesticide replacement.

Each spray repetition included the following steps: (1) attaching a new target to the target base, (2) setting the nozzle aperture to the desired value, (3) opening the spray flow, (4) starting the conveyor movement towards the spray jet and (5) after the entire target base has crossed the spraying jet, the spray flow is closed and the conveyor stops. During the experiment, the robot was kept at a static position to ensure the ASD was static.

Image acquisition software was designed to capture a movie using the ASD camera along the spray process. After each spray repetition, the captured movie was saved for post-analysis. Each movie was manually scanned by a human expert to extract a single frame containing the target in mid-frame. The extracted frame was analysed manually for the spray boundaries (Fig. 6). Since the spray is cone-shaped, the spray diameter was evaluated by measuring the distance (in pixel units) between the upper and lower spray boundaries.

The experiments were performed at three distances between the ASD and the target (0.5, 1 and 1.5 m). For each distance, the nozzle angular position was between 175 and 210 with increments of 5 (units in potentiometer Ω). Three measurements were conducted for each distance-aperture combination. All experiments were performed at dawn ensuring no-wind conditions (this was confirmed by measuring the wind speed using Skywatch Xplorer 1).

The experimental results shown in Fig. 7 reveal the correlation between the nozzle aperture and the spray diameter for three measured distances. The

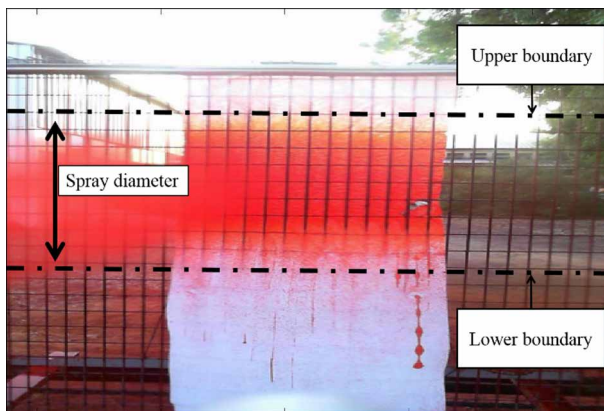


Figure 6 Example of a single frame extracted from captured spraying movie. Using the captured frame, the boundaries (upper and lower) and the spray diameter of the sprayed target were extracted.

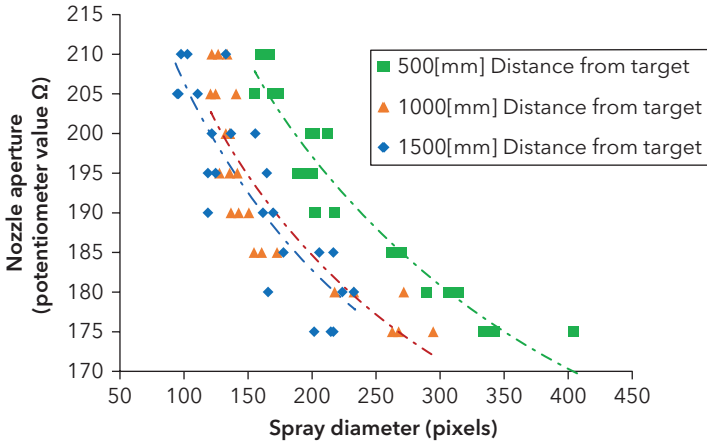


Figure 7 Experimental results of the spray diameter for three measured distances.

measured spray diameter increases as the distance increases. In theory, the three curves are supposed to unite since both the camera's field of view and the spraying cone have a linear trajectory. The spray dispersion is probably caused by the spray jet turbulence and air drag that affects the spray dispersion.

The spray diameter increases with the increase in distance between the nozzle and the target. This is because in the experiment the spray diameter is measured using the digital camera, which is located at the same distance as the spraying nozzle (Fig. 4, the spraying nozzle and the camera are located together), and is expressed using pixel units. Therefore, the measured spray diameter does not increase with the increase in distance but remains approximately constant due to the digital camera perspective.

Table 4 presents the curve fitting parameters for Fig. 7, where NA is the nozzle aperture and SD is the spray diameter.

By using the resulting curves for the different distances, the nozzle aperture can be calculated after extracting the target diameter. The spraying distance in most commercial vineyards is between 500 and 1500 mm. In order to correlate between the spraying distance and the nozzle aperture, an interpolation of the distance and the nozzle aperture can be applied.

Table 4 Experimental results summary

| Distance | Trend line (power) | R^2 |
|----------|----------------------------------|-------|
| 500 | NA = 600.22·SD ^{-0.210} | 0.911 |
| 1000 | NA = 490.97·SD ^{-0.184} | 0.782 |
| 1500 | NA = 467.12·SD ^{-0.177} | 0.761 |

3.1.2 ASD performance evaluation

An experiment was conducted in order to evaluate the performance of the ASD while implementing the results of the previous experiment (Table 4). Currently, the robotic sprayer is designed to perform the spraying task in step mode (Fig. 8): the robot travels a single step along the vineyard row, stops, captures images from the field, sprays the targets and moves another step forward. The experiment is based on the same work procedure. The robot movement speed was constant. One of the secondary goals of this experiment was to provide insights regarding the overall work procedure of the complete spraying system which will include the robot equipped with an ASD.

During the experiment, the ASD was attached to the robotic sprayer and was operated similarly to the planned robotic procedure which moved in step mode along the vineyard row (Fig. 8). During this experiment, the robotic sprayer was programmed to track a straight line placed at a 1.6 m distance from the target base (red plastic strip 50 mm width) (Fig. 9a). The robot was programmed to travel 1.6 m at each step. The ASD is mounted perpendicular to the robot's travel direction and faces the target's base (Fig. 9a). The target's base is a polyethylene net (50 mesh), 11 m long, stretched between two anchoring poles and positioned parallel to the line at the floor. The targets are attached to the target's base and the centre of the target is positioned 1.55 m high. In order to ensure a single target per image, the targets were positioned at intervals of 1.6 m, similar to the robot's travel distance.

The targets are blue polyethylene round circles with varying diameters (300, 250, 230, 210, 190, 170 and 150 mm). To simplify the detection and classification of the targets, a red circle was attached to the centre of the main target. The diameter of the red circle was one-third of the blue circle diameter.

Artificial targets were used to enable accurate target detection. The targets consisted of a round, blue, polyethylene target with different diameters (150, 170, 190, 210, 230, 250 and 300 mm). A round, red, polyethylene target was mounted on to the centre of the blue target. The diameter of the red target was one-third of the blue corresponding target (Figs. 9b and 10).

The target detection algorithm was based on colour thresholding and was implemented using MATLAB software equipped with the image processing toolbox. The detailed description of the target detection algorithm is presented in Berenstein and Edan (2018).

Following the detection process, the programme extracts the coordinates of the detected target's centre and the minimum closing circle diameter in pixel units. These measures are used to control the sprayer (i.e. direct the PTU towards the target centre and adjust the spraying diameter according to the closing circle diameter).

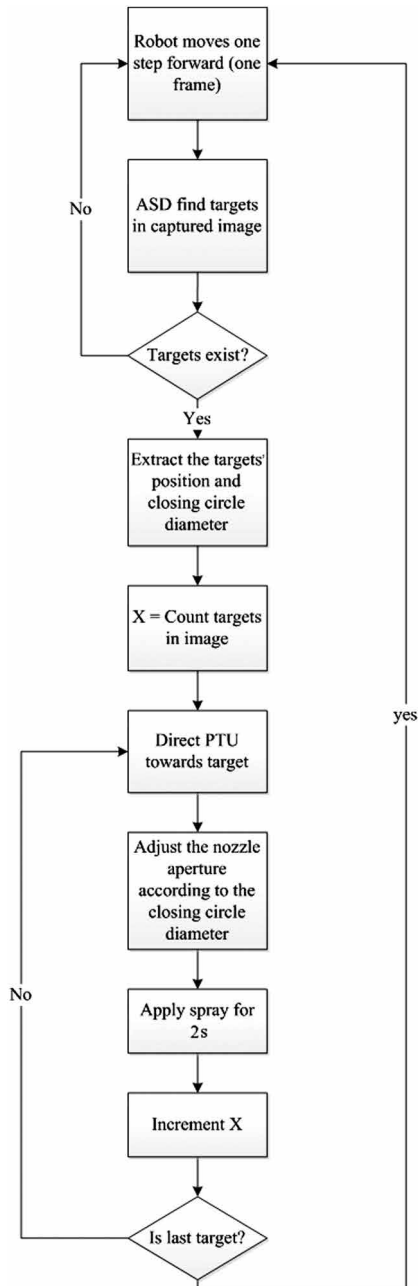


Figure 8 Robotic sprayer work procedure. The following experimental procedure was based on this figure procedure including the steps of directing the PTU towards the target core, adjusting the spraying nozzle and the actual spraying.

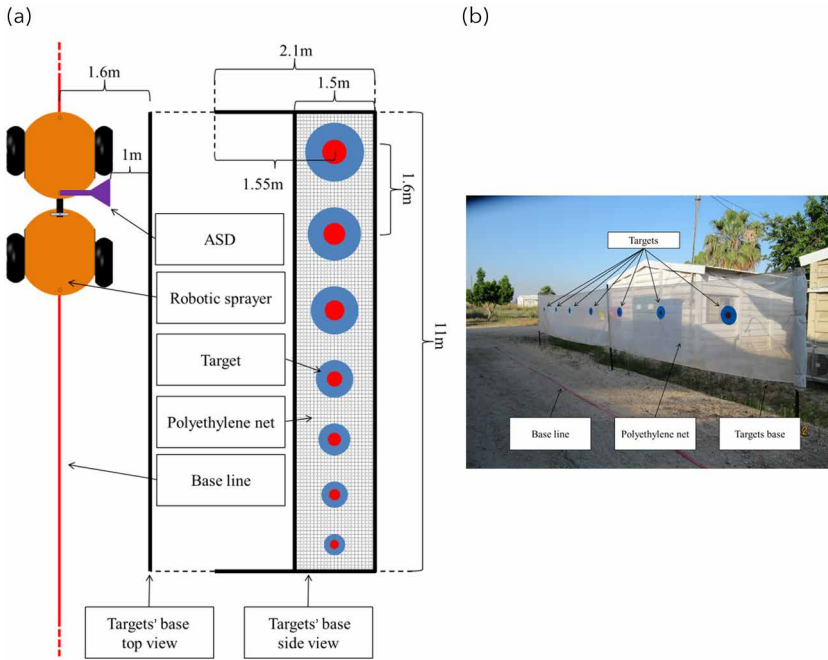


Figure 9 Experiment configuration. (a) Experiment scheme, (b) field view of the experiment.

The target detection algorithm, with all of its steps and unique values, was developed specifically for the artificial targets that were used in the experiments and it is not the core of this work. Needless to say that in order to use the suggested ASD, a specific target detection algorithm must be developed for the specific crop.

Similar to the previous experiment, a red water-soluble food dye (Florma red 696) was used as pesticide replacement to simplify the detection of the spray deposition.

The sprayed area was evaluated by both manually measuring the sprayed area's diameter immediately after each spray and image processing of images captured immediately after each spray (Fig. 10).

The experiment included 12 repetitions of the robot travelling along the line on the floor and spraying the seven targets attached to the target base. Each target was sprayed for 2 s. All experiments were conducted early morning. Measured wind speed was zero in all experiments (measured using Skywatch Xplorer 1).

The results described here use the ASD in automatic mode: the ASD automatically directs the PTU towards the target centre and adjusts the spray diameter according to the closing circle diameter of the detected artificial target.



Figure 10 Image captured immediately after spraying.

A visual inspection revealed that each target was fully covered by the spray. Experimental results are summarized in Fig. 11. The spray flows under gravitation force (Fig. 10) increasing the spray spot size which complicates the spray diameter analysis and was eliminated from the spray diameter evaluation.

The results of the automatically adjustable spray diameter show a constant increase of the sprayed diameter with the increase in target size; however, the ratio between the sprayed diameter and the target size decreases. This ratio can be addressed as the false detection ratio, and according to Fig. 11, this

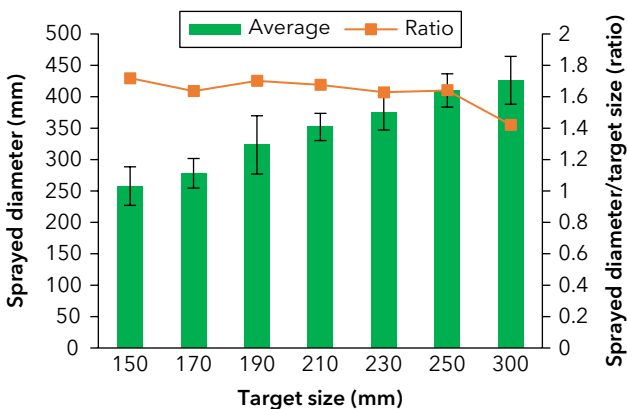


Figure 11 Experimental results. Each column represents the average sprayed diameters of 12 sprays (robot repetitions). The resulting standard deviation are shown in each column. The orange line (secondary axis on the right) measures the ratio between the sprayed diameter and the target size.

ratio decreases with the increase of the target size. The 150 mm diameter target was sprayed with coverage diameter of ~250 mm, whereas a 300 mm diameter target was sprayed with coverage of ~425 mm.

3.2 Agri-robotic platforms: description and experiments

A robotic platform was designed and built to serve as a research tool for investigating methods and devices designated for the agricultural domain in general and specifically for vineyard operations (Berenstein, 2016). The robot was designed to include all the necessary equipment, hardware and software required to accomplish autonomous and semi-autonomous (human-assisted) field tasks such as navigation along the vineyard row and spraying accurately towards the target area using the ASD (Section 3.1) (Berenstein and Edan, 2017).

3.2.1 Platform description

The robotic chassis (Fig. 12a) is assembled from two identical platforms that are interconnected using a two degrees of freedom (DOF) universal joint (cardan joint). The first DOF is used to improve the turning radius and the second DOF allows the platform designers to neglect the need for a complicated suspension system. Although the robot is capable of turning using differential steering, allowing a relative angle between the platforms contributes to a smaller turning radius and minimizes side slip of the wheels, resulting in reduced wear of the vehicle and less ground trace. The platform payload is designed for 300 kg. A modular approach is taken with four identical wheel modules. Each wheel module consists of an ATV wheel (0.5 m diameter), wheel shoulder that connects the wheel to the platform and a 24 V-480 W electric motor. The electric motor is fixed to the platform and connected to the wheel using chain wheels. Using incremental encoders connected to each wheel, the wheel position and speed can be controlled using a developed kinematic model (Berenstein, 2016; Zaidner and Shapiro, 2016).

The robot is equipped with an electrical box that is mounted on to the front platform and contains a PC with an i7 processor, 7" touch screen, two electric motor controllers (Roboteq AX3500) and some small peripheral aids (e.g. Arduino boards, step motor controller). Other equipment is mounted on the platform including two colour cameras (Microsoft LifeCam Studio) (one facing forward for navigation and the second facing sideways for target detection), two car batteries 12 V 110 A/h, power generator 2500 W (Geko 2801) and commercial sprayer (200 L tank with internal combustion engine connected to a liquid pressure pump). A gamepad controller (Microsoft Xbox 360) is wirelessly connected to the robot platform and is used for manual manoeuvring of the robotic platform.

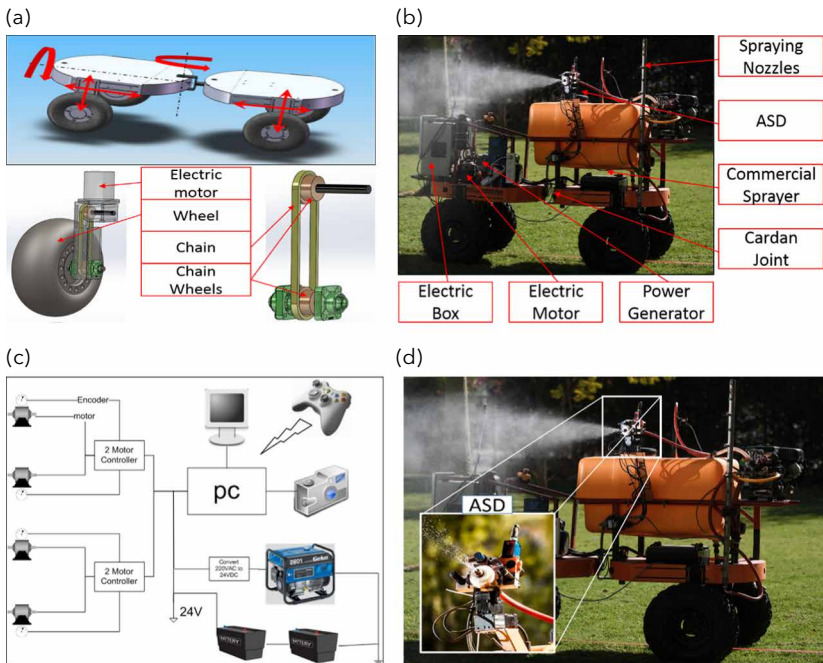


Figure 12 Robotic sprayer. (a) CAD drawing of two identical platforms interconnected using a two-DOF universal joint and wheel unit, (b) complete robotic sprayer with all of the main components and peripheral accessories attached, (c) robotic sprayer electric power scheme, (d) a focused ASD image within the overall robotic sprayer (lower right).

The robot uses a fan-less spraying design in order to minimize the spraying drift and to achieve highly accurate spraying. The focus of the current experiments was to evaluate the detection and control aspects of the sprayer. It must be noted that it is important to follow up with agronomy experiments to validate the sprayer efficiency.

3.2.2 An integrative site-specific sprayer experiment

An experiment was designed to evaluate the human-robot collaboration framework for the site-specific target spraying task, focusing on the integrative performance of the three main components of the collaboration framework that were previously tested and evaluated separately: human marking methods (Berenstein and Edan, 2012a), levels of human-robot collaboration (Berenstein and Edan, 2012b) and the spraying device (Berenstein and Edan, 2018). For simplification and better control and evaluation, artificial targets were set in an artificial outdoor environment. The human-robot task was to spray the targets as accurately as possible, within a limited time frame that corresponded to the

sprayer speed as it advanced along the row. To simulate real-world conditions the human operator was located at Ben-Gurion University of the Negev, Be'er Sheva, Israel, 90 km south of the robotic platform, which was located at Beit Dagan, Israel.

To focus on the target detection/spraying tasks, the robotic platform was programmed to autonomously follow a red line on the floor (red plastic strip 50 mm width) that was fixed at a 1.6 m distance in parallel to the target's base (Fig. 13a). During each step, the robot travels 1 m to completely change the current frame point of view. The robot's travel speed was set to 0.2 m/s. The ASD was mounted on to the robot, perpendicular to the robot's travel direction, facing the target's base (Fig. 13). Fifty targets were randomly spread along an 18 m long path and were set at least 20 cm apart, imitating grape clusters.

Artificial targets were constructed from blue polyethylene plastic and were hand cut according to four shape patterns (Berenstein and Edan, 2017). In order to be as close as possible to commercial field conditions, the experiment included pre-defined TP and FP rates. Two types of targets were used: 38 targets that can be detected by the robotic sprayer (targets with a red circle in the middle of the target) and 12 targets that cannot be detected by the robotic sprayer (targets with a yellow circle in the middle of the target).

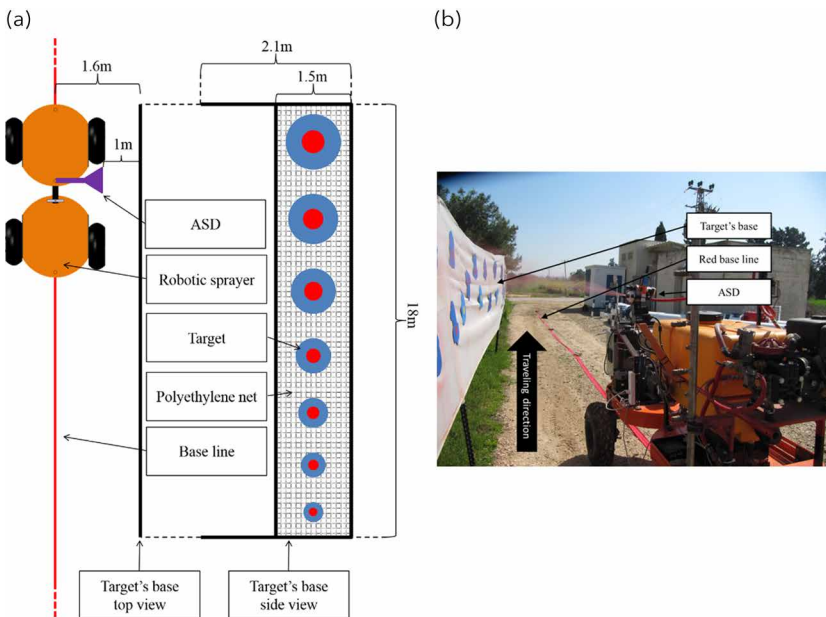


Figure 13 Robotic platform following red strip. (a) Experimental scheme including the robotic platform and target base and (b) a photo of the robotic platform during the experiment.

An artificial target detection algorithm was developed specifically for detecting the artificial targets and the colour of the circle in the middle (red for robot detectable and yellow for targets not detected). The target detection algorithm was based on simple colour thresholding and was implemented using MATLAB software equipped with the image processing toolbox. The algorithm was based on isolating the blue target in the image (the background of the image is the target base, which is white in colour) and identifying the colour of the circle in mid-target.

Since artificial targets were used in the experiment, the artificial target detection algorithm can reach a 100% TP rate and close to zero FP. In order to match vineyard field conditions, an FP area was added to the detected target surroundings. The pre-defined FPs were added using the MATLAB image processing tool. The mathematical morphology operation dilation was used to expand the computer detected target. Since each of the captured images is unique in the sense of different numbers of targets, target orientation and position, the added FP area is different for each image. The FP rate was set between 10% and 20%, corresponding to field FP results evaluated in Berenstein et al. (2010) in field conditions with an average of 17.3% (with a standard deviation of 5.5).

Using the ASD, the targets were sprayed with red water-soluble food dye (Florma red 696). Each target was sprayed for 1 s and immediately after the spraying operation stopped, an image of the spray was captured and saved.

The communication between the robot and the remote human was based on the TCP-IP protocol. The robot obtained internet access using a smartphone HotSpot (4G LTE with random switching to 3G). The remote human-computer was connected to a high-speed academic network (Ben-Gurion University of the Negev internet) with a maximum rate of 1 Gbit/s.

The human task was to mark the target area using one of the marking methods and one of the suggested human-robot collaborations described above. The human used a desk computer equipped with a 21" screen. Each user was trained before the experiment with 20 images according to the training rate evaluated in Berenstein and Edan (2012a).

The spray quality was evaluated using four methods:

- 1 Marking comparison: comparison between the targets that exist in the image and the marked areas. The performance measures were TP and FP rates.
- 2 Spraying comparison: comparison between the targets that exist in the image and the theoretically sprayed areas. The performance measures were TP and FP rates.
- 3 Qualitative evaluation: analysis of the sprayed target (Fig. 14). Each sprayed target image was presented to an expert and was graded on a 1-5 scale (Fig. 14). The performance measure was the TP rate.

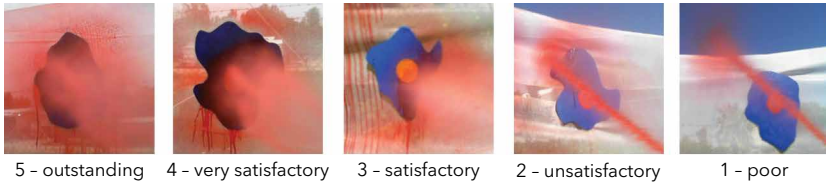


Figure 14 Target spraying evaluation scale 5 (outstanding)→1 (poor).

- 4 Spraying material estimation: an estimation of the quantity of spraying material used was conducted based on the ASD development results (Berenstein and Edan, 2018). The estimation compares the quantity of liquid that was used in each of the spraying experiments above compared to a simulated experiment of the robot continuously driving along the targets' base with three open nozzles (similar to the traditional spraying method; Fig. 1b).

Twenty male and female students aged 25-40 participated in the experiments and were divided into two groups, one for each marking method (CDC and free hand). Each participant practised the three collaboration levels. For each collaboration level, the robot travelled a single time along the target base with steps of 1 m. The image switching time was set to 12 s.

For the fourth collaboration level (autonomous) the robot performed ten repetitions in each of which the robot travelled along the target's base with 1 m intervals, captured the target's frame, analysed the captured frame using the artificial target detection algorithm and sprayed towards each of the detected targets.

4 Conclusion

The experimental results of the target marking and collaboration levels indicate that the desired hit and FA values that can be selected by the farmer, and the best marking method and image switching time can be chosen. The highest hit rate was measured while using the first collaboration method (fully manual with no robot assistance). However, this was achieved only for the long switching time. This collaboration level also yielded high FA. When using the faster switching time, the best collaboration level is level 3. The lowest FA was measured while using collaboration level 2 with the free hand marking method for both image switching times.

The ASD and spraying method show the ability to perform the spraying task efficiently and economically. Pesticide application is reduced by spraying individual targets by directing the spraying device towards the centre of the target using a PTU and setting the diameter of the spraying according to the

shape and size of the target (according to the closing circle diameter of the target). The suggested ASD can be incorporated for different agricultural crops and for a variety of commercial applications.

The overall spraying duration for a single target was 11 s. This duration included general software commands, communication between main software and peripherals (MATLAB, Arduino), machine vision, PTU repositioning, spraying nozzle aperture adjustment, spraying and capture of image post-spraying. It also included some software pauses located at critical points of the software. These pauses were used to control the experiment and to verify that the ASD is functioning as designed. The accumulated time of the pauses was 8 s and spray time was 2 s. By eliminating the software pauses, the spraying time for a single target can be reduced to 3 s including the 2 s spraying time. Further time reduction can be achieved by optimizing the machine vision algorithms and the overall ASD control software.

An exercise was conducted to evaluate the possible pesticide savings when using the ASD in comparison with a traditional spraying technique, with the robot travelling at constant speed with open nozzles. The estimation was based on the number of targets (7.89) per frame presented in Berenstein and Edan (2012c) and on a robot travelling speed of 0.33 m/s (speed needed to spray targets for 1 s while using spraying nozzles with spray diameter of 0.33 m). The estimation assumes spraying one side of a single row in a commercial vineyard with a row length of 100 m. The expected pesticide use while using the ASD was 26.27 L and when using traditional spraying techniques (three nozzles constantly open) the expected pesticide use was 48.45 L. The estimation shows that pesticide use can be reduced by up to 45% when using the ASD.

An experiment to evaluate the elements of the collaborative human-robot framework working in sync was designed, implemented and evaluated. The experiment proves the feasibility of human-robot collaboration for the complex task of targeted spraying considering both TP and FP rates. The collaborative spraying system reduces the quantity of sprayed material by 50%, which has both economic and environmental impacts.

Results obtained can be used to implement a human-robot operational system by deciding on the best target-marking method and collaboration level according to the selected criterion. For example, if the TP rate is prioritized to ensure maximum application, full manual collaboration should be employed with a CDC marking method. To achieve the lowest FP rate (to minimize waste of material), collaboration level 2 should be employed using the free hand marking method. This is important since in the spraying task the selected criterion can change along the season depending on the conditions of pests, and environmental and growing conditions. For example, when there is a high risk of dangerous pests it is more important to ensure high coverage of targets (maximize TP rate) than wasted material (FPs). When risks are low the farmer prefers to save spray material as much as possible (minimize FPs).

With minor adaptations, the human-robot collaborative framework can be easily used with other agricultural applications such as fruit picking, yield and disease monitoring and field exploration. For full robot operation, crop-specific target detection (e.g. Berenstein et al., 2010) and navigation algorithms (e.g. Rovira-Más et al., 2015) must be integrated. The framework can also be used in other commercial applications that require complex target detection such as border control and hazardous material environment.

5 Future trends

The modern agricultural industry is facing several challenges such as worldwide population growth and ageing (Gerland et al., 2014), climate changes affecting crops and migration (both rural-to-urban and political). Using field robots in the agricultural industry may help humanity to cope with these challenges.

As described in Section 2, several agricultural robots were developed and tested over the past three decades; however, there are several challenges that must be solved before deploying these robots in a commercial environment. BlueRiver is the first to present a smart commercial agricultural-selective sprayer. The BlueRiver device is carried by a tractor in the field driven by a human. By using deep-learning techniques and deploying GPUs at the edge, they were able to develop a reliable weed detection system. Developing an autonomous spraying robot brings new challenges such as accuracy of the navigation and spraying, the robustness of the system to weather, light, thermal and other external factors in the field. Other limitations are the safety and legal aspects. An autonomous robot operating in the field must be safe to humans and animals that might enter along the robot's operations. As the robot may be considered as an agent acting on the behalf of others, legal responsibility for the actions of a robot falls on the individual who grants the robot permission to act on their behalf (Asaro, 2007).

Future research can also concentrate on improving the human-remote perception by adding advanced sensors (e.g. stereo vision, 3D cameras, a combination of RGB and LIDAR). It must be noted that if sensors are added, efficient design methods must be employed to display the sensed information so as to maximize information display while minimizing distraction. Hence this is an area recommended for future research. However, evaluating the robotic sprayer performance in real-world conditions is necessary.

An advanced remote human interface can also be developed in future work. We suggest that such an interface be implemented on a web platform to allow human control from different devices, such as smartphones, handheld computers, tablets and laptops. Another subject for future work related to the interface design can be the evaluation of different pointing devices such as touch screen, 3D mouse and a digital pen, and their effect on the human

marking performance similar to what has been recently investigated by Adamides (2016) for teleoperation tasks.

In order to maximize the farmer's benefits, the overall spraying process must be economically optimized. Both the robotic sprayer and the human operator have operational costs (e.g. pesticide material, human salary, robot power consumption); the sprayed pesticides also influence the economics of the system (e.g. a sprayer missing the fruit can draw pests and damage the crop, and over-spraying can damage the foliage and exceed pesticide regulations).

6 Where to look for further information

Agricultural engineering journals and conferences are the best source for past and up-to-date information. One of the leading sources is the *Journal of Field Robotics* that presents the state-of-the-art research on agricultural robotics in general.

Other sources of information can be found in the leading agricultural and engineering journals and conferences:

- International Conference on Robotics and Automation (ICRA)
- *Biosystems Engineering*
- *IEEE Transactions on Automation Science and Engineering (T-ASE)*
- *IEEE Transactions on Robotics*
- AgEng Conference

7 References

- Adamides, G. 2016. User interfaces for human-robot interaction: Application on a semi-autonomous agricultural robot sprayer. Ph.D. thesis. Open University of Cyprus.
- Adamides, G., Katsanos, C., Constantinou, I., Christou, G., Xenos, M., Hadzilacos, T. and Edan, Y. 2017. Design and development of a semi-autonomous agricultural vineyard sprayer: Human-robot interaction aspects. *Journal of Field Robotics* 34(8), 1407-26. doi:10.1002/rob.21721.
- Arima, S., Shibusawa, S., Kondo, N. and Yamashita, J. 2003. Traceability based on multi-operation robot: Information from spraying, harvesting and grading operation robot. *Proceedings 2003 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM 2003)*, 20-24 July 2003, pp. 1204-9, vol. 2.
- Asaro, P. M. 2007. Robots and responsibility from a legal perspective. *Proceedings of the IEEE International Conference on Robotics and Automation*, Rome, pp. 20-4.
- Bac, C. W., Henten, E. J., Hemming, J. and Edan, Y. 2014. Harvesting robots for high-value crops: State-of-the-art review and challenges ahead. *Journal of Field Robotics* 31(6), 888-911. doi:10.1002/rob.21525.
- Bak, T. and Jakobsen, H. 2004. Agricultural robotic platform with four wheel steering for weed detection. *Biosystems Engineering* 87(2), 125-36. doi:10.1016/j.biosystemseng.2003.10.009.

- Berenstein, R. 2016. A human-robot cooperative vineyard selective sprayer. Ph.D. thesis, Ben-Gurion University of the Negev.
- Berenstein, R. and Edan, Y. 2012a. Evaluation of marking techniques for a human-robot selective vineyard sprayer. *International Conference of Agricultural Engineering (CIGR-AgEng)*, Valencia, Spain (Unpublished), C-1090.
- Berenstein, R. and Edan, Y. 2012b. Human-robot cooperative precision spraying: Collaboration levels and optimization function. *Symposiums on Robot Control (SYROCO)*, Dubrovnik, Croatia (Unpublished).
- Berenstein, R. and Edan, Y. 2012c. Robotic precision spraying methods. *ASABE Annual International Meeting*, Dallas, Texas.
- Berenstein, R. and Edan, Y. 2017. Human-robot collaborative site-specific sprayer. *Journal of Field Robotics* 34(8), 1519–30. doi:10.1002/rob.21730.
- Berenstein, R. and Edan, Y. 2018. Automatic adjustable spraying device for site-specific agricultural application. *IEEE Transactions on Automation Science and Engineering* 15(2), 641–50. doi:10.1109/TASE.2017.2656143.
- Berenstein, R., Shahar, O. B., Shapiro, A. and Edan, Y. 2010. Grape clusters and foliage detection algorithms for autonomous selective vineyard sprayer. *Intelligent Service Robotics* 3(4), 233–43. doi:10.1007/s11370-010-0078-z.
- Berenstein, R., Hočevar, M., Godeša, T., Edan, Y. and Ben-Shahar, O. 2015. Distance-dependent multimodal image registration for agriculture tasks. *Sensors* 15(8), 20845–62. doi:10.3390/s150820845.
- Blasco, J., Aleixos, N., Roger, J. M., Rabatel, G. and Molto, E. 2002. AE–Automation and emerging technologies: Robotic weed control using machine vision. *Biosystems Engineering* 83(2), 149–57. doi:10.1006/bioe.2002.0109.
- Bradley, D., Thayer, S., Stentz, A. and Rander, P. 2004. Vegetation detection for mobile robot navigation. Tech. Rep. CMU-RI-TR-04-12. Pittsburgh, PA: Robotics Institute, Carnegie Mellon University.
- Breiman, L., Friedman, J., Stone, C. J. and Olshen, R. A. 1984. *Classification and Regression Trees*. CRC Press.
- Bulanon, D. M., Kataoka, T., Okamoto, H. and Hata, S. 2004. Development of a real-time machine vision system for the apple harvesting robot. *SICE 2004 Annual Conference*, 4–6 August 2004, pp. 595–8, vol. 1.
- Bulanon, D. M., Burks, T. F. and Alchanatis, V. 2009. Image fusion of visible and thermal images for fruit detection. *Biosystems Engineering* 103(1), 12–22. doi:10.1016/j.biosystemseng.2009.02.009.
- Canny, J. 1986. A computational approach to edge detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 8(6), 679–98. doi:10.1109/TPAMI.1986.4767851.
- Chang, C.-L. and Song, G.-B. 2017. Vision-based guidance control scheme for autonomous navigation of 4WDS agricultural vehicle in a narrow space environment. *2017 ASABE Annual International Meeting*. St. Joseph, MI: ASABE.
- Chang, C.-L., Song, G.-B. and Lin, K.-M. 2016. Two-stage guidance control scheme for high-precision straight-line navigation of a four-wheeled planting robot in a greenhouse. *Transactions of the American Society of Agricultural and Biological Engineers* 59(5), 1193–204. doi:10.13031/trans.59.11801.
- Cho, S. I. and Ki, N. H. 1999. Autonomous speed sprayer guidance using machine vision and fuzzy logic. *Transactions of the American Society of Agricultural Engineers* 42, 1137–43.

- Conner, D. C., Greenfield, A., Atkar, P. N., Rizzi, A. A. and Choset, H. 2005. Paint deposition modeling for trajectory planning on automotive surfaces. *IEEE Transactions on Automation Science and Engineering* 2(4), 381-92. doi:10.1109/TASE.2005.851631.
- Dasgupta, S., Meisner, C., Wheeler, D., Xuyen, K. and Thi Lam, N. 2007. Pesticide poisoning of farm workers-implications of blood test results from Vietnam. *International Journal of Hygiene and Environmental Health* 210(2), 121-32. doi:10.1016/j.ijheh.2006.08.006.
- Diago, M., Correa, C., Millan, B., Valero, C., Barreiro, P. and Tardaguila, J. 2012. Grapevine yield and leaf area estimation using supervised classification methodology on RGB images taken under field conditions. *Sensors* 12, 1698-706.
- Diao, X. D., Zeng, S. X. and Tam, V. W. Y. 2009. Development of an optimal trajectory model for spray painting on a free surface. *Computers and Industrial Engineering* 57(1), 209-16. doi:10.1016/j.cie.2008.11.010.
- Edan, Y., Kondo, N. and Shufeng, H. 2009. Automation in agriculture. In: Nof, S. Y. (Ed.), *Handbook of Automation*. Berlin: Springer Verlag.
- Elkabetz, P., Edan, Y., Grinstein, A. and Pasternak, H. 1998. Simulation model for evaluation of site-specific sprayer design. *ASAE Annual International Meeting*, Orlando, FL.
- English, A., Ross, P., Ball, D. and Corke, P. 2014. Vision based guidance for robot navigation in agriculture. *2014 IEEE International Conference on Robotics and Automation (ICRA)*, 31 May-7 June 2014, pp. 1693-8.
- From, P. J., Gunnar, J. and Gravidahl, J. T. 2011. Optimal paint gun orientation in spray paint applications-experimental results. *IEEE Transactions on Automation Science and Engineering* 8(2), 438-42. doi:10.1109/TASE.2010.2089450.
- Gat, G., Gan-Mor, S. and Degani, A. 2016. Stable and robust vehicle steering control using an overhead guide in greenhouse tasks. *Computers and Electronics in Agriculture* 121, 234-44. doi:10.1016/j.compag.2015.12.019.
- Gazquez, J. A., Castellano, N. N. and Manzano-Agugliari, F. 2016. Intelligent low cost telecontrol system for agricultural vehicles in harmful environments. *Journal of Cleaner Production* 113, 204-15. doi:10.1016/j.jclepro.2015.11.015.
- Gerland, P., Raftery, A. E., Ševčíková, H., Li, N., Gu, D., Spoorenberg, T., Alkema, L., Fosdick, B. K., Chunn, J., Lalic, N., et al. 2014. World population stabilization unlikely this century. *Science* 346(6206), 234-7. doi:10.1126/science.1257469.
- Gil, E., Escol, A., Rosell, J. R., Planas, S. and Val, L. 2007. Variable rate application of plant protection products in vineyard using ultrasonic sensors. *Crop Protection* 26(8), 1287-97. doi:10.1016/j.cropro.2006.11.003.
- González, R. S., Rodríguez, F., Sánchez-Hermosilla, J. and Donaire, J. G. 2009. Navigation techniques for mobile robots in greenhouses. *Applied Engineering in Agriculture* 25(2), 153-65. doi:10.13031/2013.26324.
- Goudy, H. J., Bennett, K. A., Brown, R. B. and Tardif, F. J. 2001. Evaluation of site-specific weed management using a direct-injection sprayer. *Weed Science* 49(3), 359-66. doi:10.1614/0043-1745(2001)049[0359:EOSWJM]2.0.CO;2.
- Guan, Y., Chen, D., He, K., Liu, Y. and Li, L. 2015. Review on research and application of variable rate spray in agriculture. *IEEE 10th Conference on Industrial Electronics and Applications (ICIEA)*. IEEE, pp. 1575-80.
- Hannan, M., Burks, T. and Bulanon, D. M. 2010. A machine vision algorithm combining adaptive segmentation and shape analysis for orange fruit detection. *Agricultural Engineering International: CIGR Journal*.

- Harper, N. and McKerrow, P. 2001. Recognising plants with ultrasonic sensing for mobile robot navigation. *Robotics and Autonomous Systems* 34(2-3), 71-82. doi:10.1016/S0921-8890(00)00112-3.
- Hiremath, S. A., Van Der Heijden, G. W. A. M., Van Evert, F. K., Stein, A. and Ter Braak, C. J. F. 2014. Laser range finder model for autonomous navigation of a robot in a maize field using a particle filter. *Computers and Electronics in Agriculture* 100, 41-50. doi:10.1016/j.compag.2013.10.005.
- Huang, Y., Hoffmann, C., Fritz, B. and Lan, Y. 2008. Development of an unmanned aerial vehicle-based spray system for highly accurate site-specific application. *ASAE Annual International Meeting*, Rhode Island.
- Jeon, H. Y., Tian, L. F. and Grift, T. 2005. Development of an individual weed treatment system using a robotic arm. *ASABE Annual International Meeting*, Tampa, FL.
- Jiang, G., Zhao, C. and Si, Y. 2010. A machine vision based crop rows detection for agricultural robots. *2010 International Conference on Wavelet Analysis and Pattern Recognition*, 11-14 July 2010, pp. 114-18.
- Kapach, K., Barnea, E., Mairon, R., Edan, Y. and Ben-Shahar, O. B. 2012. Computer vision for fruit harvesting robots-state of the art and challenges ahead. *International Journal of Computational Vision and Robotics* 3(1/2), 4-34. doi:10.1504/IJCVR.2012.046419.
- Komasilovs, V., Stalidzans, E., Osadcuks, V. and Mednis, M. 2013. Specification development of robotic system for pesticide spraying in greenhouse. *2013 IEEE 14th International Symposium on Computational Intelligence and Informatics (CINTI)*, 19-21 November 2013, pp. 453-7.
- Lameski, P., Zdravetski, E. and Kulakov, A. 2018. Review of automated weed control approaches: An environmental impact perspective. In: Kalajdziski, S. and Ackovska, N. (Eds), *ICT Innovations 2018. Engineering and Life Sciences. ICT 2018. Communications in Computer and Information Science*, vol. 940. Cham: Springer, pp. 132-47.
- Lamm, R., Slaughter, D. and Giles, D. 2002. Precision weed control system for cotton. *Transactions of the American Society of Agricultural Engineers* 45, 231-8.
- Lee, W. S., Slaughter, D. C. and Giles, D. K. 1999. Robotic weed control system for tomatoes. *Precision Agriculture* 1(1), 95-113. doi:10.1023/A:1009977903204.
- Li, M., Imou, K., Wakabayashi, K. and Yokoyama, S. 2009. Review of research on agricultural vehicle autonomous guidance. *International Journal of Agricultural and Biological Engineering* 2, 1-16.
- Luo, L., Tang, Y., Zou, Z., Wang, C., Zhang, P. and Feng, W. 2016. Robust grape cluster detection in a vineyard by combining the AdaBoost framework and multiple color components. *Sensors* 16, 2098-312.
- Mandow, A., Gomez-De-Gabriel, J. M., Martinez, J. L., Munoz, V. F., Ollero, A. and Garcia-Cerezo, A. 1996. The autonomous mobile robot Aurora for greenhouse operation. *IEEE Robotics and Automation Magazine* 3(4), 18-28. doi:10.1109/100.556479.
- McCool, C. S., Beattie, J., Firn, J., Lehnert, C., Kulk, J., Bawden, O., Russell, R. and Perez, T. 2018. Efficacy of mechanical weeding tools: A study into alternative weed management strategies enabled by robotics. *IEEE Robotics and Automation Letters* 3, 1184-90. doi:10.1109/LRA.2018.2794619.
- Nishiwaki, K., Amaha, K. and Otani, R. 2004. Development of nozzle positioning system for precision sprayer. *Automation Technology for Off-Road Equipment, Kyoto, Japan*. Kyoto, Japan.

- Oberti, R., Marchi, M., Tirelli, P., Calcante, A., Iriti, M., Tona, E., Hočevár, M., Baur, J., Pfaff, J., Schütz, C., et al. 2016. Selective spraying of grapevines for disease control using a modular agricultural robot. *Biosystems Engineering* 146, 203–15. doi:10.1016/j.biosystemseng.2015.12.004.
- Ogawa, Y., Kondo, N., Monta, M. and Shibusawa, S. 2006. *Spraying Robot for Grape Production: Springer Tracts in Advanced Robotics*. Berlin: Springer.
- Pérez-Ruiz, M., Slaughter, D. C., Fathallah, F. A., Gliever, C. J. and Miller, B. J. 2014. Co-robotic intra-row weed control system. *Biosystems Engineering* 126, 45–55. doi:10.1016/j.biosystemseng.2014.07.009.
- Pérez-Ruiz, M., Gonzalez-De-Santos, P., Ribeiro, A., Fernández-Quintanilla, C., Peruzzi, A., Vieri, M., Tomic, S. and Agüera, J. 2015. Highlights and preliminary results for autonomous crop protection. *Computers and Electronics in Agriculture* 110, 150–61. doi:10.1016/j.compag.2014.11.010.
- Pergher, G. and Petris, R. 2008. Pesticide dose adjustment in vineyard spraying and potential for dose reduction. *Agricultural Engineering International: The CIGR EJournal X*.
- Peteinatos, G. G., Weis, M., Andújar, D., Rueda Ayala, V. and Gerhards, R. 2014. Potential use of ground-based sensor technologies for weed detection. *Pest Management Science* 70(2), 190–9. doi:10.1002/ps.3677.
- Pimentel, D. and Lehman, H. 1993. *The Pesticide Question: Environment, Economics, and Ethics*. London: Chapman & Hall.
- Reid, J. F., Zhang, Q., Noguchi, N. and Dickson, M. 2000. Agricultural automatic guidance research in North America. *Computers and Electronics in Agriculture* 25(1-2), 155–67. doi:10.1016/S0168-1699(99)00061-7.
- Reus, J., Leendertse, P., Bockstaller, C., Fomsgaard, I., Gutsche, V., Lewis, K., Nilsson, C., Pussemier, L., Trevisan, M., Van Der Werf, H., et al. 2002. Comparison and evaluation of eight pesticide environmental risk indicators developed in Europe and recommendations for future use. *Agriculture, Ecosystems and Environment* 90(2), 177–87. doi:10.1016/S0167-8809(01)00197-9.
- Rogan, W. J. and Chen, A. 2005. Health risks and benefits of bis (4-chlorophenyl)-1, 1,1-trichloroethane (DDT). *The Lancet* 366(9487), 763–73. doi:10.1016/S0140-6736(05)67182-6.
- Rovira-Más, F., Reid, F. J. and Zhang, Q. 2006. Stereovision data processing with 3D density maps for agricultural vehicles. *Transactions of the American Society of Agricultural and Biological Engineers* 49, 1213–22.
- Rovira-Más, F., Millot, C. and Sáiz-Rubio, V. 2015. Navigation strategies for a vineyard robot. *ASABE Annual International Meeting*, Orleans, LA.
- Sa, I., Ge, Z., Dayoub, F., Upcroft, B., Perez, T. and McCool, C. 2016. DeepFruits: A fruit detection system using deep neural networks. *Sensors* 16(8), 1222. doi:10.3390/s16081222.
- Sahir Arıkan, M. A. and Balkan, T. 2000. Process modeling, simulation, and paint thickness measurement for robotic spray painting. *Journal of Robotic Systems* 17(9), 479–94. doi:10.1002/1097-4563(200009)17:9<479::AID-ROB3>3.0.CO;2-L.
- Sharifi, M., Fathy, M. and Mahmoudi, M. T. 2002. A classified and comparative study of edge detection algorithms. *International Conference Proceedings on Information Technology: Coding and Computing*. IEEE, pp. 117–20.
- Singh, S., Burks, T. F. and Lee, W. S. 2005. Autonomous robotic vehicle development for greenhouse spraying. *Transactions of the American Society of Agricultural Engineers* 48, 2355–61.

- Slaughter, D. C., Giles, D. K. and Downey, D. 2008. Autonomous robotic weed control systems: A review. *Computers and Electronics in Agriculture* 61(1), 63-78. doi:10.1016/j.compag.2007.05.008.
- Song, Y., Sun, H., Li, M. and Zhang, Q. 2015. Technology application of smart spray in agriculture: A review. *Intelligent Automation and Soft Computing* 21(3), 319-33. doi: 10.1080/10798587.2015.1015781.
- Steward, B. L., Tian, L. F. and Tang, L. 2002. Distance-based control system for machine vision-based selective spraying. *Transactions of the American Society of Agricultural Engineers* 45, 1255.
- Strand, B. and Baerveldt, A. J. 2002. An agricultural mobile robot with vision-based perception for mechanical weed control. *Autonomous Robots* 13(1), 21-35. doi:10.1023/A:1015674004201.
- Swan, S. H., Kruse, R. L., Liu, F., Barr, D. B., Drobnis, E. Z., Redmon, J. B., Wang, C., Brazil, C. and Overstreet, J. W. 2003. Semen quality in relation to biomarkers of pesticide exposure. *Environmental Health Perspectives* 111(12), 1478-84. doi:10.1289/ehp.6417.
- Tellaeché, A., Burgosartizú, X. P., Pajares, G., Ribeiro, A. and Fernández-Quintanilla, C. 2008. A new vision-based approach to differential spraying in precision agriculture. *Computers and Electronics in Agriculture* 60(2), 144-55. doi:10.1016/j.compag.2007.07.008.
- Toda, M., Kitani, O., Okamoto, T. and Torii, T. 1999. Navigation method for a mobile robot via sonar-based crop row mapping and fuzzy logic control. *Journal of Agricultural Engineering Research* 72(4), 299-309. doi:10.1006/jaer.1998.0371.
- Vázquez-Arellano, M., Griepentrog, H. W., Reiser, D. and Paraforos, D. S. 2016. 3-D imaging systems for agricultural applications—A review. *Sensors* 16(5), 618. doi:10.3390/s16050618.
- Vitzrabin, E. and Edan, Y. 2016. Adaptive thresholding with fusion using a RGBD sensor for red sweet-pepper detection. *Biosystems Engineering* 146, 45-56. doi:10.1016/j.biosystemseng.2015.12.002.
- Vuong, V. L., Slaughter, D. C., Nguyen, T. T., Fennimore, S. A. and Giles, D. K. 2017. An automated system for crop signaling and robotic weed control in processing tomatoes. *2017 ASABE Annual International Meeting*. St. Joseph, MI: ASABE.
- Xue, J. and Xu, L. 2010. Autonomous agricultural robot and its row guidance. *2010 International Conference on Measuring Technology and Mechatronics Automation*, 13-14 March 2010, pp. 725-9.
- Zaidner, G. and Shapiro, A. 2016. A novel data fusion algorithm for low-cost localisation and navigation of autonomous vineyard sprayer robots. *Biosystems Engineering* 146, 133-48. doi:10.1016/j.biosystemseng.2016.05.002.
- Zhao, D. J., Zhao, Y., Wang, X. L. and Zhang, B. 2016. Theoretical design and first test in laboratory of a composite visual servo-based target spray robotic system. *Journal of Robotics* 2016, 1-11. doi:10.1155/2016/1801434.